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FIN11 Trading and Market Microstructure

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FIN11 Term Paper

Trading in European Carbon Allowances

Information Efficiency and Short-Run Trading Opportunities in EUA contracts



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Abstract

With annual trading volumes of around EUR 770 billion, EU emission allowances (EUAs) have developed into the world's largest financial climate asset, linking climate policy directly to capital markets. In this paper, we investigate the degree to which EUA prices efficiently incorporate information from coal, gas, and power markets and then examine what this implies for price discovery and speculative trading in EUA contracts.

Using daily data from 2013–2025, we analyze long-run price formation through cointegration analysis and short-run return dynamics using VAR models, impulse responses, forecast error variance decompositions, and Granger causality tests. To contextualize the empirical results within actual market practice, we complement the analysis with interviews of professional traders, including Ola Kvennås (Statkraft) and Morten Nilsen (Kinect Energy).

The evidence reveals a clear asymmetry in price discovery. Coal and power prices anchor the long-run equilibrium of EUA prices, consistent with fuel-switching fundamentals. In contrast, short-run EUA returns behave like those of a highly liquid financial asset: shocks from fuel markets are absorbed within one to two trading days. Fuel-price shocks explain only a small share of EUA return variance, and causal relationships are weak, unstable, and often statistically insignificant. Interview insights reinforce this pattern, pointing to speculative positioning, liquidity constraints, and risk limits, rather than fuel-price information.

From a market microstructure perspective, the near absence of short-run pass through from fuel markets to EUA returns indicates a high degree of short horizon informational efficiency. Publicly observable fuel prices provide almost no incremental information beyond what is already incorporated into EUA prices. Instead, short-run EUA dynamics appear to be dominated by speculative order flow, liquidity conditions, and trader positioning as emphasized in the trader interviews. For market participants, simple trading strategies based on public fuel or spread signals are unlikely to yield persistent excess returns. Short-term carbon trading instead behaves much more like a financial market, where price changes largely reflect microstructure-driven information processing rather than fundamental shifts in fuel costs.

1. Introduction 4
2. Background 5
3. Theoretical Framework 6
3.1 Carbon Pricing and Fuel Switching 6
3.2 Market Microstructure and Liquidity Effects 7
3.3 Price Discovery and Cointegration 8
3.4 Carbon as a Financial Asset 8
3.5 Long-Term Price Formation and Integrated Framework 9
4. Data 10
4.1 Data sources and sample period 10
4.2 Variable construction and transformation 10
4.3 Descriptive statistics 12
4.4 Stationarity tests 13
5. Methodology 15
5.1 Framework 15
5.2 VECM specification 16
5.3 VAR specification 16
5.4 Dynamic Interdependence Analysis: IRFs, ... 17
5.5 FEVD and Granger Causality 18
6. Analysis 18
6.1 VECM main results and interpretation 18
6.2 Energy model: Power-Coal-Gas-EUA 21
6.3 Margin model: CSS-CDS-EUA 24
6.4 Comparison of the energy and margin models 28
6.5 Main findings 28
7. Reflection and weaknesses 29
8. Conclusion 30
9. Sources 31
Declaration on the use of AI tools in the work on this assignment 33
10. Appendix 34
Interviews 34
IRF figures 39
Codes 43

1. Introduction

An EU allowance (EUA) is a tradable permit in the EU Emissions Trading System (EU ETS) that gives the holder the right to emit one metric ton of CO_2-equivalent during a compliance period. Since the launch of the EU ETS in 2005, EUAs have evolved from a policy instrument into one of the largest environmental assets in global financial markets (European Commission, n.d.). In 2023, the value of traded carbon allowances worldwide reached about EUR 881 billion, of which roughly EUR 770 billion (around 87%) came from the EUAs, making it by far the dominant segment of global carbon markets. The market supports daily trading of about EUR 3 billion in EUAs for spot contracts, and roughly ten times that amount for futures contracts (Homaio, 2024). A large share of this activity is intermediated by financial institutions, highlighting how the EUA market has developed into a trading arena for both compliance buyers and financial investors, with an expanding scope for speculative participation (European Securities and Markets Authority, 2025).

As EUA trading has expanded, carbon and energy markets have become increasingly intertwined. In Europe's power sector, coal- and gas-fired plants take both fuel prices and the cost of carbon allowances into account when deciding how to operate. Shifts in fuel prices and EUA prices affect which technology sits at the margin. When gas becomes expensive relative to coal, or vice versa, the marginal technology often switches. Expected emissions change, and so does demand for EUAs (Ampudia et al., 2022). Because of these links, price developments in coal, gas and power markets are natural reference points for traders when forming expectations about short-run movements in EUA prices. These interactions matter for both traders and hedgers, because the way EUA prices adjust to energy-market shocks affects how carbon and fuel price risk is perceived and managed in practice.

To ground our study in market practice, we interviewed Ola Kvennås, Head of Nordic Trading at Statkraft. He noted: *"If you do your homework and check the numbers, it doesn't matter whether you're trading against Goldman, Citadel, or anyone else. Even an ordinary person in front of a PC in Trøndelag can compete with the big players if the analysis is good enough."* His remark highlights that EUA trading has become a competitive arena where both large institutions and smaller traders meet, and that any edge depends on how well available information is analyzed. In a market where EUA prices are closely linked to coal, gas and power, we investigate how strongly information from these energy markets is incorporated into EUA prices. We also examine whether short-run movements in these markets leave room

for speculative trading strategies. Motivated by these considerations, we pose the following research question:

"How informationally efficient are EUA prices with respect to price information from coal, gas, and power markets, and do any short-run adjustment lags create economically exploitable opportunities for speculative trading in the EU ETS?"

2. Background

The EU ETS is a "cap and trade" system designed to deliver cost effective reductions in greenhouse gas emissions and to help the European Union meet its commitments under the Kyoto Protocol. Covered installations must surrender allowances equal to their verified annual emissions, where noncompliance is sanctioned by financial penalties (International Carbon Action Partnership, n.d.). The core principle is that a binding cap creates scarcity, which in turn generates a carbon price that incentivizes abatement and low carbon investment.

Since its launch, the system has been revised several times, with important consequences for market functioning and price dynamics. Phase I (2005–2007) largely served as a pilot, with generous free allocation, no banking between phases, and substantial overallocation of allowances. When verified emissions revealed a large surplus in 2006, EUA prices collapsed and ended phase I at zero, highlighting the need for structural reform in the market. Phase II (2008–2012) tightened the cap and allowed banking into later phases. The global financial crisis again reduced industrial activity and therefore emissions, creating a surplus, so prices remained low and volatile despite increased auctioning and broader coverage (European Commission, n.d.-a).

A more fundamental redesign occurred in Phase III (2013–2020). The system moved from national to a single EU wide cap, expanded the range of covered sectors and greenhouse gases, and shifted toward auctioning as the default allocation rule. Nevertheless, the accumulated surplus continued to depress prices through the mid 2010s. The decision to introduce the Market Stability Reserve (MSR), adopted in 2015 and implemented from 2019, marked a turning point, by automatically adjusting auction volumes in response to the surplus. The MSR transformed the EU ETS from an oversupplied market into one where scarcity is actively managed and EUA prices began a sustained upward trend (European Commission, n.d.-b).

Phase IV (2021–2030) builds on this architecture. Under the “Fit for 55” package, the annual cap reduction has been accelerated, free allocation further restricted, and the maritime sector brought into the system (International Carbon Action Partnership, n.d.). In parallel, the Carbon Border Adjustment Mechanism (CBAM) has been introduced to reduce carbon leakage and strengthen the integrity of the market. As a result, the EU ETS has become a more policy driven market in which expectations about long run scarcity also play a central role in price formation.

3. Theoretical Framework

The interaction between carbon, coal and gas prices in the EU ETS can be understood as the outcome of two tightly linked mechanisms. The first is fundamental: fuel switching in the power sector ties EUA prices to relative fuel costs and technology, so that coal, gas and power prices should anchor the long-run value of carbon. The second mechanism is microstructural: market structure and liquidity determine how fast fuel information enters EUA prices. If the EU ETS is efficient, this happens almost immediately; if not, short-run deviations may create speculative opportunities.

3.1 Carbon Pricing and Fuel Switching

Over successive phases, the EU ETS has evolved into a liquid and financially integrated market. EUAs are actively traded on exchanges such as ICE Endex and the European Energy Exchange (EEX).

Magnus Commodities (2016) explains that the clean dark spread (CDS) and clean spark spread (CSS) represent the theoretical generation margins of coal- and gas-fired plants after accounting for fuel and CO_2 costs.

$$CDS = P_{el} - \frac{P_{coal}}{\eta_{coal}} - EF_{coal} \times P_{CO_2}$$

$$CSS = P_{el} - \frac{P_{gas}}{\eta_{gas}} - EF_{gas} \times P_{CO_2}$$

where P_{el} denotes the electricity price (€/MWh), P_{coal} and P_{gas} are fuel prices (€/MWh fuel), η represents thermal efficiency, EF is the emission factor (tCO_2/MWh), and P_{CO_2} is the EUA price (€/tCO_2).

The implied carbon switching price is based on the idea that fuel costs and plant efficiencies determine the relative marginal cost of coal-and gas-fired power generation. As discussed in Salovaara (2011), variations in fuel prices and conversion efficiencies drive the cost competitiveness between the two technologies. Equating the marginal costs of coal and gas generation and solving for the carbon price yields:

$$P^*_{CO_2} = \frac{\frac{P_{coal}}{\eta_{coal}} - \frac{P_{gas}}{\eta_{gas}}}{EF_{gas} - EF_{coal}}$$

Own derivation based on the marginal cost framework in Salovaara (2011).

3.2 Market Microstructure and Liquidity Effects

Market microstructure theory explains how trading rules, information asymmetries, and liquidity conditions shape price discovery (Harris, 2003). The EUA market is organized primarily as a continuous, order-driven system, where limit and market orders interact in a central order book (ICE Endex, 2023). Market microstructure determines the speed at which fuel information is incorporated into EUA prices: in a highly efficient market with deep liquidity, short-run adjustment lags should be minimal, limiting the scope for speculative trading strategies based on public fuel signals.

High liquidity enables the fast incorporation of new information into prices, whereas low liquidity slows adjustment and increases volatility (Foucault, Pagano, & Röell, 2013, pp. 260–269). Pastor and Stambaugh (2003, p. 642) show that expected returns compensate for exposure to aggregate liquidity risk. In the EU ETS, liquidity shocks can therefore influence both the cost of capital for compliance firms and the expected return on EUA futures.

3.3 Price Discovery and Cointegration

The fuel-switching mechanism and gradual adjustment dynamics discussed in Sections 3.1 can be cast in an econometric framework using cointegration and error-correction models. Following Creti, Jouvet and Mignon (2011), let $P_{CO_2,t}$, $P_{gas,t}$, and $P_{coal,t}$ denote the logarithmic prices of CO_2 allowances, natural gas, and coal. A possible long-run equilibrium specification is:

$$P_{CO_2,t} = \alpha + \beta_1 P_{gas,t} + \beta_2 P_{coal,t} + \varepsilon_t,$$

where stationarity of the residual ε_t indicates that the series are cointegrated. According to the standard cointegration framework of Engle and Granger (1987), short-run adjustments toward the long-run equilibrium can be written in an error-correction form:

$$\Delta P_{CO_2,t} = \phi \varepsilon_{t-1} + \Gamma \Delta X_t + u_t$$

where Γ captures short-term effects and ΔX_t includes changes in fundamentals such as fuel prices. The error-correction coefficient $\phi < 0$ measures the speed at which CO_2 prices return to equilibrium. This is consistent with both the empirical VECM estimates reported by Creti et al. (2011) and the theoretical adjustment mechanism described by Engle and Granger (1987). A more negative ϕ indicates faster correction of deviations and therefore greater market efficiency.

3.4 Carbon as a Financial Asset

As liquidity and speculative participation have grown in the EU ETS, EUAs have increasingly exhibited characteristics associated with financial assets rather than purely compliance instruments (Wei et al., 2024). In this framework, the carbon price can be understood as consisting of two components: a fundamental component tied to the marginal abatement cost of achieving emissions reductions, and an asset-pricing component reflecting risk premia. The latter arises because compliance entities use EUA futures for hedging exposure to energy and policy uncertainty, while investors demand compensation for bearing liquidity, volatility, and regulatory risk (Wei et al., 2024).

This financialization implies that EUA returns may co-move with global risk factors, including broader measures of market uncertainty such as the Chicago Board Options Exchange Volatility Index (VIX). If trading strategies based on deviations from the switching

benchmark earn excess returns, these may reflect not only mispricing but also compensation for bearing policy risk, liquidity risk, and volatility risk captured by indicators such as the VIX. At the same time, if trading strategies based on deviations from switching fundamentals did generate consistent excess returns, this would imply that traders can systematically profit from publicly available fuel-price information. Such a result would directly challenge the informational efficiency of the EU ETS and demonstrate that short-run speculative opportunities can arise even in a market that is widely viewed as mature and highly developed.

3.5 Long-Term Price Formation and Integrated Framework

Long-term allowance prices in the EU ETS are primarily determined by expectations about future scarcity, which in turn depend on the evolution of the emissions cap and the mechanisms governing cumulative supply. The central structural driver is the Linear Reduction Factor (LRF), which reduces the annually issued number of allowances according to a predetermined trajectory (International Carbon Action Partnership, n.d.). This rule-based decline provides a predictable long-term scarcity path and ensures that the cap remains consistent with the EU's climate targets. Because the LRF is fixed by legislation and operates independently of short-term market fluctuations, it anchors long-run price expectations but has limited relevance for high-frequency price dynamics.

A second supply mechanism is the Market Stability Reserve (MSR), which adjusts auction volumes in response to the size of the allowance surplus. When the Total Number of Allowances in Circulation (TNAC) exceeds the upper threshold, the MSR withdraws a fixed share of the surplus; when TNAC falls below the lower threshold, it releases allowances back into the market. Since 2023, excess volumes held in the reserve are also subject to permanent cancellation, further tightening long-run supply. Because these adjustments operate at an annual frequency and primarily influence medium- to long-term scarcity expectations, the MSR does not directly affect short-run EUA return dynamics. (European Commission, n.d.-b.).

While these structural mechanisms anchor long-run price levels, they do not determine how quickly new information is incorporated into EUA prices in real time. Informational frictions, liquidity constraints, and policy uncertainty can delay or distort this adjustment, generating short-term deviations (Chevallier, 2011). Microstructure theory explains how order flow and trading depth mediate the transmission of information (Kyle, 1985). In the long run, the

interaction between these forces ensures convergence between EUA prices and fundamental values. In the short-run, however, mispricings may arise when information diffuses slowly or when liquidity temporarily evaporates.

The combined framework therefore motivates our empirical strategy: long-run cointegration tests whether structural fundamentals anchor EUA prices, while short-run VAR dynamics reveal how quickly the market incorporates new information.

4. Data

This section describes the dataset used in the empirical analysis. We outline the sources, instruments, sample period and transformations, and report key descriptive statistics and stationarity tests.

4.1 Data sources and sample period

All price series are obtained from Refinitiv Eikon´s financial database. The database provides end-of-day quotes for exchange-traded futures and spot indices across carbon, fuel, power and oil markets. For each market, we rely on the standard benchmark contracts used in European trading practice and download continuous time series constructed by the data vendor where available. When prices are originally quoted in USD, we convert them into EUR using daily EUR/USD spot rates, so that all carbon, fuel and power prices are expressed in a consistent currency.

Our analysis is based on daily close price observations from 1. January 2013 to 1. November 2025, therefore focusing on Phase III and IV of the EU ETS. The dataset comprises December maturing continuous EUA futures traded on EEX, monthly ICE Europe Rotterdam coal futures, monthly TRPC natural gas TTF futures, TRPC Electricity German Baseload monthly continuation and ICE Europe Brent Crude Electronic Energy future. All series are mapped to a common daily trading calendar, and we retain all days with valid prices for at least one instrument and use forward fill to complete the dataset.

To capture potential structural changes across ETS phases the sample is split into Phase III (2013-2020) and phase IV (2021-2025).

4.2 Variable construction and transformation

We construct two types of price series:

i. Log price levels

For the core energy system (EUA, coal, gas, power), we transform the prices to log levels which are used for cointegration and VECM analysis:

$$r_t = \ln(P_t)$$

ii. Log returns

We also transform price series to log returns:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Returns are used for the VAR models to analyze short-term dynamics. To reduce the influence of extreme events, the return series are winsorized at the 1st and 99th percentiles.

iii. Clean dark and clean spark spreads

CDS and CSS are constructed from the underlying fuel, power and carbon prices, as explained in the theory section. Since spreads can have negative values and may exhibit structural breaks, we use first differences of the level series:

$$\Delta CSS_t = CSS_t - CSS_{t-1} \qquad \Delta CDS_t = CDS_t - CDS_{t-1}$$

We use differenced spreads in a separate VAR specification evaluating margin dynamics.

4.3 Descriptive statistics

We provide descriptive statistics for all price series, as well as CSS and CDS below.

	Mean	**Std. Dev.**	**Min.**	**Max.**	**Skewness**	**Kurtosis**
EUA return	0.000709	0.033520	-0.43207	0.238234	-1.107998	17.83837
Coal return	-0.000265	0.014617	-0.18134	0.171610	-0.002849	37.23950
Gas return	-0.000356	0.029129	-0.21072	0.381368	2.332044	26.45501
Power return	-0.000094	0.028646	-0.23905	0.259893	0.345247	15.48765
CDS change	0.002435	1.062087	-7.98100	9.978015	0.740959	17.06026
CSS change	0.007494	1.005944	-9.45052	8.073740	-0.697570	19.47956
Power	3.559160	0.220468	2.836150	4.154185	0.168648	0.611166
Coal	4.389129	0.287096	3.727985	4.787519	-0.320944	-1.310057
Gas	2.842047	0.381092	1.289233	3.379293	-1.257886	1.817339
EUA	2.204070	0.662937	1.011601	3.416743	0.545566	-1.252406

Table 1: Phase III descriptive statistics (the level values are log values)

	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis
EUA return	0.000838	0.024823	-0.177347	0.161378	-0.406663	4.899736
Coal return	0.000373	0.035300	-0.532995	0.325766	-2.525028	55.806950
Gas return	0.000633	0.058354	-0.385446	0.478866	0.309748	10.562379
Power return	0.000680	0.054582	-0.277732	0.329984	0.522466	6.511069
CDS change	0.017754	11.787466	-82.658628	102.061853	0.931014	19.324637
CSS change	0.010145	8.683155	-83.153220	79.959580	1.240662	29.915540
Power	4.665846	0.596939	3.437208	6.453625	0.699524	-0.019251
Coal	4.970468	0.440096	4.081725	6.185038	0.791926	0.065256
Gas	3.809805	0.649400	2.561096	5.739793	0.640091	-0.019565
EUA	4.210081	0.292247	3.136798	4.608564	-1.652663	2.603805

Table 2: Phase IV Descriptive statistics

4.4 Stationarity tests

To assess the time series properties of our variables, we apply Augmented Dickey Fuller ADF and KPSS tests to both price levels and return series. The test results (Table 3&4) indicate that log price levels for EUA, fuels and power are non-stationary, while daily log returns and changes in the spread based variables are stationary at conventional significance levels. Stationarity results hold across both phases as well as the phases combined. Our modeling strategy is to use VECM on log-levels for long-run equilibrium relationships and VAR on returns / first differences for short-run dynamics.

	ADF (levels)	ADF p-value	KPSS (levels)	KPSS p-value	ADF (diff/ret)	ADF diff p-value	KPSS (diff/ret)	KPSS diff p-value
EUA	-0.400	0.910	5.366	0.01	-12.971	0.000	0.136	0.1
Coal	-1.449	0.559	1.330	0.01	-42.236	0.000	0.167	0.1
Gas	-2.438	0.131	2.928	0.01	-6.458	0.000	0.062	0.1
Power	-3.051	0.030	0.876	0.01	-46.516	0.000	0.074	0.1
CDS	-2.582	0.097	1.935	0.01	-10.010	0.000	0.046	0.1
CSS	-1.760	0.401	5.592	0.01	-28.737	0.000	0.043	0.1

Table 3: ADF and KPSS on log levels and log returns (diff) for Phase III. N = 2019

	ADF (levels)	ADF p-value	KPSS (levels)	KPSS p-value	ADF (diff/ret)	ADF diff p-value	KPSS (diff/ret)	KPSS diff p-value
EUA	-3.442	0.010	1.990	0.010	-16.732	0.0	0.296	0.1
Coal	-1.941	0.313	1.111	0.010	-34.761	0.0	0.265	0.1
Gas	-2.017	0.279	0.871	0.010	-18.115	0.0	0.247	0.1
Power	-2.163	0.220	0.978	0.010	-12.253	0.0	0.177	0.1
CDS	-2.916	0.044	0.862	0.010	-9.655	0.0	0.029	0.1
CSS	-5.457	0.000	0.499	0.042	-9.994	0.0	0.019	0.1

Table 4: ADF and KPSS on log levels and log returns (diff) for Phase IV. N = 1318

5. Methodology

5.1 Framework

The empirical analysis is grounded in a dynamic market framework in which energy prices, fuel spreads and EUA prices are jointly determined. A vector autoregressive (VAR) model on returns and differenced spreads is therefore an appropriate empirical tool, as it treats all variables as endogenous and captures their mutual interactions over multiple lags (Sims, 1980). To capture more long-run relationships it is appropriate to use a vector error correction model (VECM) for log level series (Johansen, 1988). In addition, we read the short-run coefficients as an indication of how much predictable adjustment could realistically be captured by simple speculative strategies based on public fuel information.

A VAR framework is particularly suitable for analyzing the EUA market for two reasons. First, the simultaneous determination of electricity, coal, gas and carbon prices creates endogeneity problems in standard regression models. VAR models address this by modelling joint dynamics without imposing strong structural assumptions. Second, energy and carbon prices have shown substitution mechanisms in earlier phases, typically between coal and gas in power generation (Alberola et al., 2008). In these scenarios VAR models can represent through impulse responses and forecast error variance decomposition. This is consistent with current findings that emission markets are similar to financial assets, with persistent volatility and nonlinear adjustment patterns.

The VECM framework is suitable for the energy market for essentially the opposite reasons that justifies the use of standard VAR. While VAR models are designed for stationary variables, VECM models account for the fact that many energy and carbon price series are non-stationary in levels, but still share long-run equilibrium relationships. VECM models capture long-run equilibrium relationships between variables that are jointly determined by technological, regulatory or market-wide constraints (Johansen, 1988). By combining short-run dynamics with an error-correction term, the VECM framework quantifies how quickly variables such as power, coal, gas and EUA prices adjust when they deviate from their shared equilibrium path.

5.2 VECM specification

The VECM is estimated separately in each ETS phase:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{k-1}\Delta Y_{t-k+1} + \varepsilon_t$$

Where Y_t = (ln Power_t, ln Coal_t, ln Gas_t, ln EUA_t)', β contains the cointegration vectors and α contains adjustment coefficients.

Johansen trace statistics show Phase III rank=1 and Phase IV rank=2. This means long run relationships between energy and carbon markets change fundamentally across phases, which justifies the use of phase-specific VECM estimation.

Lag length is selected using Akaike's (AIC) and Bayesian (BIC) information criteria.

5.3 VAR specification

The general p-lag VAR model is formulated as:

$$Y_t = c + A_t Y_{t-1} + \cdots + A_p Y_{t-p} + u_t$$

Where Y_t is the vector of endogenous variables and u_t is a vector of serially uncorrelated innovations.

Two model specifications are employed:

Model 1: Energy market system

$$Y_t = (Power_t,\ Coal_t,\ Gas_t,\ EUA_t)'$$

Model 2: Margin-based system

$$Y_t = (CSS_t,\ CDS_t,\ EUA_t)'$$

Lag length is selected using Akaike's (AIC) and Bayesian (BIC) information criteria for the Margin based system. For the energy market system, we imposed lag=5 rather than relying on automatic information criteria. AIC and BIC information criteria selected lag 2 and 1 for respectively Phase III and IV. This created very unstable systems with explosive roots. Using lag = 5 restored stationarity (although still technically unstable).

Model adequacy is evaluated through a set of standard diagnostic tests. Autocorrelation is examined using the Durbin-Watson statistic and Ljung-Box Q-tests, while model stability is assessed by looking at the characteristic roots. Finally, residual diagnostics, including tests for

normality and heteroskedasticity (such as ARCH tests), are conducted to ensure that the model assumptions are satisfied.

To derive orthogonalized shocks for the impulse response analysis, the reduced-form VAR innovations are decomposed using a Cholesky factorization. The ordering is based on economic reasoning about contemporaneous causal flows:

Energy system (Model 1):

$$\text{Power} \rightarrow \text{Coal} \rightarrow \text{Gas} \rightarrow \text{EUA}.$$

This structure reflects the assumption that electricity prices influence input fuel demand, coal affects gas via substitution possibilities in thermal generation, and EUA prices react contemporaneously to changes in all upstream variables.

Margin-based system (Model 2):

$$\text{CSS} \rightarrow \text{CDS} \rightarrow \text{EUA},$$

This identification strategy allows estimation of meaningful structural shocks without imposing a full structural model.

5.4 Dynamic Interdependence Analysis: IRFs,

Impulse response functions (IRFs) trace the effect of a one-standard-deviation shock to one variable on the current and future values of all variables in the VAR. We find IRFs central to understanding the transmission channels between fuel prices and the carbon market, as they trace how shocks in fuel prices propagate to carbon prices (Ahnelöv & Hagström, 2025).

Because the reduced-form innovations are generally correlated, orthogonalized IRFs are computed based on the Cholesky decomposition (Pesaran, 2025, pp. 586-587). The analysis employs a 20-day forecast horizon, which is appropriate for short term dynamics in energy and allowance markets (Ahnelöv & Hagström, 2025).

To assess statistical significance, 1,000 bootstrap replications are used to construct confidence intervals. An impulse response is interpreted as statistically significant when its confidence interval does not include zero at the relevant horizon.

5.5 FEVD and Granger Causality

Forecast error variance decomposition (FEVD) quantifies how much of the forecast uncertainty in EUA price changes is attributable to shocks in the other variables in the system. FEVD complements the IRF analysis by identifying which shocks contribute most to the variability in EUA price forecasts, rather than tracing how these shocks propagate over time.

Variance shares are reported for 1-day, 5-day and 10-day horizons, enabling evaluation of both immediate and medium-term drivers of EUA variability. This helps to determine whether EUA dynamics are primarily driven by fuel markets, power sector profitability or internal EUA market dynamics.

Granger causality tests are conducted to examine whether lagged values of one variable contain predictive information about another. In economic terms, Granger causality indicates a leading relationship in the data generating process, although it does not imply structural or behavioral causation (Seth, 2007).

The tests are implemented through F-tests of the joint hypothesis that the lagged coefficients of the potential driving variable are equal to zero. Rejection of the null hypothesis at conventional significance levels indicates evidence of Granger causality.

6. Analysis

In this section, we present and interpret the empirical results. We examine how fuel and spread variables relate to EUA returns, assess the strength and persistence of these effects, and summarize what the findings imply for short-run EUA price dynamics. We also use the results to shed light on whether publicly observable fuel and spread information is likely to support systematic speculative trading.

6.1 VECM main results and interpretation

We use VECM to explore possible long-run equilibrium relationships in both phases, as well as the full sample period (2013-2025).

The full sample VECM indicates one cointegrating relation in log-levels linking power, coal, gas and EUA. The long-run β-values are listed in table 4. The strong negative beta value of power suggests that at equilibrium high power prices are associated with lower EUA levels. High significant beta-value of coal suggest that coal moves with EUA price. Gas has little and

insignificant long-run coefficient, implying that the gas price has been a weak driver of EUA over the interval.

The loading coefficients are also listed in table 4. Power and gas show the most pronounced and statistically significant error-correction. Coal adjusts only weakly. The EUA loading is small and not statistically significant. Economically this suggests that the long-run anchor is a shared equilibrium, where EUA is best read as the common price that power and gas adjust to. This essentially means that EUA behaves closer to a long-run fundamental, while power and gas absorb most of the disequilibrium correction.

For Phase III the VECM rank is the same as in the full sample VECM (1), but we see a much clearer structure. Power and coal show the same basic pattern, with power having a high negative beta-value (~-3.5***), and coal a high positive (~1.15***). The market was more stable and less exposed to extreme gas and coal shifts in this period. Gas becomes significant with a positive beta-value (~1.19***).

The loading coefficients are somewhat changed from the full sample VECM. Power still shows a strong significant error-correction (α~.0055***). Coal becomes significant but with negative alpha. EUA still has little significant error-correction. This means that also in Phase III EUA price seems to behave closer to a long-run fundamental. But this time coal absorbs more of the disequilibrium corrections.

Phase IV VECM has a completely different structure. For this VECM analysis cointegration analysis shows two relationships and was therefore run with rank=2. This essentially means that the market has two independent long-run relationships.

For the first equilibrium we have completely different beta-values from before. Coal has a strong negative beta (-9.26***), whereas gas has a strong positive beta (6.32***). It seems plausible that this change comes from the energy crises, leading to a situation where coal and gas create their own long-run equilibrium.

In the second equilibrium power is set to β=1 with a strong negative alpha. This means that power corrects sharply to this equilibrium. This makes sense as the power market was under pressure and reacted much more to the crisis than the EUA.

The loading coefficients also vary from the other VECM analysis. Power has a somewhat significant error correction in both equilibriums, the second being both stronger and more significant. EUA reacts weakly in the first equilibrium. Coal and gas don’t adjust much, which

could indicate that prices were largely driven by politics and supply shocks rather than by a stable long-run connection with EUA prices.

Variable	Beta(1)	Alpha(1)	Beta(2)	Alpha(2)
Full sample				
Coal	3.5636***	-0.0006		
EUA	1.0000***	0.0012		
Gas	0.0570	0.0038***		
Power	-3.6606***	0.0050***		
Phase III				
Coal	1.1519***	-0.0025***		
EUA	1.0000***	0.0008		
Gas	1.1885***	-0.0024		
Power	-3.4981***	0.0055***		
Phase IV				
Coal	-9.2597***	0.0009	-1.6262***	-0.0008
EUA	1.0000***	-0.0020*	-0.0000***	0.0084
Gas	6.3211***	-0.0029	0.2289	-0.0001
Power	0.0000***	0.0047*	1.0000***	-0.0398***

Table 4: Results VECM: Lag order 2 for all samples. Rank 1 for full-sample and Phase III, rank 2 for Phase IV. *** for p<0.01, ** for p<0.05, * for p<0.1

6.2 Energy model: Power-Coal-Gas-EUA

The VAR analysis of daily return show that power, coal and gas only contain limited information about short-run EUA dynamics. Multiple lagged coefficients for returns are statistically significant, but the magnitudes are small and signs vary across phases. This instability suggests weak effects from fundamental costs in daily EUA price movements. The lagged EUA return is close to zero and generally insignificant. This reinforces the interpretation that EUA behaves as a high-frequency financial asset, with a random walk pattern where yesterday's return doesn't affect today's return.

Granger causality tests provide some evidence of directional linkages from the energy market to carbon prices. Coal returns frequently Granger-cause EUA returns, whereas gas produces weaker and more irregular effects. But it is important to notice that the significant causal relationships vary noticeably across phases, reflecting structural differences in between phases.

IRFs show that shocks to power and coal prices generate short term, small adjustments in EUA returns. The responses typically disappear within one or two days, and confidence intervals often cover zero. In all specifications, EUA absorbs shocks quickly, which again is typical for high frequency financial assets.

The FEVD results reinforce the same conclusion. At all horizons tested, power, coal and gas jointly explain only a small share of EUA return variance. Thus, energy fundamentals seem to have limited effect on daily EUA returns. For speculative traders, this suggests that CSS and CDS shocks on their own contain little useful information, since their impact on near term EUA returns appears economically negligible.

	Phase III	**Phase IV**	**Full**
N (number of observations)	2019	1318	3338
lag	5.0000	5.0000	5.0000
max_root	7.9411	2.5929	5.6135
Durbin-Watson	1.9977	1.9983	2.0004
Ljung-box p-value	0.9882	0.9998	0.9976
ARCH p-value	0.0000	0.0000	0.0000
Jarque Bera p-value	0.0000	0.0000	0.0000
Granger Causality Power	0.3458	0.5819	0.2655
Granger Causality Coal	0.1006	0.0062	0.0072
Granger Causality Gas	0.2373	0.4526	0.1009
FEVD1 Power	0.0910	0.1071	0.0842
FEVD1 Coal	0.0093	0.0124	0.0073
FEVD1 Gas	0.0209	0.0034	0.0080
FEVD1 EUA	0.8788	0.8771	0.9005
FEVD5 Power	0.0944	0.1078	0.0843
FEVD5 Coal	0.0114	0.0169	0.0080
FEVD5 Gas	0.0219	0.0060	0.0093
FEVD5 EUA	0.8722	0.8693	0.8984
FEVD10 Power	0.0945	0.1078	0.0844
FEVD10 Coal	0.0115	0.0170	0.0080

FEVD10 Gas	0.0219	0.0063	0.0093
FEVD10 EUA	0.8721	0.8689	0.8983

Table 5: VAR results energy model

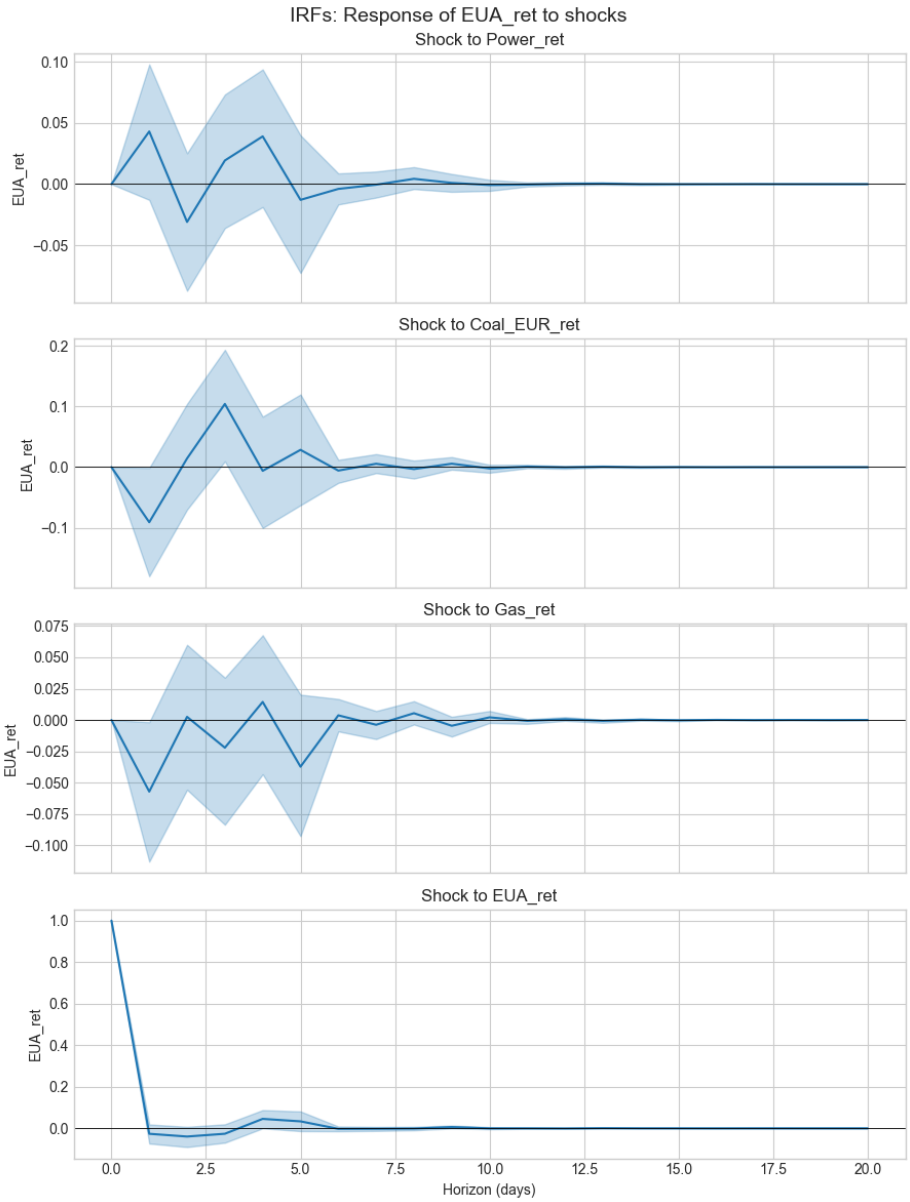


Figure 1: Phase III IRFs

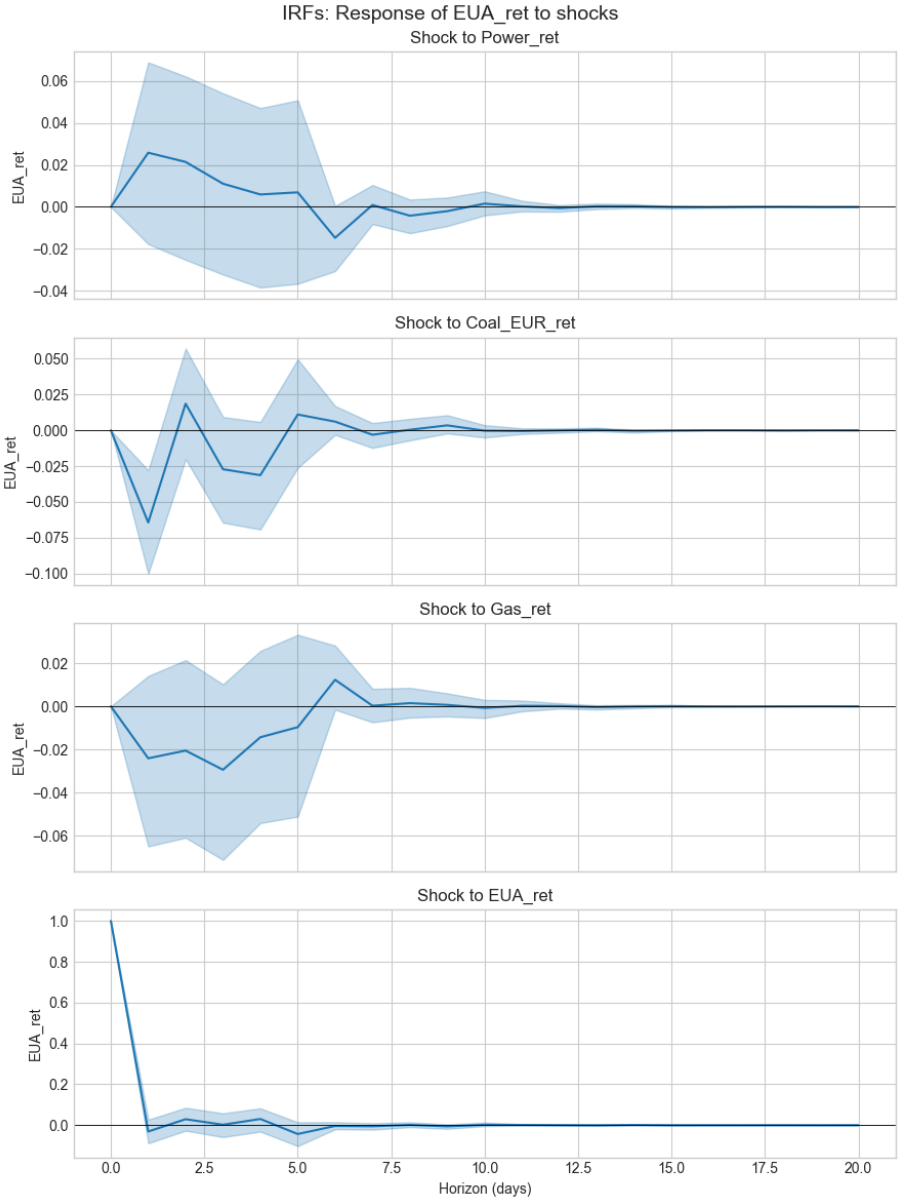


Figure 2: Phase IV IRFs

6.3 Margin model: CSS-CDS-EUA

VAR results for the margin model show almost no direct link between CDS and CSS conditions and daily EUA returns. CSS and CDS changes are generally insignificant, and when significant their effects are economically unimportant. In both phases EUA returns are almost entirely self-driven, consistent with efficient pricing.

Granger causality tests seem to support this pattern. Neither CSS or CDS changes consistently Granger-cause EUA returns. Note however, that in Phase IV CSS changes does Granger-cause EUA returns at longer lags, but the effect remains small. These findings suggests that CDS and CSS changes do not shape EUA price movements.

IRFs show little dynamic transmission from CDS and CSS into EUA returns. Confidence intervals are wide and often include zero. This indicates an absence of systematic short-term effects from spreads to the EUA market.

FEVD results also support the same view. Across the tested horizons CSS and CDS together explains under three percent of EUA return variance. This suggests that the CSS and CDS has close to zero impact on the daily EUA price movements.

	Phase III	**Phase IV**	**Full**
N (number of observations)	2019	1318	3338
lag	3.0000	3.0000	3.0000
max_root	2.9853	3.2511	4.4008
Durbin-Watson	1.9960	1.9959	1.9976
Ljung-box p-value	0.4602	0.9801	0.5128
ARCH p-value	0.0000	0.0000	0.0000
Jarque Bera p-value	0.0000	0.0000	0.0000
Granger Causality CSS	0.2197	0.0248	0.0290
Granger Causality CDS	0.4728	0.2610	0.3025
FEVD1 CSS change	0.0012	0.0035	0.0013
FEVD1 CDS change	0.0195	0.0047	0.0027
FEVD1 EUA return	0.9794	0.9918	0.9960
FEVD5 CSS change	0.0020	0.0084	0.0031

FEVD5 CDS change	0.0210	0.0080	0.0038
FEVD5 EUA return	0.9770	0.9836	0.9931
FEVD10 CSS change	0.0020	0.0085	0.0031
FEVD10 CDS change	0.0210	0.0080	0.0038
FEVD10 EUA return	0.9770	0.9835	0.9931

Table 6: VAR results margin model

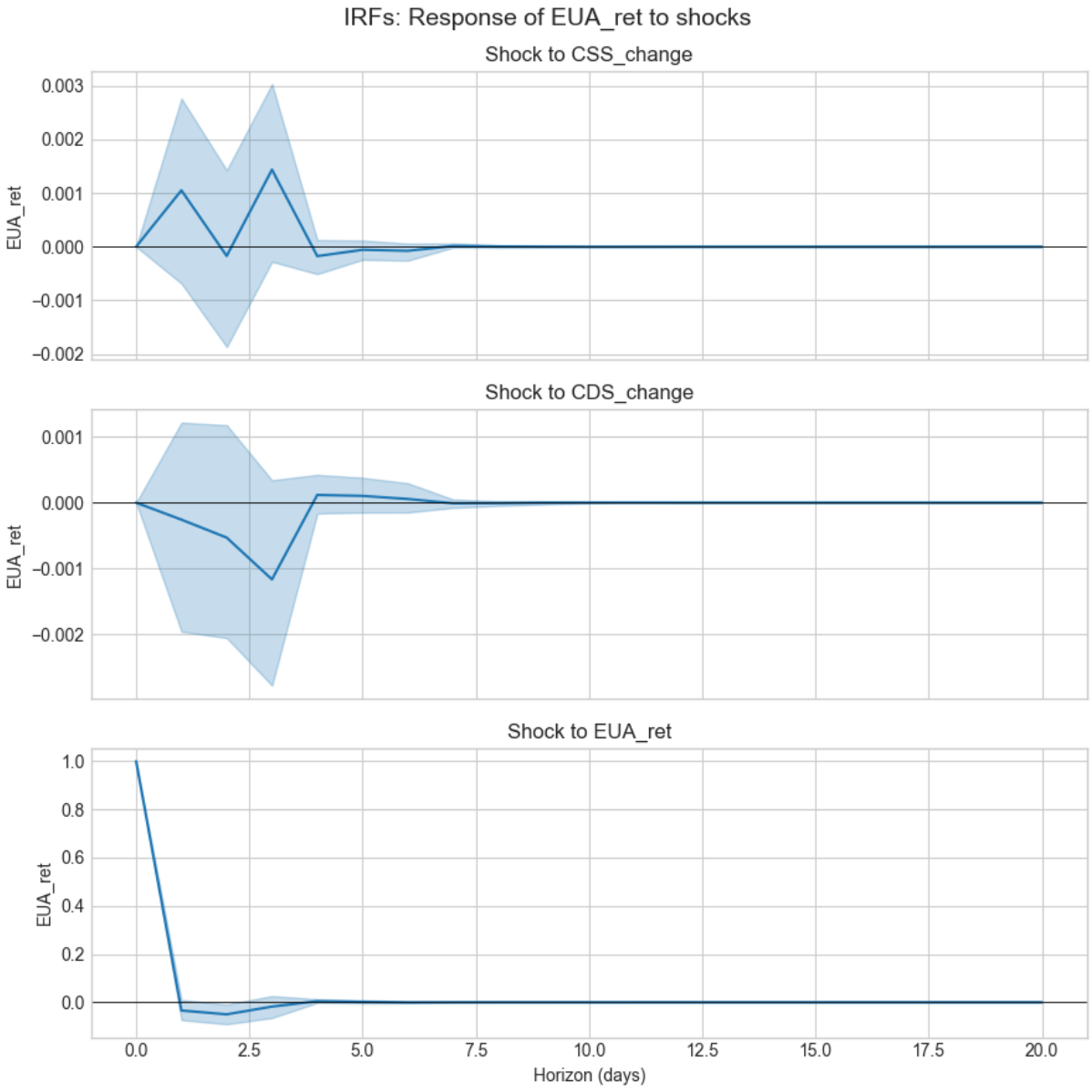


Figure 3: IRFs Phase III

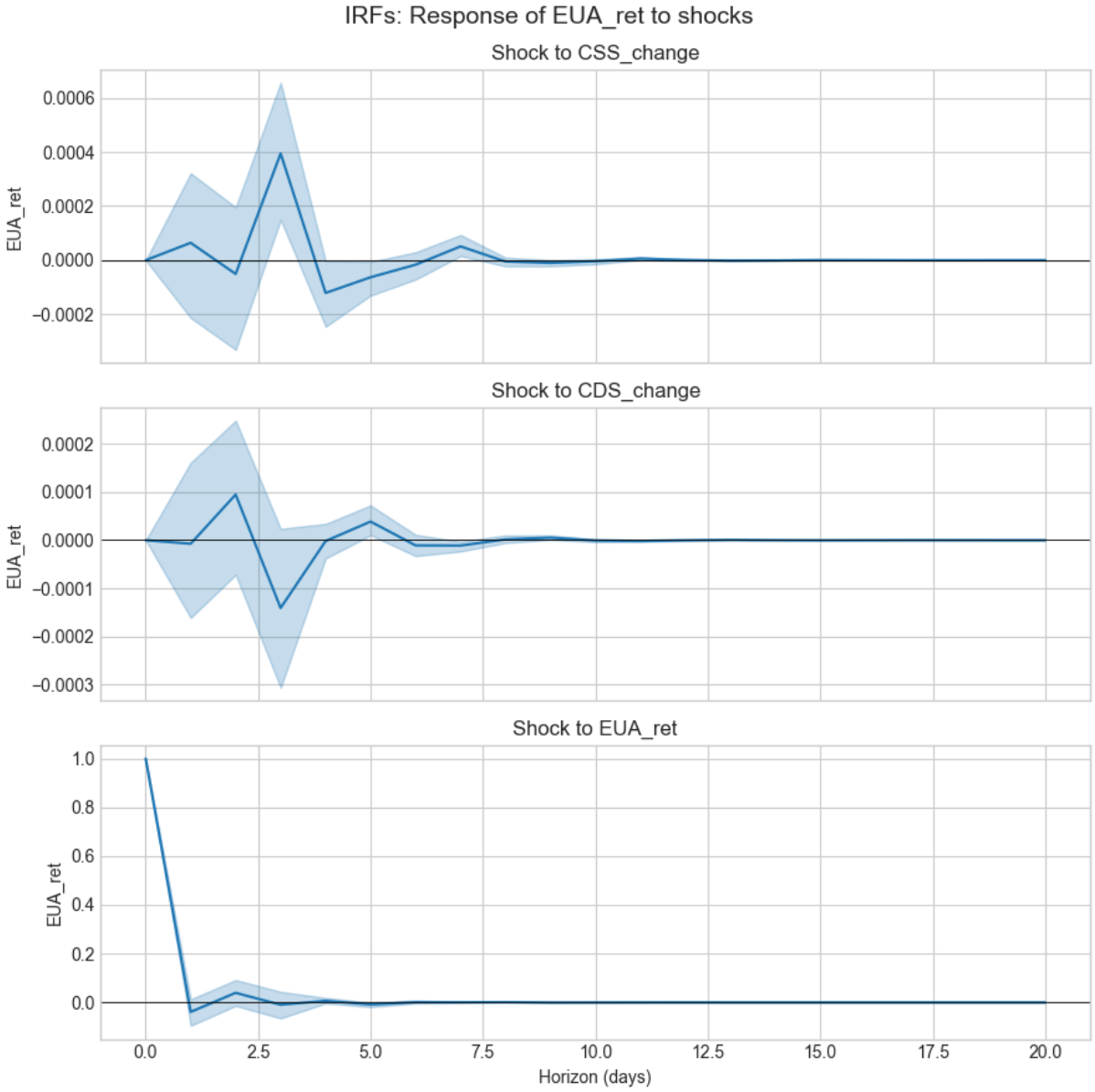


Figure 4: IRFs Phase IV

6.4 Comparison of the energy and margin models

A comparison of the two models highlights a clear asymmetry. Energy prices have small but noticeable IRF responses and a non-trivial share of short-run volatility. However, margin variables provide almost no explanatory or predictive content for daily EUA movements. This outcome aligns well with economic logic of the EU ETS. Energy markets determine marginal production costs and directly affect emissions, while credit markets influence carbon pricing only indirectly through broader economic conditions. The carbon market reacts to fundamentals tied to physical production, not to high frequency fluctuations in financial risk premiums.

Several robustness checks were performed to assess the reliability of the results. Winsorizing extreme observations and applying robust regression methods produced similar coefficient patterns which indicates that the results are not driven by outliers. Bootstrapping with both 500 and 1,000 replications yielded consistent significance patterns and confidence intervals. Alternative causality orderings within the VAR did not materially change the IRFs, which suggests that the dynamic structure is not sensitive to variable ordering. Although the VAR exhibited signs of instability, the main IRF patterns remained robust across specifications when looking at short time-horizons.

6.5 Main findings

The analysis yields several key conclusions. Coal and power emerge as the most important fundamental drivers of daily EUA returns, though their effects are small and vary across market regimes. Gas plays a weaker and inconsistent role, particularly after the structural shifts associated with the post 2021 energy crisis. Margin variables such as CSS and CDS are effectively irrelevant for short-run EUA pricing. Most importantly, the data reveal that EUA returns are largely self-driven, with short-run fluctuations dominated by internal market dynamics rather than external fundamentals. This independence suggests that there is limited inefficiency to exploit for speculative traders. Shocks from both energy market and margins dissipate rapidly, underscoring the role of market microstructure, liquidity conditions and noise trading in shaping EUA price dynamics.

7. Reflection and weaknesses

Reflecting on the modelling approach applied in this study, some methodological and conceptual weaknesses arise.

A central limitation is the use of daily data. End-of-day prices remove the intraday dynamics through which information is absorbed in the market. Order-flow imbalances, speculative trading and real-time weather updates all influence EUA prices, long before closing price. Daily data therefore flatten out important intraday movements and make it harder for the model to capture genuine causal links.

From a market microstructure perspective, an important limitation is that we do not observe order flow, bid–ask spreads, depth or trading volume. We did not have access to liquidity data, so key mechanisms such as liquidity provision, adverse selection, inventory management and noise trading are only reflected indirectly through the residuals of the VAR and VECM models.

A further limitation concerns the construction of fuel spreads and benchmark variables. Clean spark and dark spreads (CSS/CDS) are theoretical approximations based on constant efficiency parameters and standard emission factors. The spreads used in this study therefore only approximate the true marginal cost structure of the European power system.

A third weakness concerns the econometric assumptions. VAR and VECM models impose linear and stable relationships, which do not capture highly nonlinear periods such as the 2021–2023 energy crisis. The large roots in our VAR indicate limited reliability over longer horizons. Identification is also problematic: the Cholesky decomposition assumes a specific causal ordering, yet fuel and carbon markets interact contemporaneously in more complex ways. Alternative orderings could change the impulse responses, so results must be interpreted cautiously. A structural VAR with economically motivated restrictions could, in principle, provide more robust identification.

Finally, the sample has several structural breaks in the EU ETS including the MSR reforms, the LRF and the energy crisis. This makes it difficult to estimate stable relationships across such different regimes. Higher-frequency data and more flexible modelling could strengthen future work.

8. Conclusion

This paper examined how informationally efficient EUA prices are with respect to coal, gas and power markets, and whether short-run adjustment lags create scope for speculative trading. The results provide a clear picture: energy fundamentals anchor long-run EUA prices, while their ability to explain short-run movements is limited.

First, the VECM analysis shows that coal, power and EUA prices share long-run equilibrium relationships, particularly in Phase III, consistent with fuel-switching fundamentals. These findings support the idea that energy markets help determine the structural level of EUA prices over longer horizons.

Second, the VAR, IRF, FEVD and Granger causality results demonstrate that fuel markets have very limited predictive power for short-run EUA returns. Across all specifications, shocks to coal, gas and power prices generate only small and short-lived effects, and CSS and CDS spreads explain almost none of the daily variation. FEVD results show that more than 85–95% of short-run EUA return variance is self-driven, indicating that liquidity conditions, order flow and speculative activity dominate high-frequency price formation.

Third, the interviews with traders reinforce this empirical evidence. Market participants view fuel prices as important for long-term scarcity expectations and hedging strategies, but they emphasize that day-to-day EUA price movements are driven primarily by liquidity constraints, market positioning and rapid information absorption rather than by fuel-price fundamentals.

From a trading perspective, these results imply that simple strategies based on publicly available fuel-price or spread information are unlikely to generate persistent excess returns, as such information is incorporated quickly into EUA prices. Successful short-horizon trading in EUAs therefore depends more on understanding liquidity, positioning, volatility and intraday market behavior than on reacting to changes in coal, gas or power prices.

The EU ETS illustrates a market shaped by long-run scarcity, while daily price movements are hard to forecast using fuel and spread information. Short-run movements reflect internal market dynamics rather than adjustment to fuel fundamentals. This combination of long-run anchoring and short-run price behavior largely independent of fuel and spread signals makes the EU ETS an instructive example of how modern financial markets react to information across different time scales.

9. Sources

Ahnelöv, O., & Hagström, R. (2025). *Modelling carbon chaos: Understanding the effects of shocks on carbon allowances – A study of fundamental and uncertainty influences through a vector autoregressive model* (Master's thesis, Linköping University). Linköping University Electronic Press. https://liu.diva-portal.org/smash/get/diva2:1974645/FULLTEXT01.pdf

Alberola, E., Chevallier, J., & Chèze, B. (2008). Price drivers and structural breaks in European carbon prices 2005–2007. *Energy Policy, 36*(2), 787–797.

Ampudia, M., Bua, G., Kapp, D., & Salakhova, D. (2022, April 26). *The role of speculation during the recent increase in EU emissions allowance prices*. European Central Bank. https://www.ecb.europa.eu/press/economic-bulletin/focus/2022/html/ecb.ebbox202203_06~ca1e9ea13e.en.html

Bunn, D. W., & Fezzi, C. (2008). Interactions of European carbon trading and energy prices. *The Energy Journal, 29*(4), 79–96. https://www.econstor.eu/bitstream/10419/74196/1/NDL2007-063.pdf

Chevallier, J. (2011). Carbon price drivers: An updated literature review. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1811963

Creti, A., Jouvet, P.-A., & Mignon, V. (2011). *Carbon price drivers: Phase I versus Phase II equilibrium?* (CEPII Working Paper No. 2011-09). https://www.cepii.fr/PDF_PUB/wp/2011/wp2011-09.pdf

Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica, 55*(2), 251–276.

European Central Bank. (2022). Financial stability risks from energy derivatives markets. In *Financial Stability Review* (Special feature). https://www.ecb.europa.eu/press/financial-stability-publications/fsr/special/html/ecb.fsrart202211_01~173476301a.en.html

European Commission. (n.d.-a). *Development of the EU ETS 2005–2020*. Retrieved November 26, 2025, from https://climate.ec.europa.eu/eu-action/carbon-markets/eu-emissions-trading-system-eu-ets/development-eu-ets-2005-2020_en

European Commission. (n.d.-b). *EU Emissions Trading System (EU ETS).* Retrieved November 26, 2025, from https://climate.ec.europa.eu/eu-action/carbon-markets/eu-emissions-trading-system-eu-ets_en

European Commission. (n.d.-c). *Market Stability Reserve.* Retrieved November 26, 2025, from https://climate.ec.europa.eu/eu-action/carbon-markets/eu-emissions-trading-system-eu-ets/market-stability-reserve_en

European Securities and Markets Authority. (2025). *Carbon markets report: ESMA50-481369926-30552*. https://www.esma.europa.eu/sites/default/files/2025-10/ESMA50-481369926-30552_Carbon_Markets_Report_2025.pdf

Google DeepMind. (n.d.). *Nano Banana: Bring your imagination to life with Gemini 2.5 Flash Image*. Retrieved November 26, 2025, from https://deepmind.google/models/gemini-image/flash/. Note: used for support creating the front page.

Hasbrouck, J. (1995). One security, many markets: Determining the contributions to price discovery. *The Journal of Finance, 50*(4), 1175–1199. https://www.jstor.org/stable/2329348

Hasbrouck, J. (2007). *Empirical market microstructure: The institutions, economics, and econometrics of securities trading*. Oxford University Press. https://ebookcentral.proquest.com/lib/nhh-ebooks/detail.action?docID=415271

Harris, L. (2003). *Trading and exchanges: Market microstructure for practitioners*. Oxford University Press.

Hintermann, B. (2010). Allowance price drivers in the first phase of the EU ETS. *Journal of Environmental Economics and Management, 59*(1), 43–56. https://www.sciencedirect.com/science/article/pii/S0095069609000862

Homaio. (2024). *How big is the EU ETS as a financial market?* https://www.homaio.com/post/how-big-is-the-eu-ets-as-a-financial-market

International Carbon Action Partnership. (n.d.). *EU Emissions Trading System (EU ETS).* https://icapcarbonaction.com/en/ets/eu-emissions-trading-system-eu-ets

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control, 12*(2–3), 231–254.

Koch, N., Fuss, S., Grosjean, G., & Edenhofer, O. (2014). Causes of the EU ETS price drop: Recession, structural change, or renewable policies? *Energy Policy, 73*, 676–685. https://www.sciencedirect.com/science/article/pii/S0301421514003966

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica, 53*(6), 1315–1335. https://www.jstor.org/stable/1913210

London Stock Exchange Group. (n.d.). *LSEG Workspace* [Database]. Retrieved November 18, 2025, from https://www.lseg.com/en/data-analytics/products/workspace

Magnus Commodities. (2016). *Margins for electricity producers*. https://magnuscmd.com/margins-for-electricity-producers/

Pastor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111*(3), 642–685. https://www.jstor.org/stable/10.1086/374184

Pesaran, M. H. (2025). *Time series and panel data econometrics* (1st ed.). Oxford University Press.

Picir.ai. (n.d.). *Nano Banana AI image editor*. Retrieved November 26, 2025, from https://picir.ai/

Salovaara, K. (2011). *Coal-to-natural-gas fuel switching and CO_2 emissions* (M-RCBG Associate Working Paper No. 2011-08). Harvard Kennedy School, Mossavar-Rahmani Center for Business and Government. https://www.hks.harvard.edu/sites/default/files/centers/mrcbg/files/Salovaara_2011.pdf

Seth, A. (2007). Granger causality. Scholarpedia, 2(7), 1667. https://doi.org/10.4249/scholarpedia.1667

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica, 48*(1), 1–48.

Wei, Y., Cao, Y., & Wen, F. (2024). Financialisation of the European Union Emissions Trading System and its influencing factors. *International Journal of Finance & Economics*. Advance online publication. https://doi.org/10.1002/ijfe.2950

Declaration on the use of AI tools in the work on this assignment

Name (and version) of the AI tool: ChatGPT, GPT-5

Purpose of using the tool: Used for grammatical refinement of text, as well as assistance in data analysis and coding support.

TOC Appendix

Appendix 34
A1 Interviews 34
A2 IRF figures 39
A3 Codes 43

10. Appendix

Interviews

Interview with Ola Kvennås, Head of Nordic trading in Statkraft, conducted on the 24th of October 2025, written for empirical usage

We conducted an exploratory interview with Ola Kvennås, Head of Statkraft's Nordic Trading unit, to obtain background information on how proprietary trading, risk management and information flows work in the Nordic and European power markets. Kvennås has an energy-related background from NTNU and a career that spans energy consulting, analysis and finally trading. At Statkraft he mainly trades German power and EU ETS allowances, while his colleagues cover Nordic power, EPADs and various spread products. The interview is used as qualitative, empirical input to both our research design and the interpretation of our results.

Kvennås emphasized that the Nordic market must be viewed as part of a larger European power system rather than as an isolated national market. Interconnectors, common market platforms and harmonized regulation link Nordic prices to continental power prices, where the marginal unit is often thermal generation. In this setting, coal, gas and especially EU ETS prices enter as cost components for marginal plants, while weather, hydrology and demand determine how often these plants set the price. He described EUA prices as a "shadow price" on emissions, which, together with fuel prices, helps anchor forward power prices in Europe. At the same time, he stressed that in the Nordic region "weather is the single most important driver", as it affects hydrological balance, wind production and temperature-sensitive demand.

He explained that professional power traders operate under explicit risk limits and are measured primarily on P&L over time. Risk is often framed as maximum drawdown and monitored at both position and portfolio level across products, bidding zones and maturities. Within these constraints, strategies are largely fundamental and spread-based: traders look for

mispricing between hydrological resources and Nordic prices, between bidding zones and EPADs, and between power prices and CO_2- and fuel-implied generation costs. Cross-border spreads, particularly between Nordic and German power contracts, and structural differences between EPAD areas are used actively when weather patterns, transmission constraints or resource conditions cause temporary divergences from “fair value”.

Kvennås also pointed to market structure and liquidity as central for understanding price dynamics. Highly liquid Nordic system futures on Nasdaq coexist with thinner segments such as EPADs and certain cross-border and cross-product structures. Large players like Statkraft, with physical generation, internal analysis (including dedicated weather institutes) and strong balance sheets, can act as liquidity providers in these segments and “decide their own odds” to some extent. However, episodes of extreme volatility, such as during the recent European energy crisis, tighten risk limits and increase margin requirements, which can slow or distort how new information about fuel prices, CO_2 or weather is incorporated into forward power prices.

We use these insights as an empirical backdrop when modelling joint pricing in power, coal, gas and EUAs, when choosing which contracts and spreads to focus on, and when assessing whether pass-through from fuel and CO_2 prices to power prices is likely to be instantaneous or subject to delays and temporary mispricing from the perspective of actual market participants.

Interview no. 2 with Ola Kvennås and colleague, Head of Nordic trading conducted on the 20th of November 2025 in Statkraft offices in Oslo, written for empirical usage

The interview with Ola Kvennås, Head of Nordic Trading at Statkraft, and a senior colleague lasted approximately one hour and focused on the functioning of the EU Emissions Trading System (EU ETS), price formation in the EUA market, and practical trading perspectives relevant for analysis of carbon allowance prices.

Steven (Senior Colleague of Kvennås) began by characterizing the EU ETS as a regulatory, paper-based market rather than a traditional physical commodity market. EUAs are intangible allowances created by regulation, designed to limit greenhouse gas emissions from sectors such as power and industry. Unlike oil or gas, the supply of EUAs is politically determined through caps, linear reduction factors and design features such as the Market Stability Reserve (MSR). The value of the allowance thus depends on the credibility and stability of the regulatory framework, not on physical production constraints.

They then discussed the evolution of the EU ETS across phases I–IV. Phase I was described as a “trial-and-error” learning phase, with national allocation plans, generous free allocation and no banking of allowances between phases. This led to substantial oversupply and the EUA price collapsing to zero at the end of the phase. In Phase II, banking was allowed and some auctioning started, but the 2008–2009 financial crisis again created a large surplus, as industrial production and emissions dropped while installations continued to receive free allowances. The interviewees estimated that the market surplus peaked around 2 billion allowances by 2012–2013.

To address this chronic surplus, the MSR was introduced and gradually implemented. They explained the basic mechanism: when the total number of allowances in circulation exceeds a specified threshold, the MSR automatically reduces auction volumes by a given percentage, “sucking in” the surplus and tightening effective supply. According to Steven, this mechanism successfully transformed the market from heavily oversupplied to more balanced, contributing to the rise in EUA prices from around €4–5 in 2015 to around €80–90 in recent years. Phase IV continues this trend with a steeper linear reduction factor (LRF) and rebasing of the cap, while also bringing new sectors like maritime transport and aviation into the system, and preparing ETS2 for smaller sectors.

They also noted that short-term shocks – such as unusually mild winters – can temporarily depress prices when utilities find themselves over-hedged on carbon and must sell excess allowances, often leading to seasonal dips around the compliance and reporting periods (e.g., around March/April).

The discussion then turned to variables that had to be looked into for model development. In addition to gas, coal, oil prices and clean spreads, the interviewees highlighted:

- Overall economic activity (industrial production, recession vs boom),
- Regulatory and political news (EU negotiations, MSR/ETS reform announcements),
- Sector expansion (shipping, aviation, ETS2),
- Macro-financial conditions (interest rates affecting the EUA futures curve and cost of carry),
- Uncertainty measures (e.g. volatility indices),
- Weather and renewables output (cold winters, wind/solar generation),

- The size of the banked surplus and MSR intake.

They stressed that any model would work well only in periods where its underlying assumptions match market conditions; when the regime changes (new policy, crises, technological breakthroughs), model performance can quickly deteriorate.

From a trading and risk management perspective, Kvennås described EUAs as a highly volatile and policy-sensitive asset. Carbon can be traded in two main ways: (i) as a speculative position based on views about future regulation, fundamentals and macro conditions, or (ii) as a hedging component embedded in power portfolios (e.g. for gas and coal-fired plants). In the latter case, EUA exposure is adjusted in line with expected generation rather than actively traded on every news event. They mentioned that position sizing and risk limits depend on volatility, time horizon and internal mandates, and that "stop loss" concepts can be based on both price and time (e.g. exiting if a view has not materialised within a certain period).

Finally, the interview concluded with broader reflections on renewables, peak oil and energy policy. Increased renewable capacity was seen as structurally bearish for EUA demand in the power sector, but long-run EUA prices remain highly uncertain due to technology developments, global climate policy and the possibility that some of the "last tonnes" of emissions will be extremely costly to abate. On trading more generally, they emphasized the importance of robust analytics, experience, risk discipline and emotional stability (avoiding both euphoria and despair) as key sources of trading "edge".

Overall, the interview provided rich qualitative insight into how professional traders perceive the EU ETS, how they think about EUA price drivers and modelling approaches, and how regulatory design, sector coverage and expectations about future scarcity shape the dynamics of carbon prices.

Interview with Morten Nilsen, Trader at Kinect Energy, conducted on the 23rd of October 2025, written for empirical usage:

We conducted an exploratory interview with Morten Nilsen, a power trader at Kinect Energy, to gather background information on how trading, risk management and information flows work in the Nordic and European power markets, and how these link to coal, gas and CO_2.

The interview is used as qualitative, empirical input to both our research design and the interpretation of our results.

Nilsen explained that professional traders operate under strict risk limits (often defined as a maximum drawdown in NOK or percent), which constrain how much directional exposure they can take in power, fuels and CO_2. Exposure is measured as MW × hours × price and applies equally to power futures, area contracts and cross-commodity positions. Traders therefore care not only about power prices, but about how coal, gas and CO_2 jointly affect portfolio risk and margins.

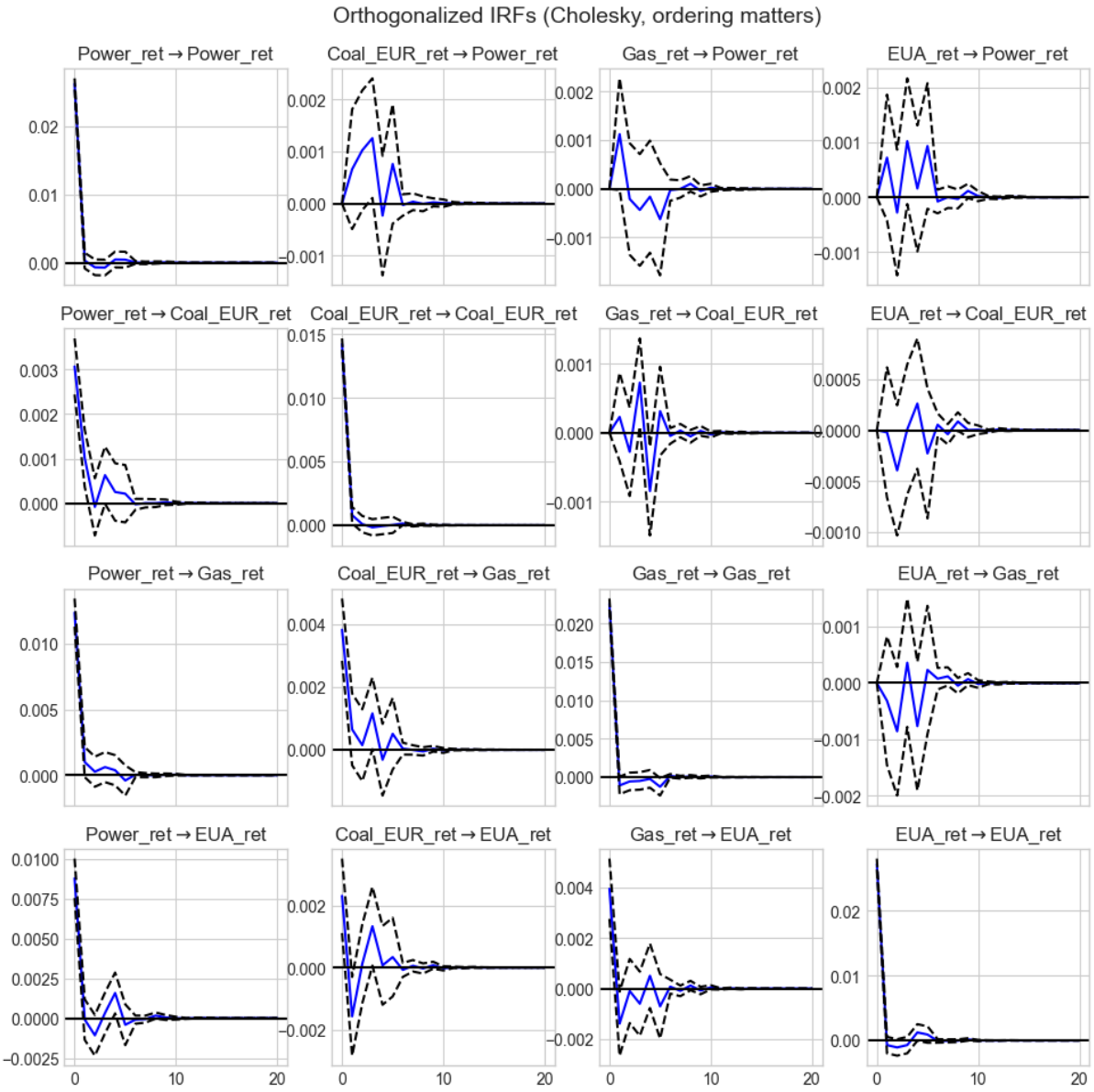
He highlighted hedging and spread trading as core strategies. Hedging is used to lock in margins when clean spark or dark spreads are attractive, while spread trading can be done across time, bidding zones, or even across commodities (e.g. power vs. gas and CO_2). This directly connects to our research question, where we study how efficiently shocks in coal, gas and CO_2 prices are transmitted into power prices and derivatives.

Nilsen also pointed to key features of market structure: Nordic system price futures on Nasdaq are highly liquid, whereas EPADs and some cross-commodity structures are much less liquid but driven by the same fundamentals (fuel costs, CO_2 prices, transmission constraints). Large producers like Statkraft have structural advantages here, as they can use their physical generation as collateral and act as liquidity providers in thinner segments of the power, fuel and carbon markets.

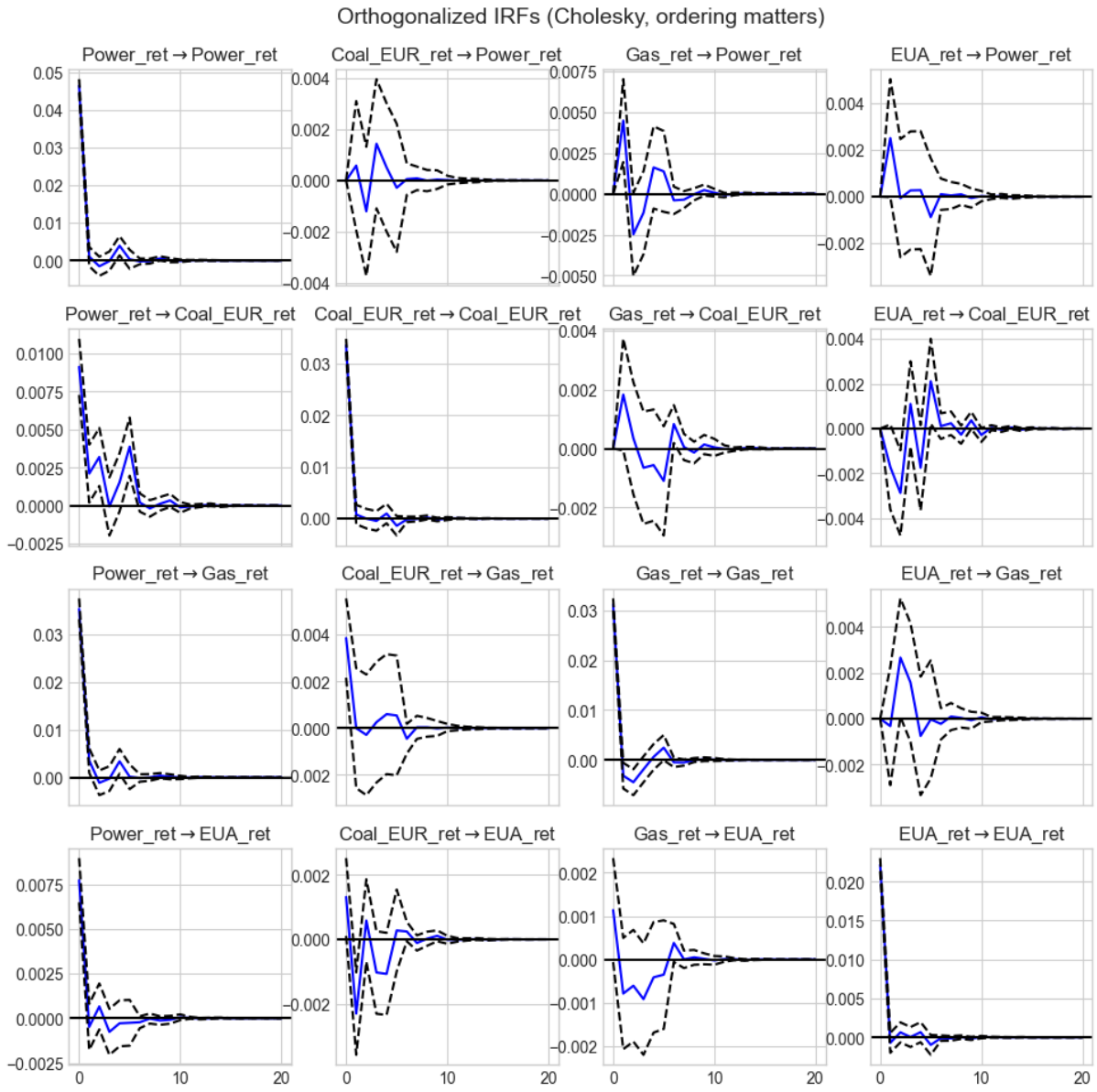
Finally, he noted that liquidity in Nordic power derivatives has declined, while bilateral OTC trading has increased, partly due to stricter regulation and higher margin requirements. This may slow or distort how information from coal, gas and CO_2 markets is incorporated into power prices. We use these insights as an empirical backdrop when assessing possible delayed or incomplete pass-through from fuel and CO_2 prices to power prices, and when specifying our empirical models of joint pricing in power, coal, gas and EUAs.

IRF figures

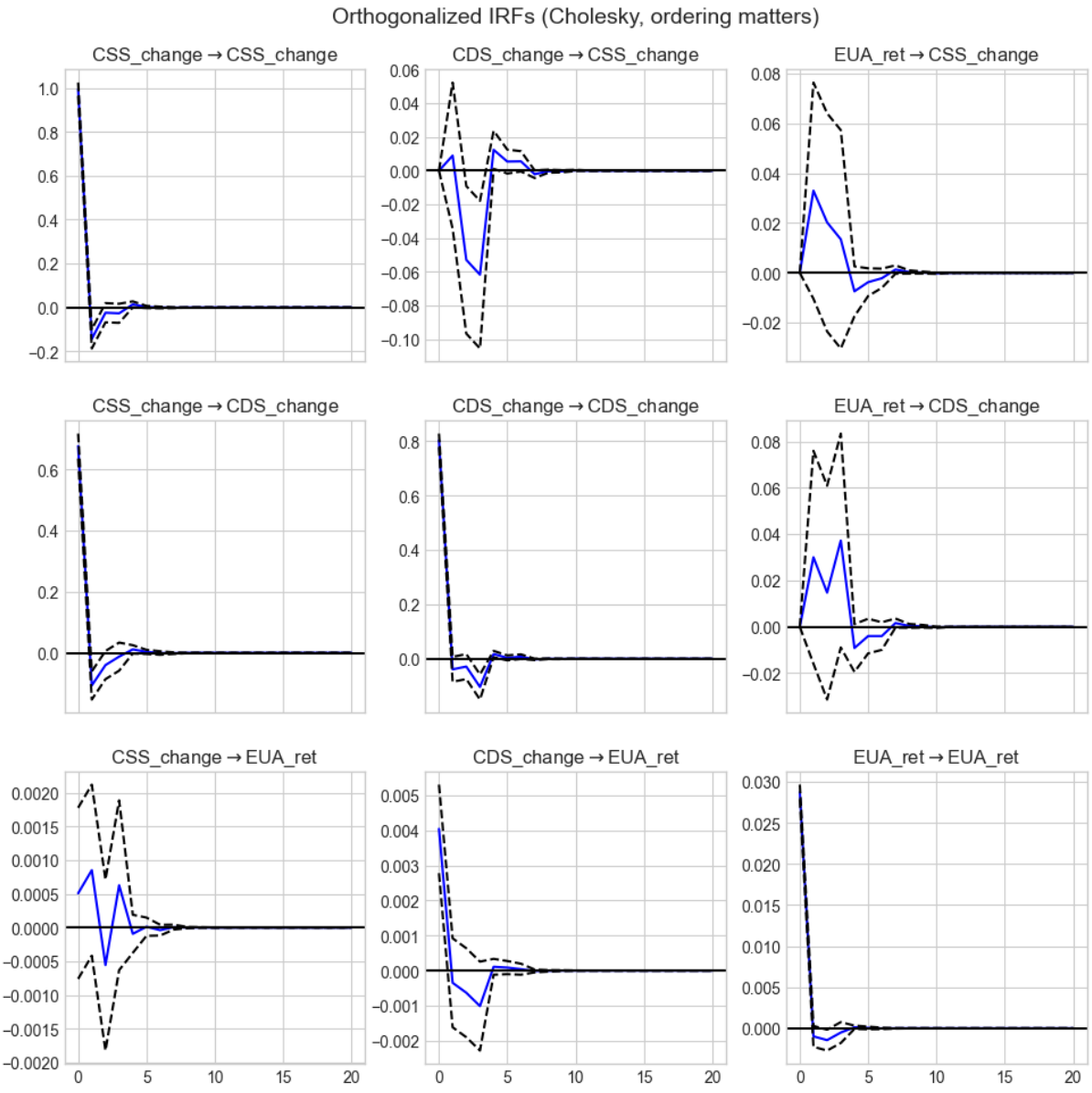
Orthogonalized IRFs (Energy model Phase III):



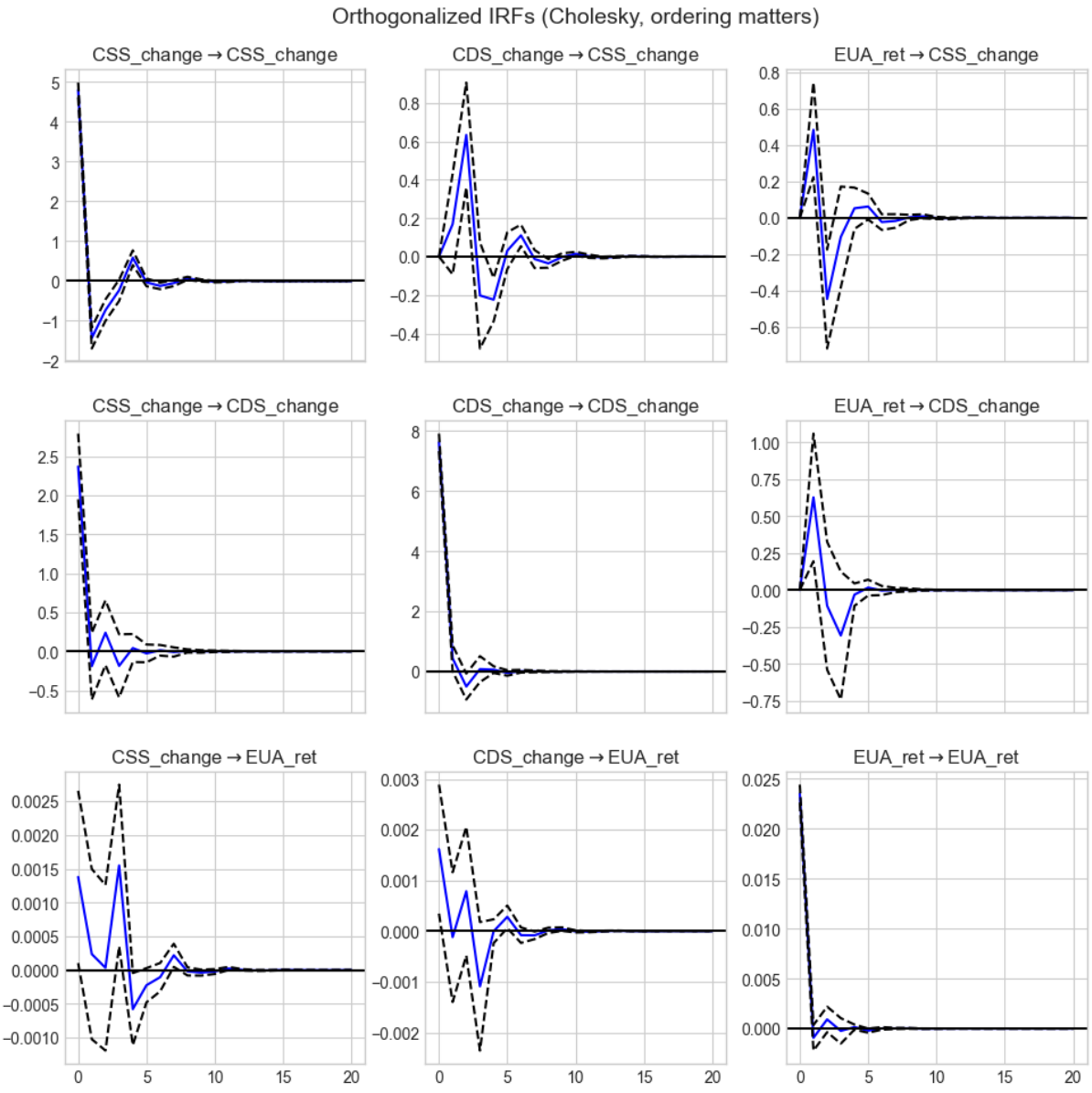
Orthogonalized IRFs (Energy model Phase IV):



Orthogonalized IRFs (Margin model phase III):



Orthogonalized IRFs (Margin model Phase IV):


Orthogonalized IRFs (Cholesky, ordering matters)
CSS_change → CSS_change
CDS_change → CSS_change
EUA_ret → CSS_change
CSS_change → CDS_change
CDS_change → CDS_change
EUA_ret → CDS_change
CSS_change → EUA_ret
CDS_change → EUA_ret
EUA_ret → EUA_ret

Codes

Out[ ]:

	ADF_stat	ADF_p	KPSS_stat	KPSS_p
EUA	-0.399501	0.910182	5.365947	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...
Power	-3.051375	0.030367	0.876007	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...
Coal_EUR	-1.448775	0.558682	1.330012	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...
Gas	-2.438082	0.131275	2.927612	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...

In [ ]:
```
st_results_phase4 = {col: stationarity_tests(df_phase4[col]) for col in df_phase4.columns}
pd.DataFrame(st_results_phase4).T
```

```
C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\3069220025.py:4: InterpolationWarning: The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is smaller than the p-value returned.

  res_kpss = kpss(series, regression='c', nlags='auto')
C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\3069220025.py:4: InterpolationWarning: The test statistic is outside of the range of p-values available in the
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look-up table. The actual p-value is smaller than the p-value returned.

  res_kpss = kpss(series, regression='c', nlags='auto')
```

Out[ ]:

	ADF_stat	ADF_p	KPSS_stat	KPSS_p
EUA	-3.441664	0.009618	1.989879	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...
Power	-2.162585	0.220104	0.978326	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...
Coal_EUR	-1.941207	0.312931	1.111099	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...
Gas	-2.016931	0.279199	0.871281	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...

In [ ]:
```
# Testing rank for VECM in phases 3 and 4
joh_phase3 = coint_johansen(df_phase3, det_order=0, k_ar_diff=2)
print(joh_phase3.lr1)  # trace stats
print(joh_phase3.cvt)  # critical values
joh_phase4 = coint_johansen(df_phase4, det_order=0, k_ar_diff=2)
print('\n', joh_phase4.lr1)  # trace stats
print(joh_phase4.cvt)  # critical values
```

```
[60.00324275 27.12152538  7.98190409  0.35861335]
[[44.4929 47.8545 54.6815]
 [27.0669 29.7961 35.4628]
 [13.4294 15.4943 19.9349]
 [ 2.7055  3.8415  6.6349]]

 [55.23982721 31.34241997 14.2978269   3.52100154]
[[44.4929 47.8545 54.6815]
 [27.0669 29.7961 35.4628]
 [13.4294 15.4943 19.9349]
 [ 2.7055  3.8415  6.6349]]
```

In [ ]:
```
# Fitting VECM for phase 3
r = 1    # Rank from above results
vecm_model_phase3 = VECM(df_phase3, k_ar_diff=2, coint_rank=r, deterministic='ci')
vecm_phase3 = vecm_model_phase3.fit()
print(vecm_phase3.summary())
```

```
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odels\tsa\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As a result, forecasts cannot be generated. To use the model for forecasting, us
e one of the supported classes of index.
  self._init_dates(dates, freq)
```

```
=== VAR sample: 2 to 2020, n=2019 ===
Lag order selection (lower = better):
 VAR Order Selection (* highlights the minimums)
=================================================
       AIC         BIC         FPE         HQIC
-------------------------------------------------
0       -7.507     -7.499*   0.0005491      -7.504
1       -7.523      -7.490   0.0005404     -7.511*
2       -7.523      -7.465   0.0005404      -7.502
3      -7.530*      -7.446  0.0005367*      -7.499
4       -7.529      -7.421   0.0005371      -7.489
5       -7.527      -7.393   0.0005386      -7.477
6       -7.523      -7.364   0.0005404      -7.465
7       -7.517      -7.333   0.0005436      -7.450
8       -7.511      -7.302   0.0005468      -7.435
9       -7.507      -7.272   0.0005495      -7.421
10      -7.504      -7.244   0.0005510      -7.408
-------------------------------------------------
Using lag = 3
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Sun, 23, Nov, 2025
Time:                     12:49:10
--------------------------------------------------------------------
No. of Equations:         3.00000    BIC:                   -7.44842
Nobs:                     2016.00    HQIC:                  -7.50125
Log likelihood:          -959.600    FPE:                0.000535727
AIC:                     -7.53189    Det(Omega_mle):     0.000527834
--------------------------------------------------------------------
Results for equation CSS_change
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                 0.005978         0.022169            0.270           0.787
L1.CSS_change        -0.148588         0.029254           -5.079           0.000
L1.CDS_change         0.005416         0.027777            0.195           0.845
L1.EUA_ret            1.148187         0.770107            1.491           0.136
L2.CSS_change        -0.000373         0.029416           -0.013           0.990
L2.CDS_change        -0.067931         0.027790           -2.444           0.015
L2.EUA_ret            0.909047         0.769442            1.181           0.237
L3.CSS_change         0.024405         0.029253            0.834           0.404
L3.CDS_change        -0.092015         0.027784           -3.312           0.001
L3.EUA_ret            0.730935         0.769758            0.950           0.342
================================================================================

Results for equation CDS_change
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                -0.000945         0.023441           -0.040           0.968
L1.CSS_change        -0.071062         0.030933           -2.297           0.022
L1.CDS_change        -0.053937         0.029371           -1.836           0.066
L1.EUA_ret            1.043002         0.814293            1.281           0.200
L2.CSS_change        -0.029744         0.031103           -0.956           0.339
L2.CDS_change        -0.040760         0.029385           -1.387           0.165
L2.EUA_ret            0.686344         0.813590            0.844           0.399
L3.CSS_change         0.072521         0.030931            2.345           0.019
L3.CDS_change        -0.144211         0.029378           -4.909           0.000
L3.EUA_ret            1.524367         0.813924            1.873           0.061
================================================================================

Results for equation EUA_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                 0.001031         0.000648            1.590           0.112
L1.CSS_change         0.001050         0.000856            1.227           0.220
L1.CDS_change        -0.000258         0.000812           -0.318           0.751
L1.EUA_ret           -0.034248         0.022525           -1.520           0.128
L2.CSS_change         0.000002         0.000860            0.002           0.998
L2.CDS_change        -0.000559         0.000813           -0.688           0.491
L2.EUA_ret           -0.052251         0.022505           -2.322           0.020
L3.CSS_change         0.001416         0.000856            1.655           0.098
L3.CDS_change        -0.001164         0.000813           -1.433           0.152
L3.EUA_ret           -0.021647         0.022514           -0.961           0.336
================================================================================

Correlation matrix of residuals
             CSS_change  CDS_change   EUA_ret
CSS_change     1.000000    0.643933  0.017474
CDS_change     0.643933    1.000000  0.117698
EUA_ret        0.017474    0.117698  1.000000



Companion roots (abs): [2.98529632 2.98529632 2.91528641 2.91528641 2.77176815 2.77176815
 2.36431811 2.36431811 2.2597957 ]
WARNING: VAR is not stable (roots >= 1). IRF/FEVD may be unreliable.

=== RESIDUAL DIAGNOSTICS ===

Durbin-Watson (per equation):
[2.00446941 2.00378008 1.99595527]

Ljung-Box Q-test (lags 5 & 10):

Residual series: CSS_change
Lag 5:
    lb_stat  lb_pvalue
5  1.956658   0.855109
Lag 10:
     lb_stat  lb_pvalue
10  7.024877   0.723094
```

```
    chosen_lag = 5
    var_res = model.fit(chosen_lag)

    # coefficients
    coef = var_res.params
    coef.index.name = 'Equation'
    out["Coefficients"] = coef

    # residual diagnostics - Durbin-Watson
    resid = var_res.resid
    dw = pd.Series(durbin_watson(resid), index=var_vars)
    out["Durbin_Watson"] = dw.to_frame("DW")

    # granger causality
    granger_rows = []
    for v in var_vars:
        if v == 'EUA_ret': continue
        g = var_res.test_causality('EUA_ret', [v], kind='f')
        granger_rows.append([v, g.test_statistic, g.pvalue])

    out["Granger"] = pd.DataFrame(granger_rows, columns=['Cause', 'F', 'p'])

    # FEVD
    fevd = var_res.fevd(n_irf)
    idx = var_vars.index('EUA_ret')
    fevd_table = pd.DataFrame({
        'h=1': fevd.decomp[idx, 1, :],
        'h=5': fevd.decomp[idx, 5, :],
        'h=10': fevd.decomp[idx, 10, :]
    }, index=var_vars)
    out["FEVD"] = fevd_table

    return out
```

In [22]:
```
tables_sub1 = runvar2_tables(df_sub1, ['Power_ret','Coal_EUR_ret','Gas_ret','EUA_ret'], "Phase3")
tables_sub2 = runvar2_tables(df_sub2, ['Power_ret','Coal_EUR_ret','Gas_ret','EUA_ret'], "Phase4")
tables_full = runvar2_tables(df_w,    ['Power_ret','Coal_EUR_ret','Gas_ret','EUA_ret'], "Full")
```

```
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odels\tsa\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As a result, forecasts cannot be generated. To use the model for forecasting, us
e one of the supported classes of index.
  self._init_dates(dates, freq)
c:\Users\Barkn\OneDrive - Norwegian School of Economics\3. semester-Barks_Yoga\FIN11\Faktisk databehandling final paper\Regressions\.venv\Lib\site-packages\statsm
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odels\tsa\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As a result, forecasts cannot be generated. To use the model for forecasting, us
e one of the supported classes of index.
  self._init_dates(dates, freq)
```

In [23]:
```
def var_summary_table(df_phase3, df_phase4, df_full, var_vars, lag=5, n_irf=11):

    def extract(df_input):
        out = {}

        model = VAR(df_input[var_vars].dropna())
        res = model.fit(lag)

        # Core info
        out["n"] = len(df_input)
        out["lag"] = lag
        out["max_root"] = np.max(np.abs(res.roots))

        # Diagnostics (EUA_ret equation index)
        eua_i = var_vars.index("EUA_ret")
        resid = res.resid.iloc[:, eua_i]

        out["DW"] = float(durbin_watson(resid))

        lb = acorr_ljungbox(resid, lags=[10], return_df=True)
        out["LB_p"] = lb["lb_pvalue"].iloc[-1]

        arch_stat, arch_p, _, _ = het_arch(resid)
        out["ARCH_p"] = arch_p

        jb_stat, jb_p, _, _ = jarque_bera(resid)
        out["JB_p"] = jb_p

        # Granger causality per variable
        for v in var_vars:
            if v == "EUA_ret":
                continue
            g = res.test_causality("EUA_ret", [v], kind="f")
            out[f"GC_{v}"] = g.pvalue

        # FEVD
        fevd = res.fevd(n_irf)
        idx = eua_i
        for h in [1, 5, 10]:
            row = fevd.decomp[idx, h, :]
            for j, v in enumerate(var_vars):
                out[f"FEVD{h}_{v}"] = row[j]

        return out

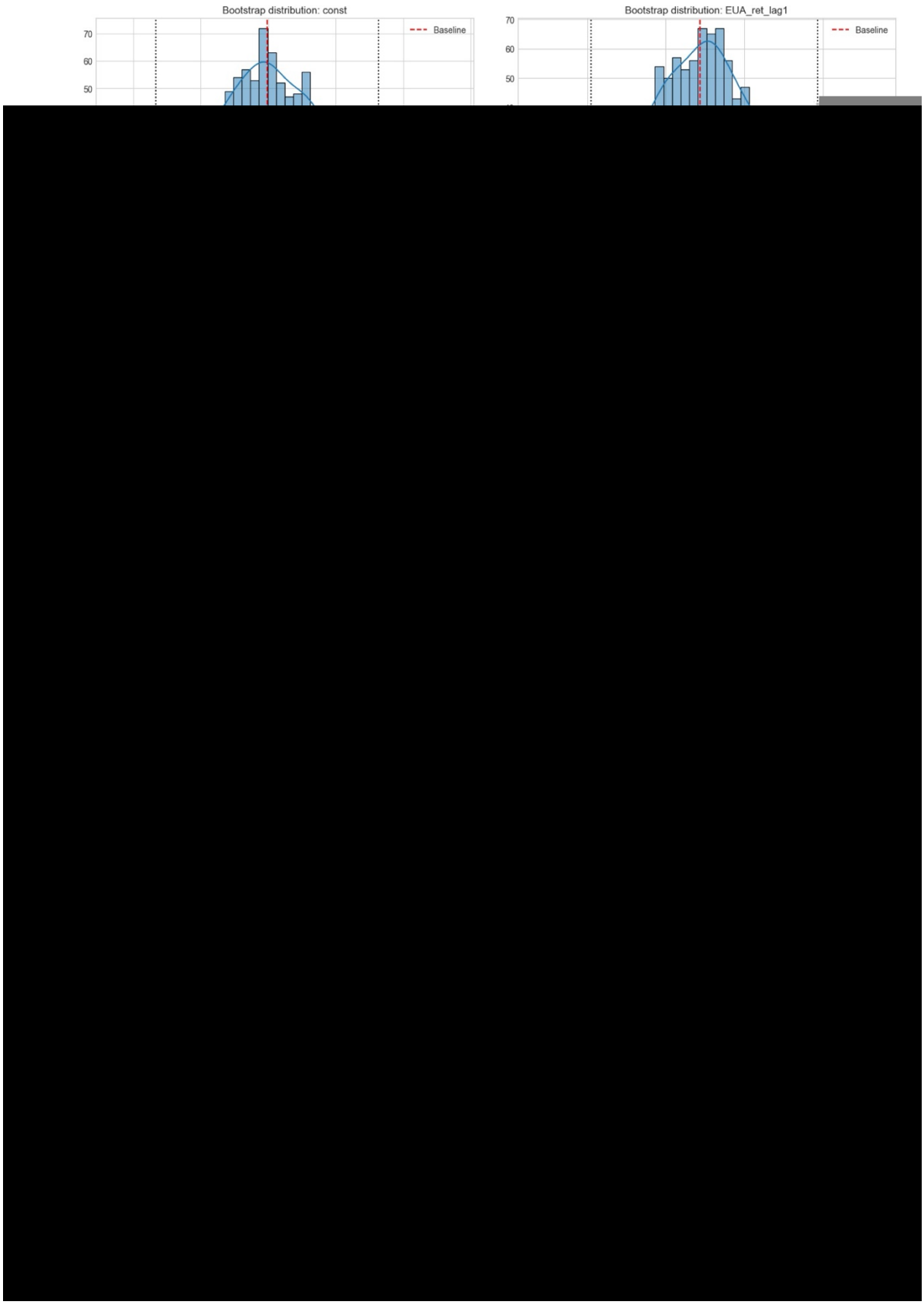
    # Extract all tables
    t3 = extract(df_phase3)
    t4 = extract(df_phase4)
    tf = extract(df_full)

    # Combine to wide format
    df_out = pd.DataFrame({
        "Phase 3": t3,
        "Phase 4": t4,
        "Full": tf
```

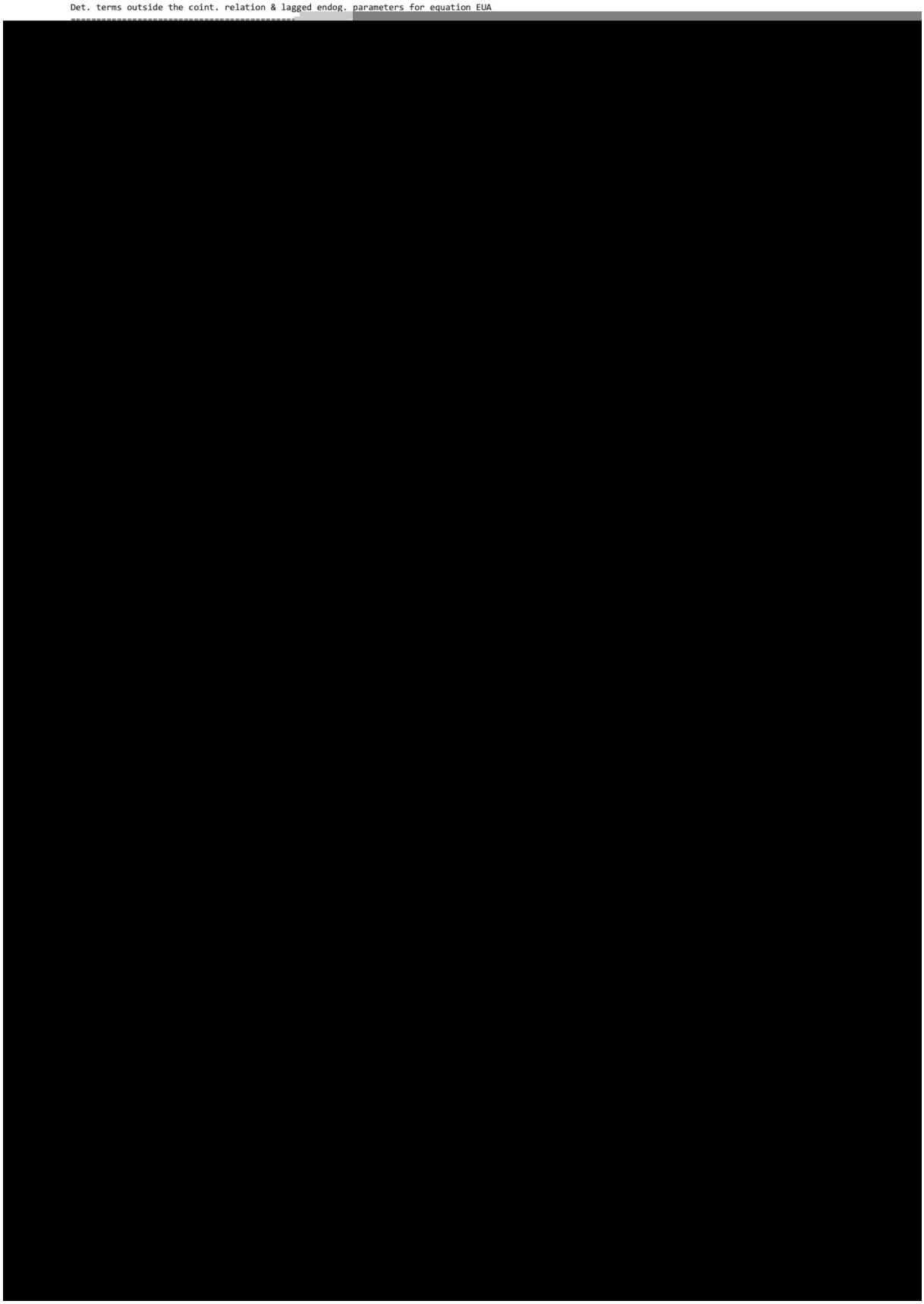
```
=== VAR sample: 2022 to 3339, n=1318 ===
Lag order selection (lower = better):
 VAR Order Selection (* highlights the minimums)
=================================================
       AIC         BIC         FPE         HQIC
-------------------------------------------------
0       -27.34     -27.32*   1.344e-12      -27.33
1       -27.40      -27.32   1.265e-12     -27.37*
2      -27.42*      -27.27  1.238e-12*      -27.36
3       -27.41      -27.20   1.249e-12      -27.33
4       -27.41      -27.14   1.249e-12      -27.31
5       -27.41      -27.08   1.244e-12      -27.29
6       -27.40      -27.01   1.258e-12      -27.25
7       -27.39      -26.93   1.270e-12      -27.22
8       -27.38      -26.86   1.285e-12      -27.18
9       -27.37      -26.78   1.301e-12      -27.15
10      -27.36      -26.71   1.314e-12      -27.11
-------------------------------------------------
Using lag = 5 (forced for stability and comparability)
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Sun, 23, Nov, 2025
Time:                     12:46:24
--------------------------------------------------------------------
No. of Equations:         4.00000    BIC:                   -27.0902
Nobs:                     1313.00    HQIC:                  -27.2974
Log likelihood:           10634.0    FPE:                1.23293e-12
AIC:                     -27.4216    Det(Omega_mle):     1.15711e-12
--------------------------------------------------------------------
Results for equation Power_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                -0.000036         0.001288           -0.028           0.978
L1.Power_ret         -0.101908         0.042747           -2.384           0.017
L1.Coal_EUR_ret      -0.003104         0.038405           -0.081           0.936
L1.Gas_ret            0.139321         0.041382            3.367           0.001
L1.EUA_ret            0.112927         0.058084            1.944           0.052
L2.Power_ret         -0.001304         0.043781           -0.030           0.976
L2.Coal_EUR_ret      -0.021292         0.038493           -0.553           0.580
L2.Gas_ret           -0.048146         0.042500           -1.133           0.257
L2.EUA_ret            0.013744         0.058216            0.236           0.813
L3.Power_ret          0.013338         0.043866            0.304           0.761
L3.Coal_EUR_ret       0.043152         0.038492            1.121           0.262
L3.Gas_ret           -0.025723         0.042810           -0.601           0.548
L3.EUA_ret           -0.010580         0.058413           -0.181           0.856
L4.Power_ret          0.048017         0.043683            1.099           0.272
L4.Coal_EUR_ret       0.013735         0.038210            0.359           0.719
L4.Gas_ret            0.045429         0.042400            1.071           0.284
L4.EUA_ret            0.007406         0.058424            0.127           0.899
L5.Power_ret         -0.025860         0.042470           -0.609           0.543
L5.Coal_EUR_ret      -0.008872         0.038089           -0.233           0.816
L5.Gas_ret            0.039615         0.041400            0.957           0.339
L5.EUA_ret           -0.027188         0.058110           -0.468           0.640
================================================================================

Results for equation Coal_EUR_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                 0.000537         0.000965            0.557           0.578
L1.Power_ret          0.007362         0.032028            0.230           0.818
L1.Coal_EUR_ret       0.019159         0.028775            0.666           0.506
L1.Gas_ret            0.061551         0.031005            1.985           0.047
L1.EUA_ret           -0.077066         0.043519           -1.771           0.077
L2.Power_ret          0.070855         0.032802            2.160           0.031
L2.Coal_EUR_ret      -0.002863         0.028840           -0.099           0.921
L2.Gas_ret            0.017992         0.031843            0.565           0.572
L2.EUA_ret           -0.130068         0.043617           -2.982           0.003
L3.Power_ret          0.013909         0.032866            0.423           0.672
L3.Coal_EUR_ret      -0.019552         0.028839           -0.678           0.498
L3.Gas_ret           -0.025946         0.032075           -0.809           0.419
L3.EUA_ret            0.034875         0.043765            0.797           0.426
L4.Power_ret          0.053789         0.032729            1.643           0.100
L4.Coal_EUR_ret       0.038504         0.028628            1.345           0.179
L4.Gas_ret           -0.009710         0.031768           -0.306           0.760
L4.EUA_ret           -0.084790         0.043773           -1.937           0.053
L5.Power_ret          0.111522         0.031820            3.505           0.000
L5.Coal_EUR_ret      -0.058154         0.028537           -2.038           0.042
L5.Gas_ret           -0.055861         0.031019           -1.801           0.072
L5.EUA_ret            0.093029         0.043539            2.137           0.033
================================================================================

Results for equation Gas_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                 0.000601         0.001314            0.457           0.648
L1.Power_ret          0.153458         0.043624            3.518           0.000
L1.Coal_EUR_ret       0.012094         0.039192            0.309           0.758
L1.Gas_ret           -0.101069         0.042231           -2.393           0.017
L1.EUA_ret           -0.014470         0.059275           -0.244           0.807
L2.Power_ret          0.098832         0.044679            2.212           0.027
L2.Coal_EUR_ret       0.004290         0.039282            0.109           0.913
L2.Gas_ret           -0.180627         0.043372           -4.165           0.000
L2.EUA_ret            0.101908         0.059409            1.715           0.086
L3.Power_ret          0.064483         0.044766            1.440           0.150
L3.Coal_EUR_ret       0.025738         0.039281            0.655           0.512
L3.Gas_ret           -0.096246         0.043688           -2.203           0.028
L3.EUA_ret            0.075537         0.059610            1.267           0.205
L4.Power_ret          0.205249         0.044572            4.605           0.000
```


Bootstrap distribution: const
Baseline
70
60
50
Bootstrap distribution: EUA_ret_lag1
Baseline
70
60
50

Det. terms outside the coint. relation & lagged endog. parameters for equation EUA



```
        ax.set_title(f"Shock to {shock}")

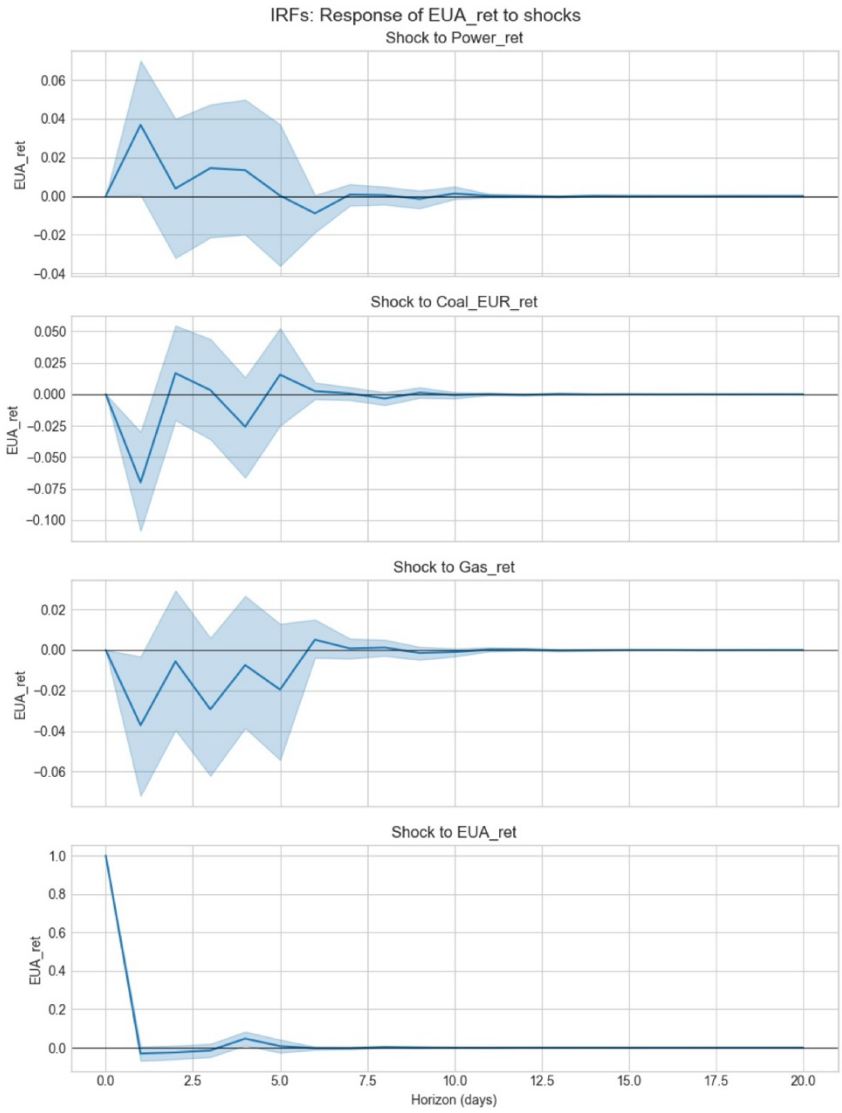
    plt.xlabel("Horizon (days)")
    plt.suptitle("IRFs: Response of EUA_ret to shocks", fontsize=14)
    plt.tight_layout()
    plt.show()

    # Granger causality
    print("\n=== Granger causality: Does X cause EUA_ret? ===")
    for v in var_vars:
        if v == 'EUA_ret':
            continue
        g = var_res.test_causality('EUA_ret', [v], kind='f')
        print(f"{v}: F={g.test_statistic:.3f}, p={g.pvalue:.4g}")

    # FEVD
    print("\n=== FEVD for EUA_ret ===")
    fevd = var_res.fevd(n_irf)
    decomp = np.asarray(fevd.decomp)

    idx = var_vars.index('EUA_ret')
    for h in [1, 5, 10]:
        row = decomp[idx, h, :]
        df_table = pd.DataFrame([row], columns=var_vars, index=[f"h={h}"])
        display(df_table.style.format("{:.4f}"))


runvar_credit(df_sub1, ['CSS_change', 'CDS_change', 'EUA_ret'], maxlags=10, n_irf=20, bootstrap_reps=1000)
runvar_credit(df_sub2, ['CSS_change', 'CDS_change', 'EUA_ret'], maxlags=10, n_irf=20, bootstrap_reps=1000)
```




```
=== Granger causality: Does X cause EUA_ret? ===
Power_ret: F=1.289, p=0.2655
Coal_EUR_ret: F=3.180, p=0.007163
Gas_ret: F=1.843, p=0.1009

=== FEVD for EUA_ret ===
```

	Power_ret	Coal_EUR_ret	Gas_ret	EUA_ret
h=1	0.0842	0.0073	0.0080	0.9005

	Power_ret	Coal_EUR_ret	Gas_ret	EUA_ret
h=5	0.0843	0.0080	0.0093	0.8984

	Power_ret	Coal_EUR_ret	Gas_ret	EUA_ret
h=10	0.0844	0.0080	0.0093	0.8983

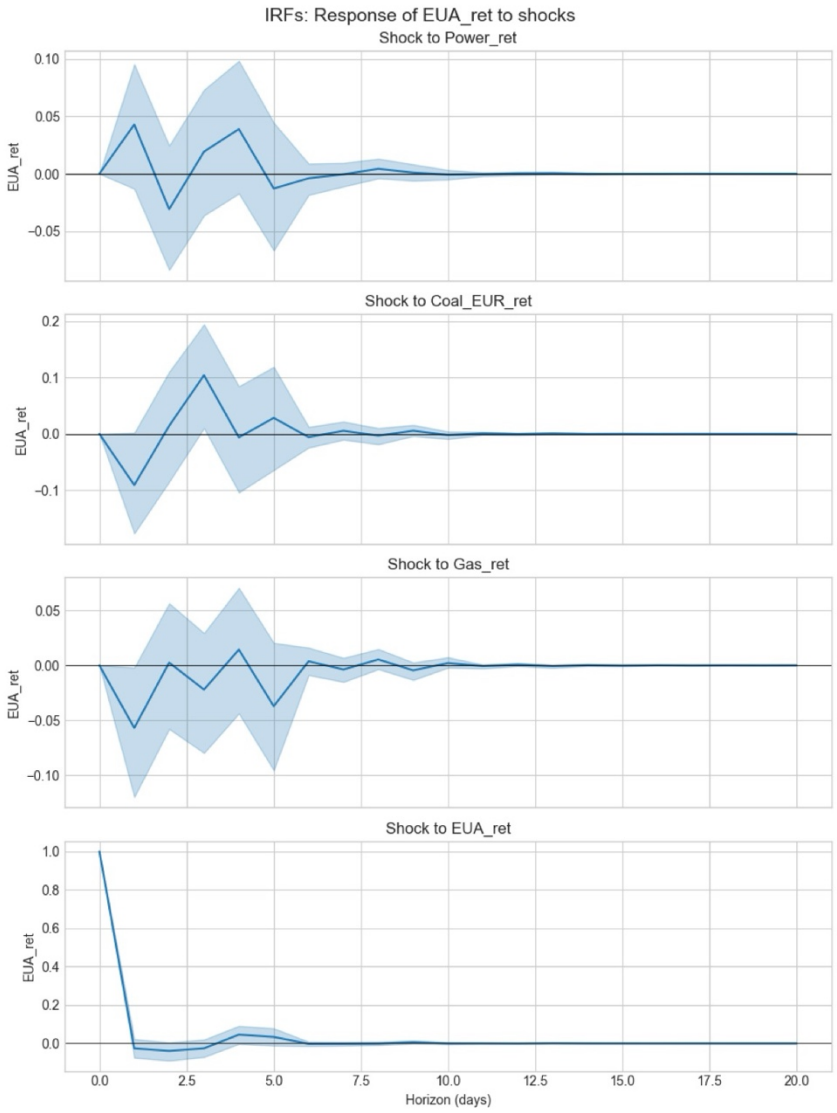
In [21]:
```python
def runvar2_tables(df_input, var_vars, sample_label, maxlags=10, n_irf=20, bootstrap_reps=1000):

    out = {}

    df_var = df_input[var_vars].dropna().copy()

    # lag selection
    model = VAR(df_var)
    sel = model.select_order(maxlags)

    lag_table = pd.DataFrame({
        'AIC': [sel.aic],
        'BIC': [sel.bic],
        'HQIC': [sel.hqic]
    }, index=[sample_label])
    out["Lag_selection"] = lag_table
```




```
=== Granger causality: Does X cause EUA_ret? ===
Power_ret: F=1.123, p=0.3458
Coal_EUR_ret: F=1.845, p=0.1006
Gas_ret: F=1.357, p=0.2373

=== FEVD for EUA_ret ===
```

	Power_ret	Coal_EUR_ret	Gas_ret	EUA_ret
h=1	0.0910	0.0093	0.0209	0.8788

	Power_ret	Coal_EUR_ret	Gas_ret	EUA_ret
h=5	0.0944	0.0114	0.0219	0.8722

	Power_ret	Coal_EUR_ret	Gas_ret	EUA_ret
h=10	0.0945	0.0115	0.0219	0.8721

```
Bootstrap 95% CI:
       coef_name  beta_hat  boot_CI_low  boot_CI_high
0          const  0.000991     0.000168      0.001817
1   EUA_ret_lag1 -0.031198    -0.059042     -0.001380
2  Brent_EUR_ret  0.149957     0.112450      0.189198
3   Coal_EUR_ret -0.104204    -0.142610     -0.062859
4        Gas_ret  0.151548     0.108932      0.196907
5      Power_ret  0.334838     0.285168      0.383792
6     CDS_change -0.002123    -0.002396     -0.001842
7     CSS_change  0.000500     0.000147      0.000855
```

In [ ]:
```python
# Plot bootstrap distributions, together with baseline and CI
coef_names = ['const','EUA_ret_lag1','Coal_EUR_ret',
              'Gas_ret','Power_ret','CDS_change','CSS_change']

fig, axes = plt.subplots(4, 2, figsize=(14, 16))
axes = axes.flatten()

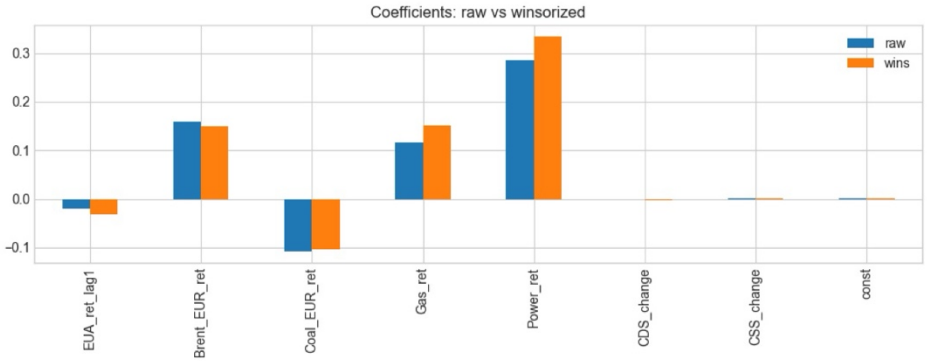
for i in range(len(beta_hat)):
    ax = axes[i]

    sns.histplot(boot_coefs[:, i], kde=True, ax=ax, bins=40)
    ax.axvline(beta_hat[i], color='red', linestyle='--', label='Baseline')
    ax.axvline(boot_ci[0][i], color='black', linestyle=':')
    ax.axvline(boot_ci[1][i], color='black', linestyle=':')

    ax.set_title(f"Bootstrap distribution: {coef_names[i]}")
    ax.legend()

plt.tight_layout()
plt.show()
```

In [14]:
```
# Coefficient comparison (to make sure winsorizing didn't change too much)
import pandas as pd
coef_df = pd.DataFrame({
    'raw': mod_raw.params,
    'raw_se': mod_raw.bse,
    'wins': mod_w.params,
    'wins_se': mod_w.bse
})
coef_df = coef_df.loc[X_cols + ['const'], :]
coef_df[['raw','wins']].plot(kind='bar', figsize=(10,4))
plt.title("Coefficients: raw vs winsorized")
plt.tight_layout()
plt.show()
```



In [ ]:
```
# Bootstrap confidence intervals with residual resampling
df_b = df_w.copy()

y = df_b['EUA_ret'].values
X = df_b[['EUA_ret_lag1','Coal_EUR_ret','Gas_ret',
          'Power_ret','CDS_change','CSS_change']]
X_const = sm.add_constant(X).values

# 2) Fit baseline model (truth model)
nw_lag = int(len(df_b) ** 0.25)

model_base = sm.OLS(y, X_const).fit(
    cov_type='HAC',
    cov_kwds={'maxlags': nw_lag}
)

beta_hat = model_base.params
resid = model_base.resid
n = len(resid)

print("Baseline coefficients:")
print(beta_hat)
print("\nBootstrap running...")


# Bootstrap: residual resampling
B = 1000
boot_coefs = np.zeros((B, len(beta_hat)))

for b in tqdm(range(B)):
    # resample residuals with replacement
    eps_star = np.random.choice(resid, size=n, replace=True)

    # bootstrap Y*
    y_star = model_base.fittedvalues + eps_star

    # refit model on simulated sample
    model_star = sm.OLS(y_star, X_const).fit(
        cov_type='HAC',
        cov_kwds={'maxlags': nw_lag}
    )

    boot_coefs[b, :] = model_star.params


# Bootstrap confidence intervals
alpha = 0.05
boot_ci = np.percentile(boot_coefs, [100*alpha/2, 100*(1-alpha/2)], axis=0)

boot_results = pd.DataFrame({
    'coef_name': ['const','EUA_ret_lag1','Coal_EUR_ret',
                  'Gas_ret','Power_ret','CDS_change','CSS_change'],
    'beta_hat': beta_hat,
    'boot_CI_low': boot_ci[0],
    'boot_CI_high': boot_ci[1]
})

print("\nBootstrap 95% CI:")
print(boot_results)
```

```
Baseline coefficients:
[ 0.00099133 -0.03119803  0.14995747 -0.10420404  0.15154792  0.33483822
 -0.00212294  0.00050011]

Bootstrap running...
100%|██████████| 1000/1000 [00:02<00:00, 465.38it/s]
```

Out[ ]:

	ADF_stat	ADF_p	KPSS_stat	KPSS_p
EUA	-0.653181	0.858507	8.379777	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...
Power	-1.512507	0.527315	4.924554	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...
Coal_EUR	-1.676826	0.44309	2.281527	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...
Gas	-1.611388	0.477247	2.532339	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...

In [ ]:
```
df_spreads = df[['CSS', 'CDS']].dropna().copy()

st_results_spreads = {col: stationarity_tests(df_spreads[col]) for col in df_spreads.columns}
pd.DataFrame(st_results_spreads).T
```

```
C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\3069220025.py:4: InterpolationWarning: The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is smaller than the p-value returned.

  res_kpss = kpss(series, regression='c', nlags='auto')
C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\3069220025.py:4: InterpolationWarning: The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is smaller than the p-value returned.

  res_kpss = kpss(series, regression='c', nlags='auto')
```

Out[ ]:

	ADF_stat	ADF_p	KPSS_stat	KPSS_p
CSS	-4.888406	0.000037	2.37483	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...
CDS	-3.837363	0.002547	1.649797	{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%...

In [ ]:
```
joh = coint_johansen(df_vecm, det_order=0, k_ar_diff=2)
print(joh.lr1)  # trace stats
print(joh.cvt)  # critical values
```

```
[57.01124043 24.09184044  4.28463015  0.37698176]
[[44.4929 47.8545 54.6815]
 [27.0669 29.7961 35.4628]
 [13.4294 15.4943 19.9349]
 [ 2.7055  3.8415  6.6349]]
```

In [ ]:
```
r = 1    # From results above, we choose cointegration rank 1

vecm_model_full = VECM(df_vecm, k_ar_diff=2, coint_rank=r, deterministic='ci')
vecm_full = vecm_model_full.fit()
print(vecm_full.summary())
```

```
c:\Users\Barkn\OneDrive - Norwegian School of Economics\3. semester-Barks_Yoga\FIN11\Faktisk databehandling final paper\Regressions\.venv\Lib\site-packages\statsm
odels\tsa\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As a result, forecasts cannot be generated. To use the model for forecasting, us
e one of the supported classes of index.
  self._init_dates(dates, freq)
```

```
        chosen_lag = int(sel.selected_orders.get('aic', np.nan))
    except Exception:
        chosen_lag = None

if chosen_lag is None or chosen_lag <= 0:
    for key in ('bic','hqic'):
        try:
            chosen_lag = int(getattr(sel, key))
            break
        except Exception:
            try:
                chosen_lag = int(sel.selected_orders.get(key, np.nan))
                break
            except Exception:
                chosen_lag = None

if chosen_lag is None or chosen_lag <= 0:
    chosen_lag = 1
print(f"Using lag = {chosen_lag}")

# Estimate VAR
var_res = model.fit(chosen_lag)
print(var_res.summary())

# Stability check
roots = np.abs(var_res.roots)
print("\nCompanion roots (abs):", roots)
if np.any(roots >= 1):
    print("WARNING: VAR is not stable (roots >= 1). IRF/FEVD may be unreliable.")
else:
    print("VAR is stable (all roots < 1).")

# Residual diagnostics

resid = var_res.resid

print("\n=== RESIDUAL DIAGNOSTICS ===")

# Durbin-Watson
print("\nDurbin-Watson (per equation):")
print(durbin_watson(resid))

# Ljung-Box Q-test for autocorrelation
print("\nLjung-Box Q-test (lags 5 & 10):")
for i, name in enumerate(var_vars):
    print(f"\nResidual series: {name}")
    for lag in [5, 10]:
        lb = acorr_ljungbox(resid.iloc[:, i], lags=[lag], return_df=True)
        print(f"Lag {lag}:")
        print(lb)

# ARCH LM test for heteroskedasticity
print("\nARCH LM tests (per equation):")
for col in resid.columns:
    stat, pval, _, _ = het_arch(resid[col])
    print(f"{col}: ARCH LM stat={stat:.4f}, p={pval:.4g}")

# Jarque-Bera normality test
print("\nJarque-Bera normality (per equation):")
for col in resid.columns:
    jb_stat, jb_p, jb_skew, jb_kurt = jarque_bera(resid[col])
    print(f"{col}: JB stat={jb_stat:.4f}, p={jb_p:.4g}")

# Point IRFs (orthogonalized hvis du vil)
irf = var_res.irf(n_irf)
fig_orth = irf.plot(orth=True)             # orth=True => Cholesky, dokumentér ordering!
plt.suptitle("Orthogonalized IRFs (Cholesky, ordering matters)", fontsize=14)
plt.show()

# IRFs
irf = var_res.irf(n_irf)
print("\nBootstrapping IRFs...")
irf_err_out = var_res.irf_errband_mc(steps=n_irf, repl=bootstrap_reps)

# parse bands
if len(irf_err_out) == 2:
    irf_lower, irf_upper = irf_err_out
else:
    _, irf_lower, irf_upper = irf_err_out

irf_point = np.asarray(irf.irfs)
irf_lower = np.asarray(irf_lower)
irf_upper = np.asarray(irf_upper)


# IRF plot (EUA_ret response)
response_idx = var_vars.index('EUA_ret')
shock_names = var_vars

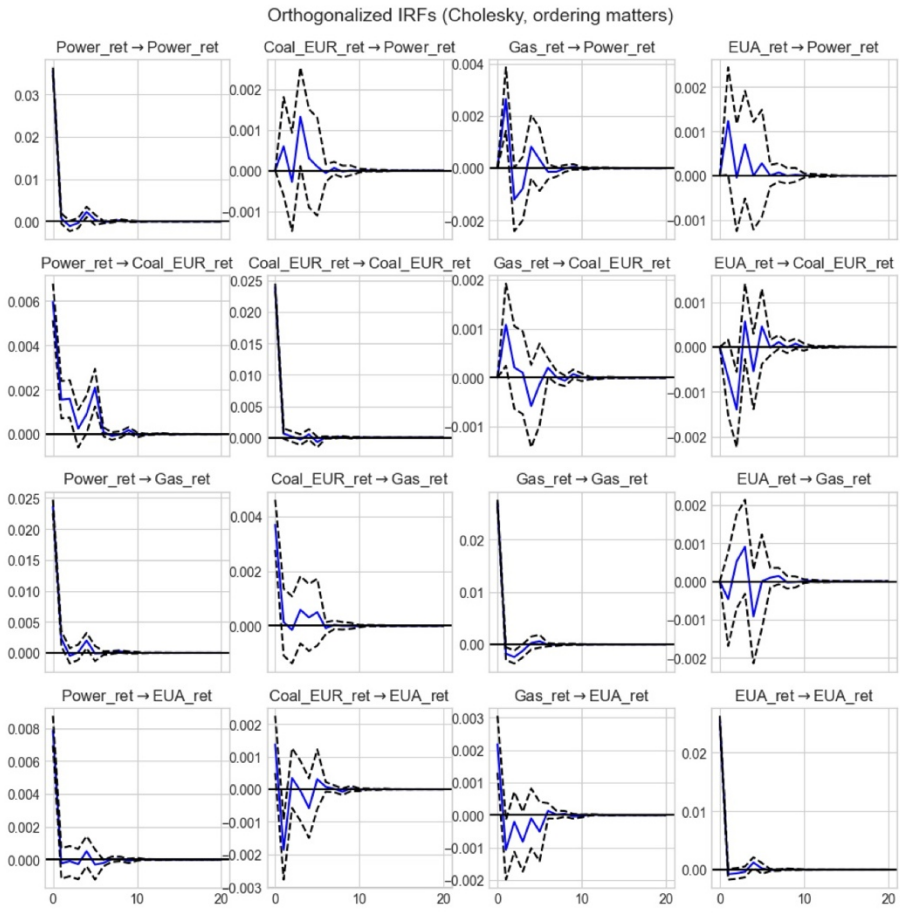
fig, axes = plt.subplots(len(shock_names), 1, figsize=(9, 3*len(shock_names)), sharex=True)

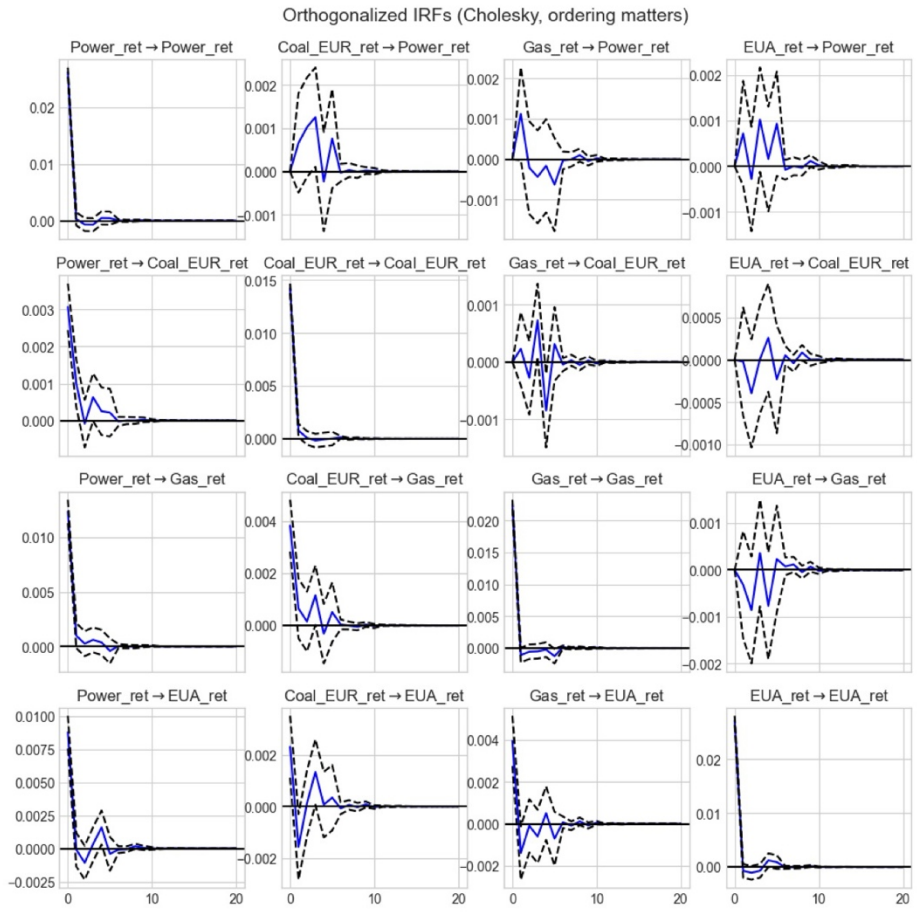
for i, shock in enumerate(shock_names):
    shock_idx = var_vars.index(shock)
    ax = axes[i]

    ax.plot(range(n_irf+1),
            irf_point[:, response_idx, shock_idx],
            label='IRF', color='C0')

    ax.fill_between(range(n_irf+1),
                    irf_lower[:, response_idx, shock_idx],
                    irf_upper[:, response_idx, shock_idx],
                    color='C0', alpha=0.25)

    ax.axhline(0, color='k', lw=0.6)
    ax.set_ylabel("EUA_ret")
```


Orthogonalized IRFs (Cholesky, ordering matters)
Power_ret → Power_ret
Coal_EUR_ret → Power_ret
Gas_ret → Power_ret
EUA_ret → Power_ret
Power_ret → Coal_EUR_ret
Coal_EUR_ret → Coal_EUR_ret
Gas_ret → Coal_EUR_ret
EUA_ret → Coal_EUR_ret
Power_ret → Gas_ret
Coal_EUR_ret → Gas_ret
Gas_ret → Gas_ret
EUA_ret → Gas_ret
Power_ret → EUA_ret
Coal_EUR_ret → EUA_ret
Gas_ret → EUA_ret
EUA_ret → EUA_ret
Bootstrapping IRFs...


Orthogonalized IRFs (Cholesky, ordering matters)
Power_ret → Power_ret
Coal_EUR_ret → Power_ret
Gas_ret → Power_ret
EUA_ret → Power_ret
Power_ret → Coal_EUR_ret
Coal_EUR_ret → Coal_EUR_ret
Gas_ret → Coal_EUR_ret
EUA_ret → Coal_EUR_ret
Power_ret → Gas_ret
Coal_EUR_ret → Gas_ret
Gas_ret → Gas_ret
EUA_ret → Gas_ret
Power_ret → EUA_ret
Coal_EUR_ret → EUA_ret
Gas_ret → EUA_ret
EUA_ret → EUA_ret
Bootstrapping IRFs...

```
    lag = int(n**0.25)
    model = sm.OLS(y, Xc).fit(cov_type='HAC', cov_kwds={'maxlags': lag})
    print(f"\n--- Results ({label})  n={n}  NW_lag={lag} ---")
    print(model.summary())
    return model

mod_raw = run_hac(df, "raw")
mod_w = run_hac(df_w, "winsorized 1%")
```

```
--- Results (raw)  n=3338  NW_lag=7 ---
                            OLS Regression Results
==============================================================================
Dep. Variable:                EUA_ret   R-squared:                       0.126
Model:                            OLS   Adj. R-squared:                  0.124
Method:                 Least Squares   F-statistic:                     22.40
Date:                Sun, 23 Nov 2025   Prob (F-statistic):           8.10e-30
Time:                        12:45:36   Log-Likelihood:                 7152.6
No. Observations:                3338   AIC:                        -1.429e+04
Df Residuals:                    3330   BIC:                        -1.424e+04
Df Model:                           7
Covariance Type:                  HAC
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0007      0.000      1.550      0.121      -0.000       0.002
EUA_ret_lag1  -0.0205      0.024     -0.866      0.386      -0.067       0.026
Brent_EUR_ret  0.1582      0.027      5.889      0.000       0.106       0.211
Coal_EUR_ret  -0.1086      0.054     -2.019      0.043      -0.214      -0.003
Gas_ret        0.1159      0.030      3.805      0.000       0.056       0.176
Power_ret      0.2865      0.042      6.898      0.000       0.205       0.368
CDS_change    -0.0016      0.000     -5.140      0.000      -0.002      -0.001
CSS_change     0.0004      0.000      1.958      0.050    -3.9e-07       0.001
==============================================================================
Omnibus:                     1317.241   Durbin-Watson:                   1.985
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            59649.416
Skew:                          -1.137   Prob(JB):                         0.00
Kurtosis:                      23.584   Cond. No.                         445.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 7 lags and without small sample correction

--- Results (winsorized 1%)  n=3338  NW_lag=7 ---
                            OLS Regression Results
==============================================================================
Dep. Variable:                EUA_ret   R-squared:                       0.166
Model:                            OLS   Adj. R-squared:                  0.164
Method:                 Least Squares   F-statistic:                     45.76
Date:                Sun, 23 Nov 2025   Prob (F-statistic):           3.02e-62
Time:                        12:45:36   Log-Likelihood:                 7613.3
No. Observations:                3338   AIC:                        -1.521e+04
Df Residuals:                    3330   BIC:                        -1.516e+04
Df Model:                           7
Covariance Type:                  HAC
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0010      0.000      2.378      0.017       0.000       0.002
EUA_ret_lag1  -0.0312      0.019     -1.621      0.105      -0.069       0.007
Brent_EUR_ret  0.1500      0.023      6.442      0.000       0.104       0.196
Coal_EUR_ret  -0.1042      0.035     -2.945      0.003      -0.174      -0.035
Gas_ret        0.1515      0.030      5.104      0.000       0.093       0.210
Power_ret      0.3348      0.036      9.361      0.000       0.265       0.405
CDS_change    -0.0021      0.000     -8.937      0.000      -0.003      -0.002
CSS_change     0.0005      0.000      1.741      0.082   -6.28e-05       0.001
==============================================================================
Omnibus:                      130.443   Durbin-Watson:                   2.000
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              358.858
Skew:                          -0.136   Prob(JB):                     1.19e-78
Kurtosis:                       4.583   Cond. No.                         362.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 7 lags and without small sample correction
```

In [13]:
```
# Robust regression (HuberT)
data = df.dropna(subset=[y_col] + X_cols).copy()
y = data[y_col]
X = sm.add_constant(data[X_cols])
rlm = sm.RLM(y, X, M=sm.robust.norms.HuberT()).fit()
print(rlm.summary())
```

```
                    Robust linear Model Regression Results
==============================================================================
Dep. Variable:                EUA_ret   No. Observations:                 3338
Model:                            RLM   Df Residuals:                     3330
Method:                          IRLS   Df Model:                            7
Norm:                          HuberT
Scale Est.:                       mad
Cov Type:                          H1
Date:                Sun, 23 Nov 2025
Time:                        12:45:36
No. Iterations:                    34
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0012      0.000      3.133      0.002       0.000       0.002
EUA_ret_lag1  -0.0460      0.013     -3.651      0.000      -0.071      -0.021
Brent_EUR_ret  0.1335      0.016      8.146      0.000       0.101       0.166
Coal_EUR_ret  -0.0843      0.018     -4.775      0.000      -0.119      -0.050
Gas_ret        0.1149      0.017      6.898      0.000       0.082       0.148
Power_ret      0.3014      0.018     16.908      0.000       0.266       0.336
CDS_change    -0.0016    8.8e-05    -18.691      0.000      -0.002      -0.001
CSS_change     0.0005      0.000      4.380      0.000       0.000       0.001
==============================================================================

If the model instance has been used for another fit with different fit parameters, then the fit options might not be the correct ones anymore .
```

```
                    Robust linear Model Regression Results
==============================================================================
Dep. Variable:                EUA_ret   No. Observations:                 3338
Model:                            RLM   Df Residuals:                     3330
Method:                          IRLS   Df Model:                            7
Norm:                          HuberT
Scale Est.:                       mad
Cov Type:                          H1
Date:                Sun, 23 Nov 2025
Time:                        12:45:36
No. Iterations:                    34
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0012      0.000      3.133      0.002       0.000       0.002
EUA_ret_lag1  -0.0460      0.013     -3.651      0.000      -0.071      -0.021
Brent_EUR_ret  0.1335      0.016      8.146      0.000       0.101       0.166
Coal_EUR_ret  -0.0843      0.018     -4.775      0.000      -0.119      -0.050
Gas_ret        0.1149      0.017      6.898      0.000       0.082       0.148
Power_ret      0.3014      0.018     16.908      0.000       0.266       0.336
CDS_change    -0.0016    8.8e-05    -18.691      0.000      -0.002      -0.001
CSS_change     0.0005      0.000      4.380      0.000       0.000       0.001
==============================================================================
```

If the model instance has been used for another fit with different fit parameters, then the fit options might not be the correct ones anymore .

In [ ]:
```
# Diagnostics for selected cols
cols = ['EUA_ret','Coal_EUR','Gas_ret','Power_ret','CDS_change','CSS_change']

def diagnostics(series):
    s = series.dropna()
    return {
        'n': s.size,
        'mean': s.mean(),
        'std': s.std(),
        'skew': float(skew(s)),
        'kurtosis': float(kurtosis(s, fisher=False)),   # fisher=False => returns "regular" kurtosis (normal=3)
        'JB_stat': None,
        'JB_p': None
    }

# compute JB using statsmodels (unpacks 4 values)
for c in cols:
    s = df[c].dropna()
    jb_stat, jb_p, sk, ku = jarque_bera(s)
    d = diagnostics(s)
    d['JB_stat'] = jb_stat
    d['JB_p'] = jb_p
    print(f"{c:12s}  n={d['n']:5d}  skew={d['skew']:.3f}  kurtosis={d['kurtosis']:.3f}  JB={d['JB_stat']:.1f} p={d['JB_p']:.3g}")
```

```
EUA_ret       n= 3338  skew=-0.990  kurtosis=20.079  JB=41115.4 p=0
Brent_EUR_ret  n= 3338  skew=-0.855  kurtosis=17.023  JB=27755.2 p=0
Coal_EUR      n= 3338  skew=2.479  kurtosis=9.699  JB=9660.0 p=0
Gas_ret       n= 3338  skew=0.761  kurtosis=21.689  JB=48902.3 p=0
Power_ret     n= 3338  skew=0.579  kurtosis=14.621  JB=18970.5 p=0
CDS_change    n= 3338  skew=1.459  kurtosis=55.171  JB=379743.1 p=0
CSS_change    n= 3338  skew=1.913  kurtosis=80.054  JB=827815.3 p=0
```

In [10]:
```
# Quantile clipping
lower_q = 0.01 # 1st percentile
upper_q = 0.99 # 99th percentile
df_w = df.copy() # df_w holds winsorized data
for c in cols:
    q_low = df[c].quantile(lower_q)
    q_high = df[c].quantile(upper_q)
    df_w[c] = df[c].clip(lower=q_low, upper=q_high)

# Compare min/max before/after
for c in cols:
    print(f"{c:12s} before min/max {df[c].min():.4g}/{df[c].max():.4g}  after min/max {df_w[c].min():.4g}/{df_w[c].max():.4g}")
```

```
EUA_ret      before min/max -0.4321/0.2382  after min/max -0.08149/0.07883
Brent_EUR_ret before min/max -0.2803/0.1811  after min/max -0.06739/0.06264
Coal_EUR     before min/max 41.6/485.4  after min/max 48.41/380.2
Gas_ret      before min/max -0.3854/0.4789  after min/max -0.12/0.1294
Power_ret    before min/max -0.2777/0.33  after min/max -0.1266/0.1266
CDS_change   before min/max -82.66/102.1  after min/max -23.7/25.08
CSS_change   before min/max -83.15/79.96  after min/max -17.14/14.78
```

In [11]:
```
# Diagnostics after winsorizing
print("Before / After: EUA_ret")
for c in cols:
    s0 = df[c].dropna()
    s1 = df_w[c].dropna()
    jb0, p0, sk0, ku0 = jarque_bera(s0)
    jb1, p1, sk1, ku1 = jarque_bera(s1)
    print(f"{c:12s}  kurt_before={kurtosis(s0, fisher=False):6.2f}  kurt_after={kurtosis(s1, fisher=False):6.2f}  JB_p_before={p0:.3g}  JB_p_after={p1:.3g}")
```

```
Before / After: EUA_ret
EUA_ret       kurt_before= 20.08  kurt_after=  4.08  JB_p_before=0  JB_p_after=3.24e-37
Brent_EUR_ret  kurt_before= 17.02  kurt_after=  4.31  JB_p_before=0  JB_p_after=3.65e-57
Coal_EUR      kurt_before=  9.70  kurt_after=  9.06  JB_p_before=0  JB_p_after=0
Gas_ret       kurt_before= 21.69  kurt_after=  5.80  JB_p_before=0  JB_p_after=1.01e-240
Power_ret     kurt_before= 14.62  kurt_after=  6.43  JB_p_before=0  JB_p_after=0
CDS_change    kurt_before= 55.17  kurt_after= 15.67  JB_p_before=0  JB_p_after=0
CSS_change    kurt_before= 80.05  kurt_after= 15.71  JB_p_before=0  JB_p_after=0
```

In [ ]:
```
# OLS with Newey-West on original vs winsorized
y_col = 'EUA_ret'
X_cols = ['EUA_ret_lag1','Coal_EUR_ret','Gas_ret','Power_ret','CDS_change','CSS_change']

def run_hac(df_input, label):
    data = df_input.dropna(subset=[y_col] + X_cols).copy()
    y = data[y_col]
    X = data[X_cols]
    Xc = sm.add_constant(X)
    n = len(data)
```

```
--- Correlation Matrix of Returns ---
              EUA_ret_lag1  Brent_EUR_ret  Coal_EUR_ret   Gas_ret  Power_ret  \
EUA_ret_lag1      1.000000       0.004836     -0.012615 -0.008598   0.028195
Brent_EUR_ret     0.004836       1.000000      0.158134  0.121155   0.109283
Coal_EUR_ret     -0.012615       0.158134      1.000000  0.284978   0.244577
Gas_ret          -0.008598       0.121155      0.284978  1.000000   0.636986
Power_ret         0.028195       0.109283      0.244577  0.636986   1.000000
CDS_change        0.026225       0.012491     -0.076867  0.500764   0.721258
CSS_change        0.043427      -0.031847     -0.079125 -0.282032   0.318193

              CDS_change  CSS_change
EUA_ret_lag1    0.026225    0.043427
Brent_EUR_ret   0.012491   -0.031847
Coal_EUR_ret   -0.076867   -0.079125
Gas_ret         0.500764   -0.282032
Power_ret       0.721258    0.318193
CDS_change      1.000000    0.384300
CSS_change      0.384300    1.000000

--- VIF ---
        variable       VIF
0          const  1.000736
1   EUA_ret_lag1  1.002525
2  Brent_EUR_ret  1.036722
3   Coal_EUR_ret  1.325157
4        Gas_ret  3.523850
5      Power_ret  3.634506
6     CDS_change  2.938177
7     CSS_change  2.351754

Observations: 3338, NW maxlags = 7

--- OLS with Newey-West (HAC) ---
                            OLS Regression Results
==============================================================================
Dep. Variable:                EUA_ret   R-squared:                       0.126
Model:                            OLS   Adj. R-squared:                  0.124
Method:                 Least Squares   F-statistic:                     22.40
Date:                Sun, 23 Nov 2025   Prob (F-statistic):           8.10e-30
Time:                        12:45:36   Log-Likelihood:                 7152.6
No. Observations:                3338   AIC:                         -1.429e+04
Df Residuals:                    3330   BIC:                         -1.424e+04
Df Model:                           7
Covariance Type:                  HAC
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0007      0.000      1.550      0.121      -0.000       0.002
EUA_ret_lag1  -0.0205      0.024     -0.866      0.386      -0.067       0.026
Brent_EUR_ret  0.1582      0.027      5.889      0.000       0.106       0.211
Coal_EUR_ret  -0.1086      0.054     -2.019      0.043      -0.214      -0.003
Gas_ret        0.1159      0.030      3.805      0.000       0.056       0.176
Power_ret      0.2865      0.042      6.898      0.000       0.205       0.368
CDS_change    -0.0016      0.000     -5.140      0.000      -0.002      -0.001
CSS_change     0.0004      0.000      1.958      0.050    -3.9e-07       0.001
==============================================================================
Omnibus:                     1317.241   Durbin-Watson:                   1.985
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            59649.416
Skew:                          -1.137   Prob(JB):                         0.00
Kurtosis:                      23.584   Cond. No.                         445.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 7 lags and without small sample correction

Durbin-Watson: 1.9854825886442395
Jarque-Bera: 59649.41630853461 0.0
Skewness: -1.1367782117355048
Kurtosis: 23.584127698060993
Breusch-Pagan: 24.363153846894267 0.0009833875205375819
```

In [ ]:
```
# winsorize 1% begge ender

cols = ['EUA_ret','Coal_EUR_ret','Gas_ret','Power_ret','CDS_change','CSS_change']
df_w = df.copy()
for c in cols:
    df_w[c] = winsorize(df_w[c].dropna(), limits=[0.01, 0.01])

# alternativ: robust regression (Huber) med statsmodels RLM
X_rlm = sm.add_constant(X)
rlm = sm.RLM(y, X_rlm, M=sm.robust.norms.HuberT()).fit()
print(rlm.summary())
```

```
                EUA  Coal_EUR       Gas     Power        DS        SS  \
EUA        1.000000  0.601525  0.590486  0.671529  0.642768  0.631814
Coal_EUR   0.601525  1.000000  0.895598  0.879041  0.726447  0.254584
Gas        0.590486  0.895598  1.000000  0.981795  0.931014  0.285685
Power      0.671529  0.879041  0.981795  1.000000  0.966208  0.462512
DS         0.642768  0.726447  0.931014  0.966208  1.000000  0.529055
SS         0.631814  0.254584  0.285685  0.462512  0.529055  1.000000
CDS        0.500599  0.685117  0.918777  0.940252  0.984932  0.455219
CSS        0.270288  0.006740  0.051051  0.228992  0.326443  0.917041
Brent      0.262214  0.566024  0.430186  0.370356  0.227828 -0.139447

                CDS       CSS     Brent
EUA        0.500599  0.270288  0.262214
Coal_EUR   0.685117  0.006740  0.566024
Gas        0.918777  0.051051  0.430186
Power      0.940252  0.228992  0.370356
DS         0.984932  0.326443  0.227828
SS         0.455219  0.917041 -0.139447
CDS        1.000000  0.307875  0.198259
CSS        0.307875  1.000000 -0.308115
Brent      0.198259 -0.308115  1.000000
```

In [ ]:
```python
# Create returns dataframe aswell as laged EUA return
df = merged_final.copy()

# Removes unusable values
df = df.replace([np.inf, -np.inf], np.nan)

# Create logarithmic returns for price variables
price_cols = ['EUA', 'Coal_EUR', 'Gas', 'Power']

for col in price_cols:
    df[f"{col}_ret"] = np.log(df[col]).diff()

# Calculate changes in CDS and CSS
df['CDS_change'] = df['CDS'].diff()
df['CSS_change'] = df['CSS'].diff()

# Create lagged EUA returns (one day)
df['EUA_ret_lag1'] = df['EUA_ret'].shift(1)

df = df.dropna()
```

In [ ]:
```python
y = df['EUA_ret']

X = df[[
    'EUA_ret_lag1',
    'Coal_EUR_ret',
    'Gas_ret',
    'Power_ret',
    'CDS_change',      # clean dark
    'CSS_change'       # clean spark
]]

# Check multicolinearity
print("\n--- Correlation Matrix of Returns ---")
print(X.corr())

X_vif = sm.add_constant(X)
vif_df = pd.DataFrame({
    'variable': X_vif.columns,
    'VIF': [variance_inflation_factor(X_vif.values, i) for i in range(X_vif.shape[1])]
})
print("\n--- VIF ---")
print(vif_df)


X_const = sm.add_constant(X)

# Newey-West lag (n^0.25)
n = len(df)
lag = int(n ** 0.25) # source: https://en.wikipedia.org/wiki/Newey%E2%80%93West_estimator
print(f"\nObservations: {n}, NW maxlags = {lag}")

# OLS with Newey-West (HAC) standard errors
model = sm.OLS(y, X_const).fit(
    cov_type='HAC',
    cov_kwds={'maxlags': lag}
)

print("\n--- OLS with Newey-West (HAC) ---")
print(model.summary())

# Residual diagnostics
resid = model.resid
print("\nDurbin-Watson:", durbin_watson(resid))

jb_stat, jb_p, skew1, kurt = jarque_bera(resid)
print("Jarque-Bera:", jb_stat, jb_p) # Test for normality, jb_p < 0.05 rejects normality
print("Skewness:", skew1) # Negative skew indicates left tail
print("Kurtosis:", kurt) # High kurtosis indicates heavy tails (normal distribution has kurtosis of 3)

bp_stat, bp_p, _, _ = het_breuschpagan(resid, X_const)
print("Breusch-Pagan:", bp_stat, bp_p) # Test for heteroscedasticity, bp_p < 0.05 rejects homoscedasticity
```

In [ ]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.stats.stattools import durbin_watson, jarque_bera
from statsmodels.stats.diagnostic import het_breuschpagan, acorr_ljungbox, het_arch
from statsmodels.stats.outliers_influence import variance_inflation_factor
from scipy.stats.mstats import winsorize
from scipy.stats import kurtosis, skew
from tqdm import tqdm
from statsmodels.tsa.stattools import adfuller, kpss
from statsmodels.tsa.api import VAR
from statsmodels.tsa.vector_ar.vecm import coint_johansen, VECM

# Set plot style
plt.style.use("seaborn-v0_8-whitegrid")

# Load data
eua = pd.read_csv("EUA.csv", parse_dates=["Date"], sep=";", dayfirst=True, decimal=",") # CFI2Zc1 (TRDPRC_1), EUR/contract
coal = pd.read_csv("ICE_COAL.csv", parse_dates=["Date"], sep=";", dayfirst=True, decimal=",") # ATWMc1 (TRDPRC_1), USD/ton
gas = pd.read_csv("TTF.csv", parse_dates=["Date"], sep=";", dayfirst=True, decimal=",") # TRNLTTFMc1 (TRDPRC_1), EUR/MWh
power = pd.read_csv("GER_BASELOAD_POWER.csv", parse_dates=["Date"], sep=";", dayfirst=True, decimal=",") # TRDEBMc1 (TRDPRC_1), EUR/MWh
eurusd = pd.read_csv("EURUSD.csv", parse_dates=["Date"], sep=";", dayfirst=True, decimal=",") # EUR= , USD/EUR
```

In [ ]:
```python
# Merge future datasets on Date
dfs = [eua, coal, gas, power]

# Rename 'Close' columns to identify the asset
names = ['EUA', 'Coal', 'Gas', 'Power']

# Merge by date
merged = dfs[0].rename(columns={"Close": names[0]})
for df, name in zip(dfs[1:], names[1:]):
    merged = pd.merge(merged, df.rename(columns={"Close": name}), on="Date", how="outer") # Include all dates, even if some assets are missing

# Sort by date
merged = merged.sort_values("Date").reset_index(drop=True)

# Forward fill for missing values
merged_ff = merged.ffill()

# Add EUR/USD to the merged dataframe
eurusd_renamed = eurusd.rename(columns={"Close": "EURUSD"})
merged_final = pd.merge(merged_ff, eurusd_renamed, on="Date", how="left") # EUR/USD can have missing values, so add with left join

# Forward fill EUR/USD missing values (if any)
merged_final["EURUSD"] = merged_final["EURUSD"].ffill()

# Change currencies
energy_content_coal = 6.7
merged_final['Coal_MWh_th'] = (merged_final['Coal'] * merged_final['EURUSD']) / energy_content_coal  # Convert coal price to EUR/MWh_th
merged_final['Coal_EUR'] = merged_final['Coal'] * merged_final['EURUSD']  # Convert Coal price to EUR/ton
```

In [3]:
```python
# Remove row with date 2012-12-31 due to outside research interval
merged_final = merged_final[merged_final['Date'] != pd.Timestamp('2012-12-31')].reset_index(drop=True) # Includes all rows except the one with date 2012-12-31
```

In [4]:
```python
'''Calculating relevant metrics'''
# Constants
eta_gas = 0.5  # Efficiency of gas power plants (MWh generated per MWh fuel input)
eta_coal = 0.35  # Efficiency of coal power plants (MWh generated per MWh fuel input)
ef_gas = 0.202  # Emission factor gas (tCO2/MWh_th)
ef_coal = 0.341  # Emission factor coal (tCO2/MWh_th)
# NOTE: Emission and efficiency factors can vary based on technology and fuel quality, but excact values are not crucial for this analysis.

# New df to use for calculations and convert coal prices to EUR/MWh_th
df = merged_final.copy()

# Raw spreads
df['DS'] = df['Power'] - (df['Coal_MWh_th'] / eta_coal)  # Dark Spread
df['SS'] = df['Power'] - (df['Gas'] / eta_gas)    # Spark Spread

# Clean spreads (including CO2 costs)
df['CDS'] = df['DS'] - (ef_coal * df['EUA'])  # Clean Dark Spread
df['CSS'] = df['SS'] - (ef_gas * df['EUA'])   # Clean Spark Spread

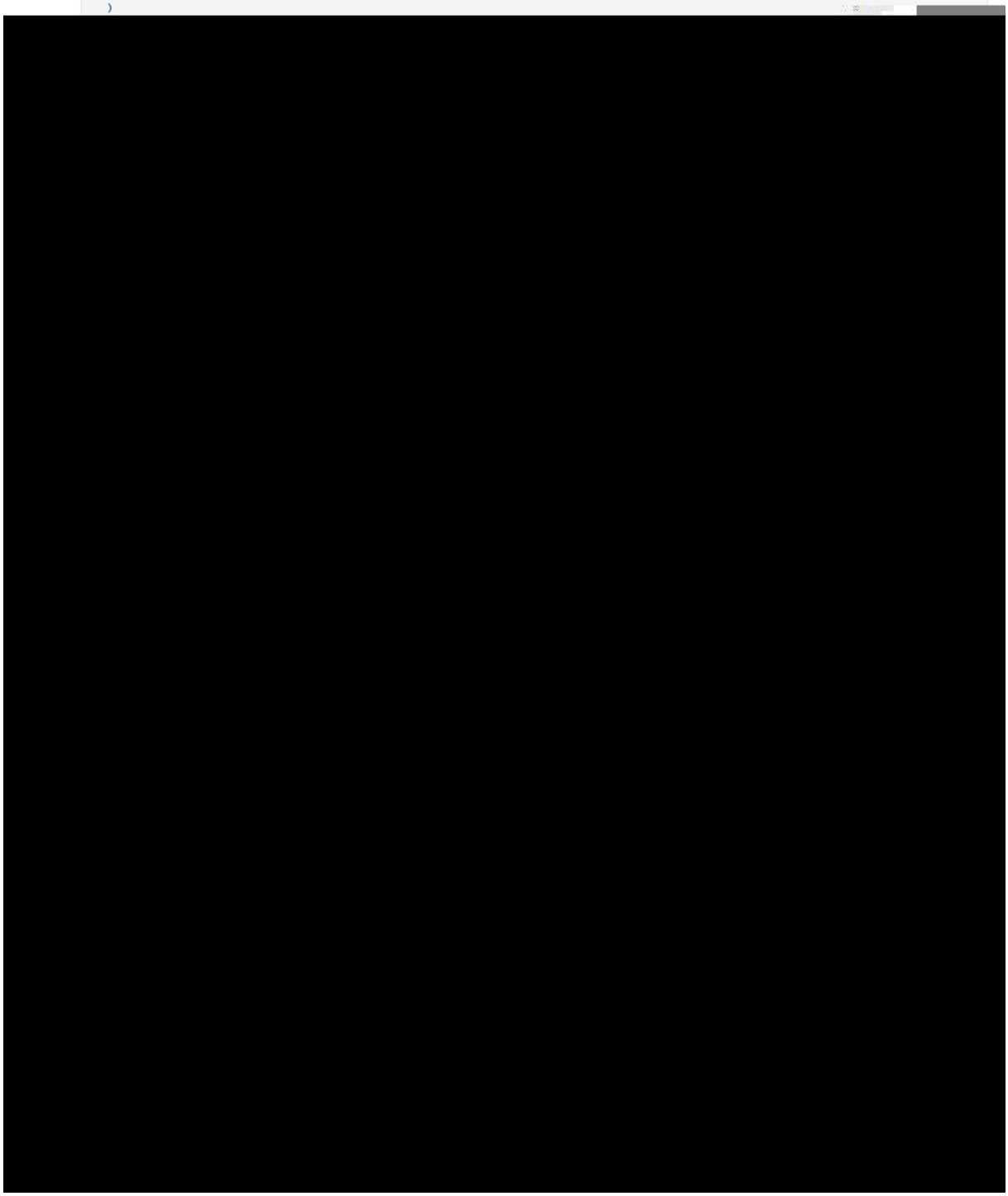
# Add spreads to merged_final
merged_final['CDS'] = df['CDS']
merged_final['CSS'] = df['CSS']
```

In [ ]:
```python
# See correlation
correlation_matrix = df[['EUA', 'Coal_EUR', 'Gas', 'Power', 'DS', 'SS', 'CDS', 'CSS']].corr()
print(correlation_matrix)
```

```
            rows.append([
                sample_label,
                var,
                betas[0], alphas[0],
                betas[1], alphas[1]
            ])

    # Collect for all three models
    collect("Full sample", alpha_full, beta_full, rank_full)
    collect("Phase 3",     alpha_p3,   beta_p3,   rank_p3)
    collect("Phase 4",     alpha_p4,   beta_p4,   rank_p4)

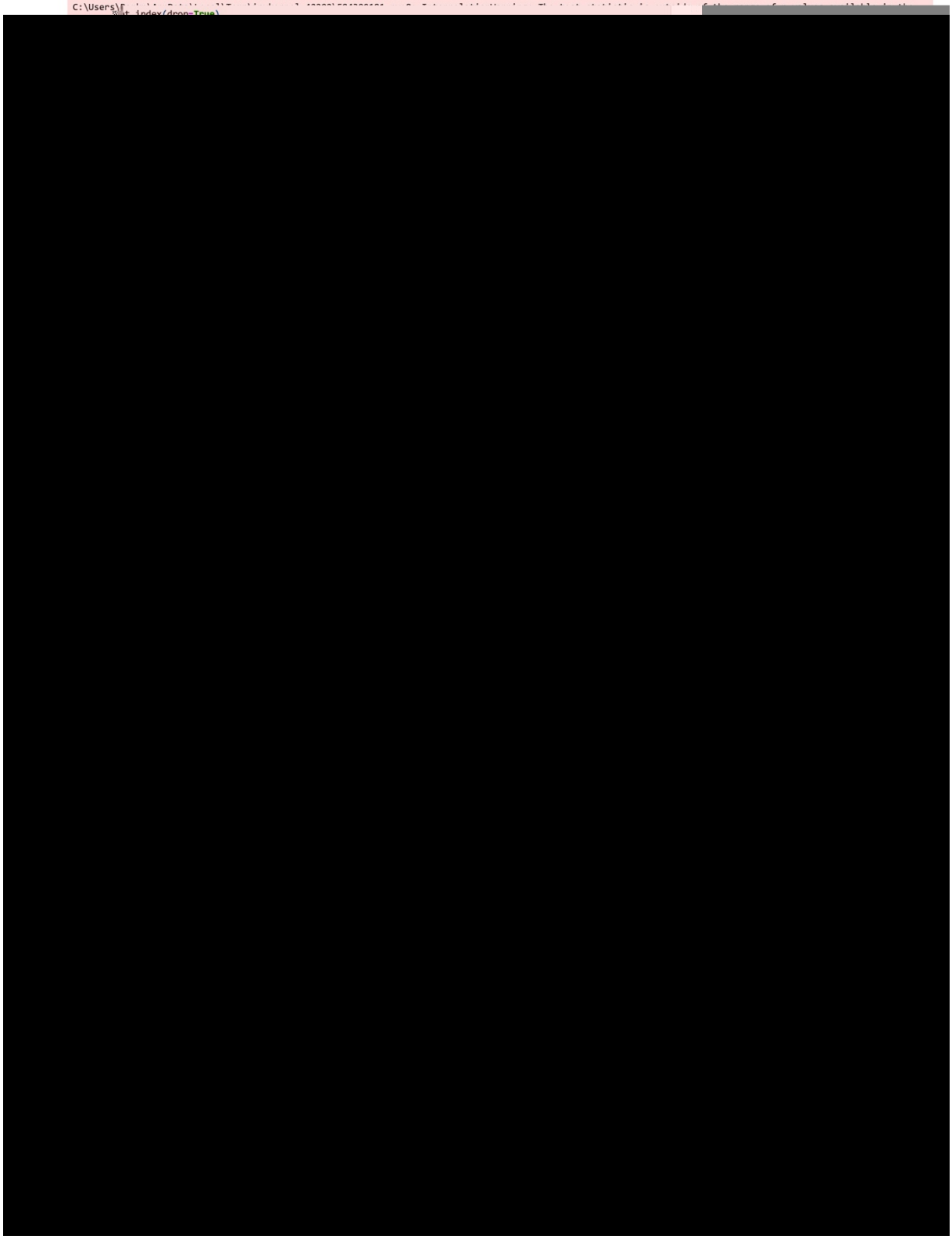
    df = pd.DataFrame(
        rows,
        columns=["Sample", "Variable",
                 "Beta(1)", "Alpha(1)",
                 "Beta(2)", "Alpha(2)"]
    )
```

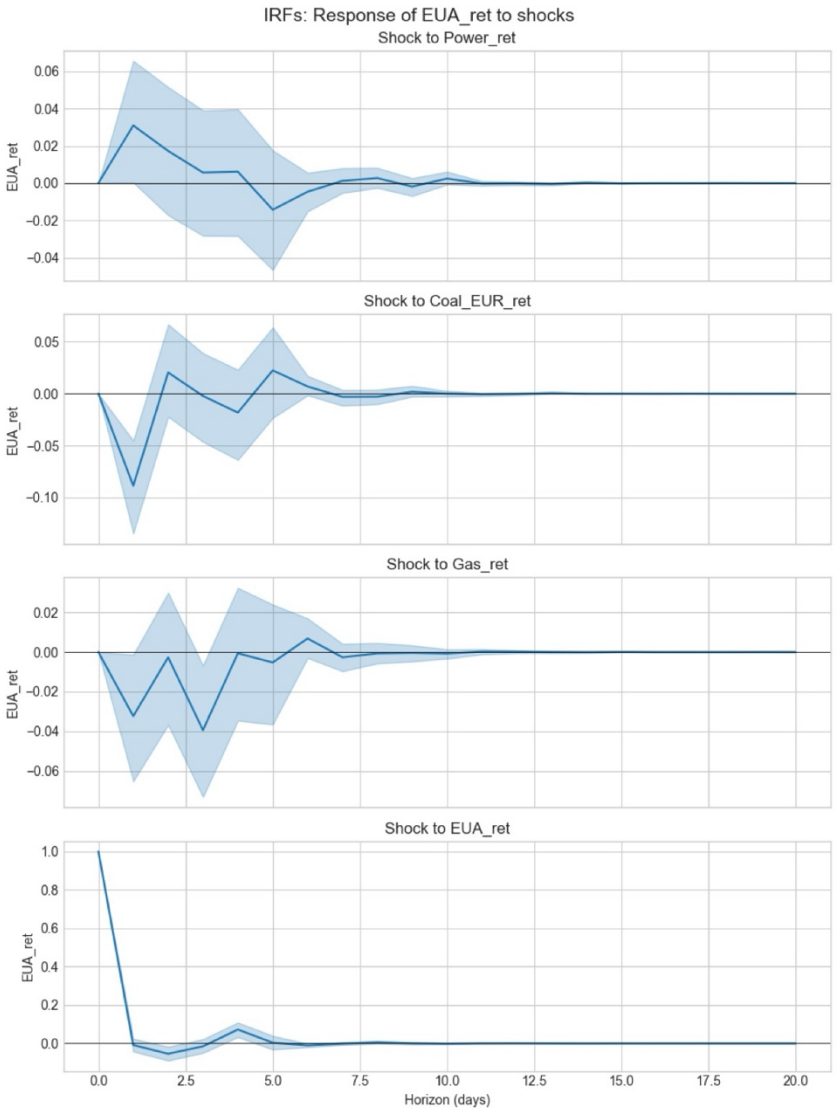


```
C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\584390181.py:8: InterpolationWarning: The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is smaller than the p-value returned.

  result = kpss(series.dropna(), regression='c', nlags='auto')
C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\584390181.py:8: InterpolationWarning: The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is greater than the p-value returned.

  result = kpss(series.dropna(), regression='c', nlags='auto')
C:\Users\
```






```
=== Granger causality: Does X cause EUA_ret? ===
Power_ret: F=1.128, p=0.343
Coal_EUR_ret: F=3.909, p=0.001528
Gas_ret: F=2.169, p=0.05466

=== FEVD for EUA_ret ===
```

	Power_ret	Coal_EUR_ret	Gas_ret	EUA_ret
h=1	0.0513	0.0081	0.0023	0.9383

	Power_ret	Coal_EUR_ret	Gas_ret	EUA_ret
h=5	0.0526	0.0087	0.0041	0.9347

	Power_ret	Coal_EUR_ret	Gas_ret	EUA_ret
h=10	0.0526	0.0087	0.0041	0.9345

In [ ]:
```python
def runvar_credit(df_input, var_vars, maxlags=10, n_irf=20, bootstrap_reps=1000):
    np.random.seed(123)

    df_var = df_input[var_vars].dropna().copy()
    print(f"\n=== VAR sample: {df_var.index.min()} to {df_var.index.max()}, n={len(df_var)} ===")

    # lag selection
    model = VAR(df_var)
    sel = model.select_order(maxlags)
    print("Lag order selection (lower = better):")
    print(sel.summary())

    chosen_lag = None
    try:
        chosen_lag = int(sel.aic)
    except Exception:
        try:
```

```
L5.Power_ret          -0.013784         0.023772           -0.580           0.562
L5.Coal_EUR_ret        0.012942         0.026133            0.495           0.620
L5.Gas_ret             0.004303         0.023385            0.184           0.854
L5.EUA_ret             0.001259         0.024320            0.052           0.959
===============================================================================

Results for equation EUA_ret
===============================================================================
                    coefficient       std. error           t-stat            prob
-------------------------------------------------------------------------------
const                  0.000972         0.000469            2.072           0.038
L1.Power_ret           0.036798         0.017824            2.064           0.039
L1.Coal_EUR_ret       -0.069977         0.019683           -3.555           0.000
L1.Gas_ret            -0.037138         0.017476           -2.125           0.034
L1.EUA_ret            -0.030421         0.018244           -1.667           0.095
L2.Power_ret           0.012349         0.018007            0.686           0.493
L2.Coal_EUR_ret        0.016333         0.019715            0.829           0.407
L2.Gas_ret            -0.009666         0.017680           -0.547           0.585
L2.EUA_ret            -0.030122         0.018254           -1.650           0.099
L3.Power_ret           0.021947         0.018038            1.217           0.224
L3.Coal_EUR_ret        0.002359         0.019705            0.120           0.905
L3.Gas_ret            -0.033970         0.017739           -1.915           0.055
L3.EUA_ret            -0.019342         0.018277           -1.058           0.290
L4.Power_ret           0.020376         0.018026            1.130           0.258
L4.Coal_EUR_ret       -0.028283         0.019639           -1.440           0.150
L4.Gas_ret            -0.014611         0.017696           -0.826           0.409
L4.EUA_ret             0.047048         0.018275            2.574           0.010
L5.Power_ret           0.007331         0.017813            0.412           0.681
L5.Coal_EUR_ret        0.021175         0.019582            1.081           0.280
L5.Gas_ret            -0.024983         0.017523           -1.426           0.154
L5.EUA_ret             0.005932         0.018223            0.326           0.745
===============================================================================

Correlation matrix of residuals
               Power_ret  Coal_EUR_ret   Gas_ret   EUA_ret
Power_ret       1.000000      0.241525  0.656456  0.291071
Coal_EUR_ret    0.241525      1.000000  0.257944  0.119761
Gas_ret         0.656456      0.257944  1.000000  0.256655
EUA_ret         0.291071      0.119761  0.256655  1.000000



Companion roots (abs): [5.61346761 5.61346761 2.28747523 2.28747523 2.17829779 2.17829779
 1.96742614 1.96742614 1.9524203  1.9245776  1.9245776  1.8881146
 1.8881146  1.88208853 1.88208853 1.86536099 1.86536099 1.82825009
 1.82825009 1.63887227]
WARNING: VAR is not stable (roots >= 1). IRF/FEVD may be unreliable.

=== RESIDUAL DIAGNOSTICS ===

Durbin-Watson (per equation):
[2.00040029 1.99638575 1.99991781 2.00044089]

Ljung-Box Q-test (lags 5 & 10):

Residual series: Power_ret
Lag 5:
    lb_stat  lb_pvalue
5  0.037197   0.999986
Lag 10:
     lb_stat  lb_pvalue
10  5.638654   0.844654

Residual series: Coal_EUR_ret
Lag 5:
    lb_stat  lb_pvalue
5  0.127579   0.999705
Lag 10:
     lb_stat  lb_pvalue
10  8.090275   0.620019

Residual series: Gas_ret
Lag 5:
    lb_stat  lb_pvalue
5  0.040001   0.999983
Lag 10:
     lb_stat  lb_pvalue
10  2.287199   0.993627

Residual series: EUA_ret
c:\Users\Barkn\OneDrive - Norwegian School of Economics\3. semester-Barks_Yoga\FIN11\Faktisk databehandling final paper\Regressions\.venv\Lib\site-packages\statsm
odels\tsa\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As a result, forecasts cannot be generated. To use the model for forecasting, us
e one of the supported classes of index.
  self._init_dates(dates, freq)
Lag 5:
   lb_stat  lb_pvalue
5  0.01065   0.999999
Lag 10:
     lb_stat  lb_pvalue
10  1.808733   0.997607

ARCH LM tests (per equation):
Power_ret: ARCH LM stat=405.0561, p=7.898e-81
Coal_EUR_ret: ARCH LM stat=99.7669, p=6.068e-17
Gas_ret: ARCH LM stat=674.7953, p=1.613e-138
EUA_ret: ARCH LM stat=407.6997, p=2.161e-81

Jarque-Bera normality (per equation):
Power_ret: JB stat=1556.3240, p=0
Coal_EUR_ret: JB stat=1064171.9304, p=0
Gas_ret: JB stat=1012.0796, p=1.697e-220
EUA_ret: JB stat=171.2075, p=6.649e-38
```

```
L5.Power_ret            0.008681         0.026000            0.334           0.738
L5.Coal_EUR_ret         0.048449         0.041522            1.167           0.243
L5.Gas_ret             -0.058995         0.026322           -2.241           0.025
L5.EUA_ret              0.004325         0.021359            0.202           0.840
================================================================================

Results for equation EUA_ret
================================================================================
                     coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                   0.000951         0.000650            1.464           0.143
L1.Power_ret            0.042964         0.028890            1.487           0.137
L1.Coal_EUR_ret        -0.090823         0.046238           -1.964           0.049
L1.Gas_ret             -0.057083         0.028976           -1.970           0.049
L1.EUA_ret             -0.026382         0.023816           -1.108           0.268
L2.Power_ret           -0.023066         0.028990           -0.796           0.426
L2.Coal_EUR_ret         0.018822         0.046349            0.406           0.685
L2.Gas_ret             -0.002626         0.029062           -0.090           0.928
L2.EUA_ret             -0.042176         0.023780           -1.774           0.076
L3.Power_ret            0.022602         0.028964            0.780           0.435
L3.Coal_EUR_ret         0.099437         0.046228            2.151           0.031
L3.Gas_ret             -0.025374         0.029041           -0.874           0.382
L3.EUA_ret             -0.030448         0.023769           -1.281           0.200
L4.Power_ret            0.041794         0.029013            1.441           0.150
L4.Coal_EUR_ret        -0.009103         0.046314           -0.197           0.844
L4.Gas_ret              0.011549         0.029185            0.396           0.692
L4.EUA_ret              0.040576         0.023808            1.704           0.088
L5.Power_ret           -0.010512         0.028912           -0.364           0.716
L5.Coal_EUR_ret         0.035836         0.046173            0.776           0.438
L5.Gas_ret             -0.040777         0.029270           -1.393           0.164
L5.EUA_ret              0.033218         0.023752            1.399           0.162
================================================================================

Correlation matrix of residuals
               Power_ret  Coal_EUR_ret   Gas_ret   EUA_ret
Power_ret       1.000000      0.210584  0.475320  0.302561
Coal_EUR_ret    0.210584      1.000000  0.243802  0.141978
Gas_ret         0.475320      0.243802  1.000000  0.274080
EUA_ret         0.302561      0.141978  0.274080  1.000000



Companion roots (abs): [7.94111094 2.21604455 2.21604455 2.20180629 2.18645984 2.18645984
 2.02272509 2.02272509 1.91212038 1.91212038 1.90195278 1.90195278
 1.76022199 1.76022199 1.75913958 1.75913958 1.74386977 1.71207857
 1.68142312 1.68142312]
WARNING: VAR is not stable (roots >= 1). IRF/FEVD may be unreliable.

=== RESIDUAL DIAGNOSTICS ===

Durbin-Watson (per equation):
[1.99522071 1.99958153 1.99637731 1.99768988]

Ljung-Box Q-test (lags 5 & 10):

Residual series: Power_ret
Lag 5:
    lb_stat  lb_pvalue
5  0.073424   0.999924
Lag 10:
     lb_stat  lb_pvalue
10  3.370747   0.971306

Residual series: Coal_EUR_ret
Lag 5:
    lb_stat  lb_pvalue
5  0.003095        1.0
Lag 10:
     lb_stat  lb_pvalue
10  4.750994   0.907179

Residual series: Gas_ret
Lag 5:
    lb_stat  lb_pvalue
5  0.091087   0.999871
Lag 10:
     lb_stat  lb_pvalue
10  4.667257   0.912269

Residual series: EUA_ret
Lag 5:
   lb_stat  lb_pvalue
5  0.02638   0.999994
Lag 10:
     lb_stat  lb_pvalue
10  2.667681     0.9882

ARCH LM tests (per equation):
Power_ret: ARCH LM stat=42.1873, p=6.945e-06
Coal_EUR_ret: ARCH LM stat=1.6343, p=0.9985
Gas_ret: ARCH LM stat=272.6114, p=9.416e-53
EUA_ret: ARCH LM stat=249.8378, p=5.871e-48

Jarque-Bera normality (per equation):
Power_ret: JB stat=4395.1117, p=0
Coal_EUR_ret: JB stat=112258.4031, p=0
Gas_ret: JB stat=2452.7566, p=0
EUA_ret: JB stat=83.8227, p=6.283e-19
c:\Users\Barkn\OneDrive - Norwegian School of Economics\3. semester-Barks_Yoga\FIN11\Faktisk databehandling final paper\Regressions\.venv\Lib\site-packages\statsm
odels\tsa\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As a result, forecasts cannot be generated. To use the model for forecasting, us
e one of the supported classes of index.
  self._init_dates(dates, freq)
```

```
=== VAR sample: 2 to 2020, n=2019 ===
Lag order selection (lower = better):
 VAR Order Selection (* highlights the minimums)
=================================================
       AIC         BIC         FPE         HQIC
-------------------------------------------------
0       -30.54     -30.53*   5.447e-14     -30.54*
1      -30.55*      -30.49  5.404e-14*      -30.53
2       -30.54      -30.44   5.445e-14      -30.50
3       -30.54      -30.40   5.433e-14      -30.49
4       -30.54      -30.35   5.460e-14      -30.47
5       -30.53      -30.30   5.498e-14      -30.45
6       -30.52      -30.24   5.554e-14      -30.42
7       -30.51      -30.19   5.609e-14      -30.39
8       -30.50      -30.13   5.674e-14      -30.37
9       -30.49      -30.08   5.716e-14      -30.34
10      -30.49      -30.03   5.747e-14      -30.32
-------------------------------------------------
Using lag = 5 (forced for stability and comparability)
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Sun, 23, Nov, 2025
Time:                     12:45:41
----------------------------------------------------------------------
No. of Equations:         4.00000    BIC:                   -30.3023
Nobs:                     2014.00    HQIC:                  -30.4504
Log likelihood:           19403.0    FPE:                5.47371e-14
AIC:                     -30.5362    Det(Omega_mle):     5.25124e-14
----------------------------------------------------------------------
Results for equation Power_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                -0.000250         0.000587           -0.426           0.670
L1.Power_ret         -0.022046         0.026093           -0.845           0.398
L1.Coal_EUR_ret       0.029801         0.041762            0.714           0.475
L1.Gas_ret            0.045151         0.026171            1.725           0.084
L1.EUA_ret            0.026598         0.021510            1.237           0.216
L2.Power_ret         -0.032579         0.026184           -1.244           0.213
L2.Coal_EUR_ret       0.074264         0.041862            1.774           0.076
L2.Gas_ret           -0.003111         0.026249           -0.119           0.906
L2.EUA_ret           -0.008373         0.021478           -0.390           0.697
L3.Power_ret         -0.041043         0.026160           -1.569           0.117
L3.Coal_EUR_ret       0.085487         0.041753            2.047           0.041
L3.Gas_ret           -0.024722         0.026230           -0.943           0.346
L3.EUA_ret            0.040921         0.021468            1.906           0.057
L4.Power_ret          0.014109         0.026204            0.538           0.590
L4.Coal_EUR_ret      -0.015351         0.041831           -0.367           0.714
L4.Gas_ret           -0.005351         0.026360           -0.203           0.839
L4.EUA_ret            0.009079         0.021503            0.422           0.673
L5.Power_ret          0.011590         0.026113            0.444           0.657
L5.Coal_EUR_ret       0.066429         0.041703            1.593           0.111
L5.Gas_ret           -0.036599         0.026436           -1.384           0.166
L5.EUA_ret            0.036734         0.021452            1.712           0.087
================================================================================

Results for equation Coal_EUR_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                -0.000220         0.000327           -0.673           0.501
L1.Power_ret          0.027772         0.014529            1.912           0.056
L1.Coal_EUR_ret       0.052444         0.023253            2.255           0.024
L1.Gas_ret            0.010277         0.014572            0.705           0.481
L1.EUA_ret           -0.000807         0.011977           -0.067           0.946
L2.Power_ret          0.003639         0.014579            0.250           0.803
L2.Coal_EUR_ret       0.006612         0.023309            0.284           0.777
L2.Gas_ret           -0.011059         0.014615           -0.757           0.449
L2.EUA_ret           -0.015140         0.011959           -1.266           0.206
L3.Power_ret          0.012560         0.014566            0.862           0.389
L3.Coal_EUR_ret      -0.024580         0.023248           -1.057           0.290
L3.Gas_ret            0.031399         0.014605            2.150           0.032
L3.EUA_ret            0.000986         0.011953            0.082           0.934
L4.Power_ret          0.023712         0.014591            1.625           0.104
L4.Coal_EUR_ret       0.001449         0.023291            0.062           0.950
L4.Gas_ret           -0.038736         0.014677           -2.639           0.008
L4.EUA_ret            0.007586         0.011973            0.634           0.526
L5.Power_ret          0.004274         0.014540            0.294           0.769
L5.Coal_EUR_ret       0.002406         0.023221            0.104           0.917
L5.Gas_ret            0.014989         0.014720            1.018           0.309
L5.EUA_ret           -0.009227         0.011945           -0.772           0.440
================================================================================

Results for equation Gas_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                -0.000673         0.000584           -1.153           0.249
L1.Power_ret          0.056669         0.025980            2.181           0.029
L1.Coal_EUR_ret       0.059978         0.041581            1.442           0.149
L1.Gas_ret           -0.046101         0.026057           -1.769           0.077
L1.EUA_ret           -0.011541         0.021417           -0.539           0.590
L2.Power_ret          0.030138         0.026070            1.156           0.248
L2.Coal_EUR_ret       0.017681         0.041680            0.424           0.671
L2.Gas_ret           -0.025614         0.026135           -0.980           0.327
L2.EUA_ret           -0.033781         0.021385           -1.580           0.114
L3.Power_ret          0.025870         0.026047            0.993           0.321
L3.Coal_EUR_ret       0.078692         0.041572            1.893           0.058
L3.Gas_ret           -0.029051         0.026116           -1.112           0.266
L3.EUA_ret            0.010818         0.021375            0.506           0.613
L4.Power_ret          0.030784         0.026090            1.180           0.238
L4.Coal_EUR_ret      -0.018559         0.041649           -0.446           0.656
L4.Gas_ret           -0.009841         0.026246           -0.375           0.708
L4.EUA_ret           -0.032231         0.021410           -1.505           0.132
```

```
        df_table = pd.DataFrame([row], columns=var_vars, index=[f"h={h}"])
        display(df_table.style.format("{:.4f}"))


# Split data in phase 3 and 4
df_sub1 = df_w.loc[:'2020-12-31'].copy()
df_sub2 = df_w.loc['2021-01-01':].copy()

# Subsample and full sample VARs
runvar2(df_sub1, ['Power_ret','Coal_EUR_ret','Gas_ret','EUA_ret'])
runvar2(df_sub2, ['Power_ret','Coal_EUR_ret','Gas_ret','EUA_ret'])
runvar2(df_w, ['Power_ret','Coal_EUR_ret','Gas_ret','EUA_ret'])
```

```
print(var_res.summary())

# Stability check
roots = np.abs(var_res.roots)
print("\nCompanion roots (abs):", roots)
if np.any(roots >= 1):
    print("WARNING: VAR is not stable (roots >= 1). IRF/FEVD may be unreliable.")
else:
    print("VAR is stable (all roots < 1).")

# Residual diagnostics
resid = var_res.resid

print("\n=== RESIDUAL DIAGNOSTICS ===")

# Durbin-Watson
print("\nDurbin-Watson (per equation):")
print(durbin_watson(resid))

# Ljung-Box Q-test for autocorrelation
print("\nLjung-Box Q-test (lags 5 & 10):")
for i, name in enumerate(var_vars):
    print(f"\nResidual series: {name}")
    for lag in [5, 10]:
        lb = acorr_ljungbox(resid.iloc[:, i], lags=[lag], return_df=True)
        print(f"Lag {lag}:")
        print(lb)

# ARCH LM test for heteroskedasticity
print("\nARCH LM tests (per equation):")
for col in resid.columns:
    stat, pval, _, _ = het_arch(resid[col])
    print(f"{col}: ARCH LM stat={stat:.4f}, p={pval:.4g}")

# Jarque-Bera normality test
print("\nJarque-Bera normality (per equation):")
for col in resid.columns:
    jb_stat, jb_p, jb_skew, jb_kurt = jarque_bera(resid[col])
    print(f"{col}: JB stat={jb_stat:.4f}, p={jb_p:.4g}")

# Point IRFs
irf = var_res.irf(n_irf)
fig_orth = irf.plot(orth=True)             # orth=True => Cholesky
plt.suptitle("Orthogonalized IRFs (Cholesky, ordering matters)", fontsize=14)
plt.show()

# IRFs
irf = var_res.irf(n_irf)
print("\nBootstrapping IRFs...")
irf_err_out = var_res.irf_errband_mc(steps=n_irf, repl=bootstrap_reps)

# parse bands
if len(irf_err_out) == 2:
    irf_lower, irf_upper = irf_err_out
else:
    _, irf_lower, irf_upper = irf_err_out

irf_point = np.asarray(irf.irfs)
irf_lower = np.asarray(irf_lower)
irf_upper = np.asarray(irf_upper)


# IRF plot (EUA_ret response)
response_idx = var_vars.index('EUA_ret')
shock_names = var_vars

fig, axes = plt.subplots(len(shock_names), 1, figsize=(9, 3*len(shock_names)), sharex=True)

for i, shock in enumerate(shock_names):
    shock_idx = var_vars.index(shock)
    ax = axes[i]

    ax.plot(range(n_irf+1),
            irf_point[:, response_idx, shock_idx],
            label='IRF', color='C0')

    ax.fill_between(range(n_irf+1),
                    irf_lower[:, response_idx, shock_idx],
                    irf_upper[:, response_idx, shock_idx],
                    color='C0', alpha=0.25)

    ax.axhline(0, color='k', lw=0.6)
    ax.set_ylabel("EUA_ret")
    ax.set_title(f"Shock to {shock}")

plt.xlabel("Horizon (days)")
plt.suptitle("IRFs: Response of EUA_ret to shocks", fontsize=14)
plt.tight_layout()
plt.show()

# Granger causality
print("\n=== Granger causality: Does X cause EUA_ret? ===")
for v in var_vars:
    if v == 'EUA_ret':
        continue
    g = var_res.test_causality('EUA_ret', [v], kind='f')
    print(f"{v}: F={g.test_statistic:.3f}, p={g.pvalue:.4g}")

# FEVD
print("\n=== FEVD for EUA_ret ===")
fevd = var_res.fevd(n_irf)
decomp = np.asarray(fevd.decomp)

idx = var_vars.index('EUA_ret')
for h in [1, 5, 10]:
    row = decomp[idx, h, :]
```

```
=== 2013–2020 ===
                            OLS Regression Results
==============================================================================
Dep. Variable:                EUA_ret   R-squared:                       0.213
Model:                            OLS   Adj. R-squared:                  0.210
Method:                 Least Squares   F-statistic:                     34.37
Date:                Sun, 23 Nov 2025   Prob (F-statistic):           1.68e-45
Time:                        12:45:41   Log-Likelihood:                 4518.3
No. Observations:                2019   AIC:                            -9021.
Df Residuals:                    2011   BIC:                            -8976.
Df Model:                           7
Covariance Type:                  HAC
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0012      0.001      2.140      0.032       0.000       0.002
EUA_ret_lag1  -0.0300      0.022     -1.381      0.167      -0.073       0.013
Brent_EUR_ret  0.1524      0.029      5.248      0.000       0.095       0.209
Coal_EUR_ret  -0.7317      0.116     -6.290      0.000      -0.960      -0.504
Gas_ret        0.1436      0.081      1.769      0.077      -0.016       0.303
Power_ret      1.1417      0.138      8.249      0.000       0.870       1.413
CDS_change    -0.0243      0.003     -7.578      0.000      -0.031      -0.018
CSS_change     0.0007      0.003      0.278      0.781      -0.004       0.006
==============================================================================
Omnibus:                       71.717   Durbin-Watson:                   1.993
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              194.289
Skew:                          -0.076   Prob(JB):                     6.47e-43
Kurtosis:                       4.512   Cond. No.                         212.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 6 lags and without small sample correction

=== 2021–nå ===
                            OLS Regression Results
==============================================================================
Dep. Variable:                EUA_ret   R-squared:                       0.230
Model:                            OLS   Adj. R-squared:                  0.226
Method:                 Least Squares   F-statistic:                     28.91
Date:                Sun, 23 Nov 2025   Prob (F-statistic):           3.07e-37
Time:                        12:45:41   Log-Likelihood:                 3237.5
No. Observations:                1318   AIC:                            -6459.
Df Residuals:                    1310   BIC:                            -6418.
Df Model:                           7
Covariance Type:                  HAC
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0008      0.001      1.339      0.180      -0.000       0.002
EUA_ret_lag1  -0.0497      0.033     -1.510      0.131      -0.114       0.015
Brent_EUR_ret  0.0885      0.033      2.707      0.007       0.024       0.153
Coal_EUR_ret  -0.1198      0.038     -3.113      0.002      -0.195      -0.044
Gas_ret        0.1082      0.042      2.559      0.010       0.025       0.191
Power_ret      0.3707      0.052      7.070      0.000       0.268       0.473
CDS_change    -0.0020      0.000     -8.146      0.000      -0.003      -0.002
CSS_change     0.0004      0.000      1.100      0.271      -0.000       0.001
==============================================================================
Omnibus:                      107.908   Durbin-Watson:                   1.981
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              359.603
Skew:                          -0.364   Prob(JB):                     8.19e-79
Kurtosis:                       5.453   Cond. No.                         606.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 6 lags and without small sample correction
```

In [20]:

```python
def runvar2(df_input, var_vars, maxlags=10, n_irf=20, bootstrap_reps=1000):
    np.random.seed(123)

    df_var = df_input[var_vars].dropna().copy()
    print(f"\n=== VAR sample: {df_var.index.min()} to {df_var.index.max()}, n={len(df_var)} ===")

    # Lag order selection
    model = VAR(df_var)
    sel = model.select_order(maxlags)
    print("Lag order selection (lower = better):")
    print(sel.summary())

    chosen_lag = None
    try:
        chosen_lag = int(sel.aic)
    except Exception:
        try:
            chosen_lag = int(sel.selected_orders.get('aic', np.nan))
        except Exception:
            chosen_lag = None

    if chosen_lag is None or chosen_lag <= 0:
        for key in ('bic','hqic'):
            try:
                chosen_lag = int(getattr(sel, key))
                break
            except Exception:
                try:
                    chosen_lag = int(sel.selected_orders.get(key, np.nan))
                    break
                except Exception:
                    chosen_lag = None

    if chosen_lag is None or chosen_lag <= 0:
        chosen_lag = 1
    chosen_lag = 5 # Force lag for stability
    print(f"Using lag = {chosen_lag} (forced for stability and comparability)")

    # Estimate VAR
    var_res = model.fit(chosen_lag)
```

```
=== VAR sample: 2 to 3339, n=3338 ===
Lag order selection (lower = better):
 VAR Order Selection (* highlights the minimums)
=================================================
       AIC         BIC         FPE         HQIC
-------------------------------------------------
0       -28.62      -28.61   3.712e-13      -28.62
1       -28.66     -28.62*   3.584e-13     -28.64*
2       -28.67      -28.60   3.553e-13      -28.64
3       -28.66      -28.57   3.562e-13      -28.63
4       -28.67      -28.54   3.553e-13      -28.62
5      -28.67*      -28.51  3.549e-13*      -28.61
6       -28.66      -28.48   3.566e-13      -28.60
7       -28.66      -28.45   3.573e-13      -28.58
8       -28.66      -28.41   3.589e-13      -28.57
9       -28.65      -28.38   3.601e-13      -28.56
10      -28.65      -28.35   3.610e-13      -28.54
-------------------------------------------------
Using lag = 5 (forced for stability and comparability)
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Sun, 23, Nov, 2025
Time:                     12:46:54
--------------------------------------------------------------------
No. of Equations:         4.00000    BIC:                   -28.5157
Nobs:                     3333.00    HQIC:                  -28.6146
Log likelihood:           28944.8    FPE:                3.53923e-13
AIC:                     -28.6697    Det(Omega_mle):     3.45142e-13
--------------------------------------------------------------------
Results for equation Power_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                -0.000143         0.000617           -0.231           0.817
L1.Power_ret         -0.055847         0.023461           -2.380           0.017
L1.Coal_EUR_ret       0.007594         0.025907            0.293           0.769
L1.Gas_ret            0.094294         0.023003            4.099           0.000
L1.EUA_ret            0.047945         0.024014            1.997           0.046
L2.Power_ret         -0.015793         0.023702           -0.666           0.505
L2.Coal_EUR_ret      -0.002686         0.025949           -0.104           0.918
L2.Gas_ret           -0.031805         0.023271           -1.367           0.172
L2.EUA_ret            0.004464         0.024026            0.186           0.853
L3.Power_ret         -0.007854         0.023743           -0.331           0.741
L3.Coal_EUR_ret       0.057739         0.025937            2.226           0.026
L3.Gas_ret           -0.025323         0.023349           -1.085           0.278
L3.EUA_ret            0.027233         0.024056            1.132           0.258
L4.Power_ret          0.040276         0.023726            1.698           0.090
L4.Coal_EUR_ret       0.009745         0.025849            0.377           0.706
L4.Gas_ret            0.028855         0.023292            1.239           0.215
L4.EUA_ret            0.001558         0.024055            0.065           0.948
L5.Power_ret         -0.005920         0.023446           -0.253           0.801
L5.Coal_EUR_ret       0.002039         0.025775            0.079           0.937
L5.Gas_ret            0.004984         0.023064            0.216           0.829
L5.EUA_ret            0.017052         0.023986            0.711           0.477
================================================================================

Results for equation Coal_EUR_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                 0.000075         0.000429            0.175           0.861
L1.Power_ret          0.017877         0.016308            1.096           0.273
L1.Coal_EUR_ret       0.021234         0.018009            1.179           0.238
L1.Gas_ret            0.042358         0.015990            2.649           0.008
L1.EUA_ret           -0.026469         0.016692           -1.586           0.113
L2.Power_ret          0.044539         0.016476            2.703           0.007
L2.Coal_EUR_ret       0.004646         0.018038            0.258           0.797
L2.Gas_ret            0.011315         0.016176            0.699           0.484
L2.EUA_ret           -0.054840         0.016701           -3.284           0.001
L3.Power_ret          0.003875         0.016504            0.235           0.814
L3.Coal_EUR_ret      -0.019122         0.018029           -1.061           0.289
L3.Gas_ret            0.000460         0.016230            0.028           0.977
L3.EUA_ret            0.018471         0.016722            1.105           0.269
L4.Power_ret          0.037869         0.016493            2.296           0.022
L4.Coal_EUR_ret       0.026592         0.017968            1.480           0.139
L4.Gas_ret           -0.014341         0.016191           -0.886           0.376
L4.EUA_ret           -0.025496         0.016721           -1.525           0.127
L5.Power_ret          0.066809         0.016298            4.099           0.000
L5.Coal_EUR_ret      -0.036962         0.017917           -2.063           0.039
L5.Gas_ret           -0.013144         0.016032           -0.820           0.412
L5.EUA_ret            0.015901         0.016673            0.954           0.340
================================================================================

Results for equation Gas_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                -0.000174         0.000626           -0.278           0.781
L1.Power_ret          0.109141         0.023787            4.588           0.000
L1.Coal_EUR_ret       0.016522         0.026267            0.629           0.529
L1.Gas_ret           -0.064339         0.023322           -2.759           0.006
L1.EUA_ret           -0.017941         0.024347           -0.737           0.461
L2.Power_ret          0.054648         0.024032            2.274           0.023
L2.Coal_EUR_ret       0.005110         0.026310            0.194           0.846
L2.Gas_ret           -0.106800         0.023594           -4.527           0.000
L2.EUA_ret            0.013891         0.024361            0.570           0.569
L3.Power_ret          0.037620         0.024073            1.563           0.118
L3.Coal_EUR_ret       0.032985         0.026297            1.254           0.210
L3.Gas_ret           -0.061047         0.023674           -2.579           0.010
L3.EUA_ret            0.033233         0.024391            1.363           0.173
L4.Power_ret          0.066728         0.024056            2.774           0.006
L4.Coal_EUR_ret       0.011635         0.026209            0.444           0.657
L4.Gas_ret           -0.002567         0.023616           -0.109           0.913
L4.EUA_ret           -0.035095         0.024389           -1.439           0.150
```

	Sample	Coefficient	Estimate	p-value	Sig
0	Full sample	α1(EUA)	0.0012	0.1109	
1	Full sample	α1(Power)	0.0050	0.0000	***
2	Full sample	α1(Coal_EUR)	-0.0006	0.3352	
3	Full sample	α1(Gas)	0.0038	0.0002	***
4	Phase 3	α1(EUA)	0.0008	0.6860	
5	Phase 3	α1(Power)	0.0055	0.0007	***
6	Phase 3	α1(Coal_EUR)	-0.0025	0.0030	***
7	Phase 3	α1(Gas)	-0.0024	0.1412	
8	Phase 4	α1(EUA)	-0.0020	0.0746	*
9	Phase 4	α2(EUA)	0.0084	0.1693	
10	Phase 4	α1(Power)	0.0047	0.0554	*
11	Phase 4	α2(Power)	-0.0398	0.0030	***
12	Phase 4	α1(Coal_EUR)	0.0009	0.5577	
13	Phase 4	α2(Coal_EUR)	-0.0008	0.9302	
14	Phase 4	α1(Gas)	-0.0029	0.2575	
15	Phase 4	α2(Gas)	-0.0001	0.9929	

PANEL C — COINTEGRATION VECTORS (β)

	Sample	Coefficient	Estimate	p-value	Sig
0	Full sample	β1(EUA)	1.0000	0.0000	***
1	Full sample	β1(Power)	-3.6606	0.0000	***
2	Full sample	β1(Coal_EUR)	3.5636	0.0000	***
3	Full sample	β1(Gas)	0.0570	0.9189	
4	Phase 3	β1(EUA)	1.0000	0.0000	***
5	Phase 3	β1(Power)	-3.4981	0.0000	***
6	Phase 3	β1(Coal_EUR)	1.1519	0.0031	***
7	Phase 3	β1(Gas)	1.1885	0.0000	***
8	Phase 4	β1(EUA)	1.0000	0.0000	***
9	Phase 4	β2(EUA)	-0.0000	0.0000	***
10	Phase 4	β1(Power)	0.0000	0.0000	***
11	Phase 4	β2(Power)	1.0000	0.0000	***
12	Phase 4	β1(Coal_EUR)	-9.2597	0.0001	***
13	Phase 4	β2(Coal_EUR)	-1.6262	0.0000	***
14	Phase 4	β1(Gas)	6.3211	0.0000	***
15	Phase 4	β2(Gas)	0.2289	0.9723	

In [ ]:
```python
def fmt(est, pval):
    return f"{est:.4f}{star(pval)}"


# Extract a variable name from "α1(EUA)"
def extract_var(name):
    return name.split("(")[1].replace(")", "")


# Function to build combined table
def build_rankaware_table(alpha_full, beta_full,
                          alpha_p3, beta_p3,
                          alpha_p4, beta_p4,
                          rank_full=1, rank_p3=1, rank_p4=2):

    rows = []

    def collect(sample_label, alpha_df, beta_df, rank):
        # Identify all variables present in alpha (one entry per rank)
        variables = sorted(set(extract_var(c) for c in alpha_df["Coefficient"]))

        for var in variables:

            # containers for rank 1 and rank 2
            betas = ["", ""]
            alphas = ["", ""]

            for r in range(rank):
                # BETA
                beta_row = beta_df[
                    (beta_df["Coefficient"] == f"β{r+1}({var})")
                ].iloc[0]

                betas[r] = fmt(beta_row["Estimate"], beta_row["p-value"])

                # ALPHA
                alpha_row = alpha_df[
                    (alpha_df["Coefficient"] == f"α{r+1}({var})")
                ].iloc[0]

                alphas[r] = fmt(alpha_row["Estimate"], alpha_row["p-value"])
```

```
C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\584390181.py:8: InterpolationWarning: The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is smaller than the p-value returned.

  result = kpss(series.dropna(), regression='c', nlags='auto')
C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\584390181.py:8: InterpolationWarning: The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is greater than the p-value returned.

  result = kpss(series.dropna(), regression='c', nlags='auto')
C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\584390181.py:8: InterpolationWarning: The test statistic is outside of the range of p-values available in the
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C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\584390181.py:8: InterpolationWarning: The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is smaller than the p-value returned.

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C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\584390181.py:8: InterpolationWarning: The test statistic is outside of the range of p-values available in the
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C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\584390181.py:8: InterpolationWarning: The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is greater than the p-value returned.

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C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\584390181.py:8: InterpolationWarning: The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is smaller than the p-value returned.

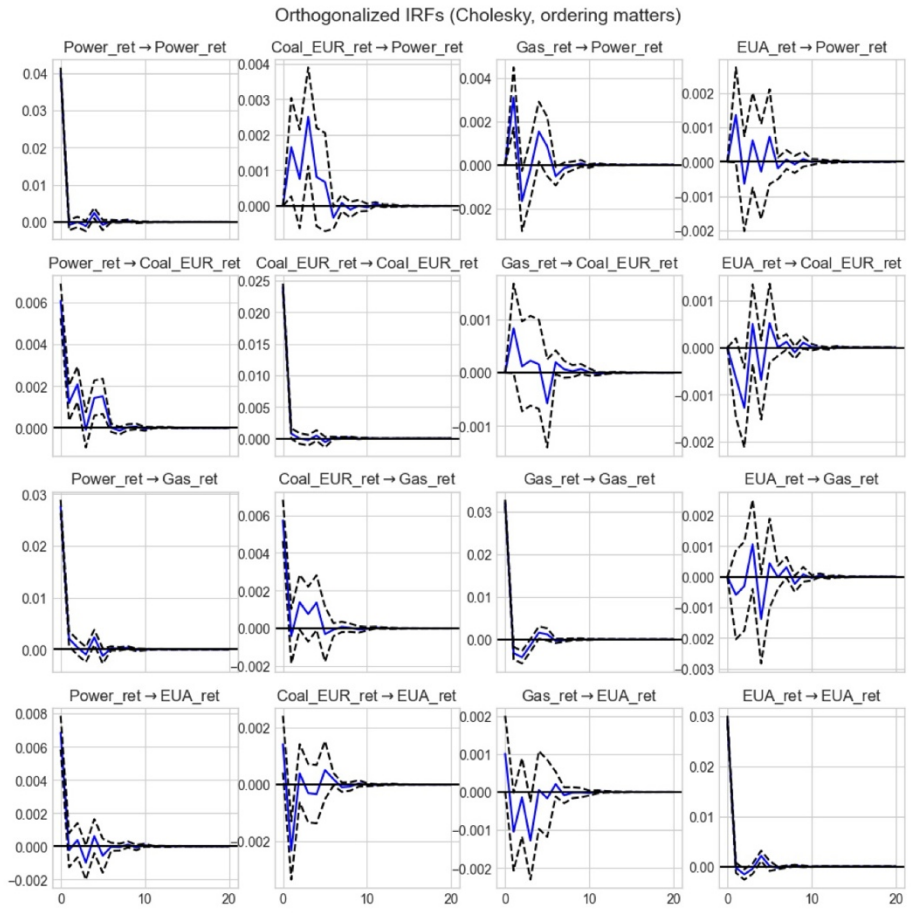
  result = kpss(series.dropna(), regression='c', nlags='auto')
C:\Users\Barkn\AppData\Local\Temp\ipykernel_42292\584390181.py:8: InterpolationWarning: The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is greater than the p-value returned.

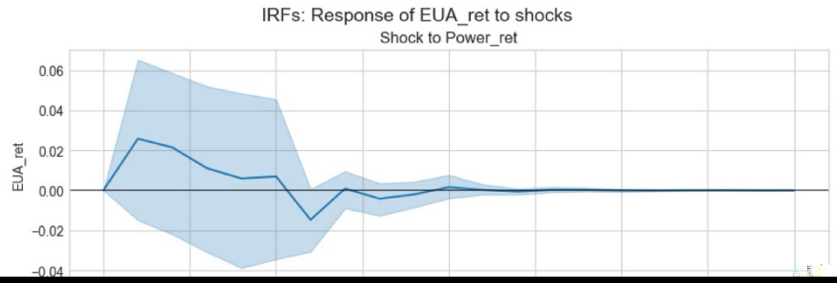
  result = kpss(series.dropna(), regression='c', nlags='auto')
```

Out[ ]:

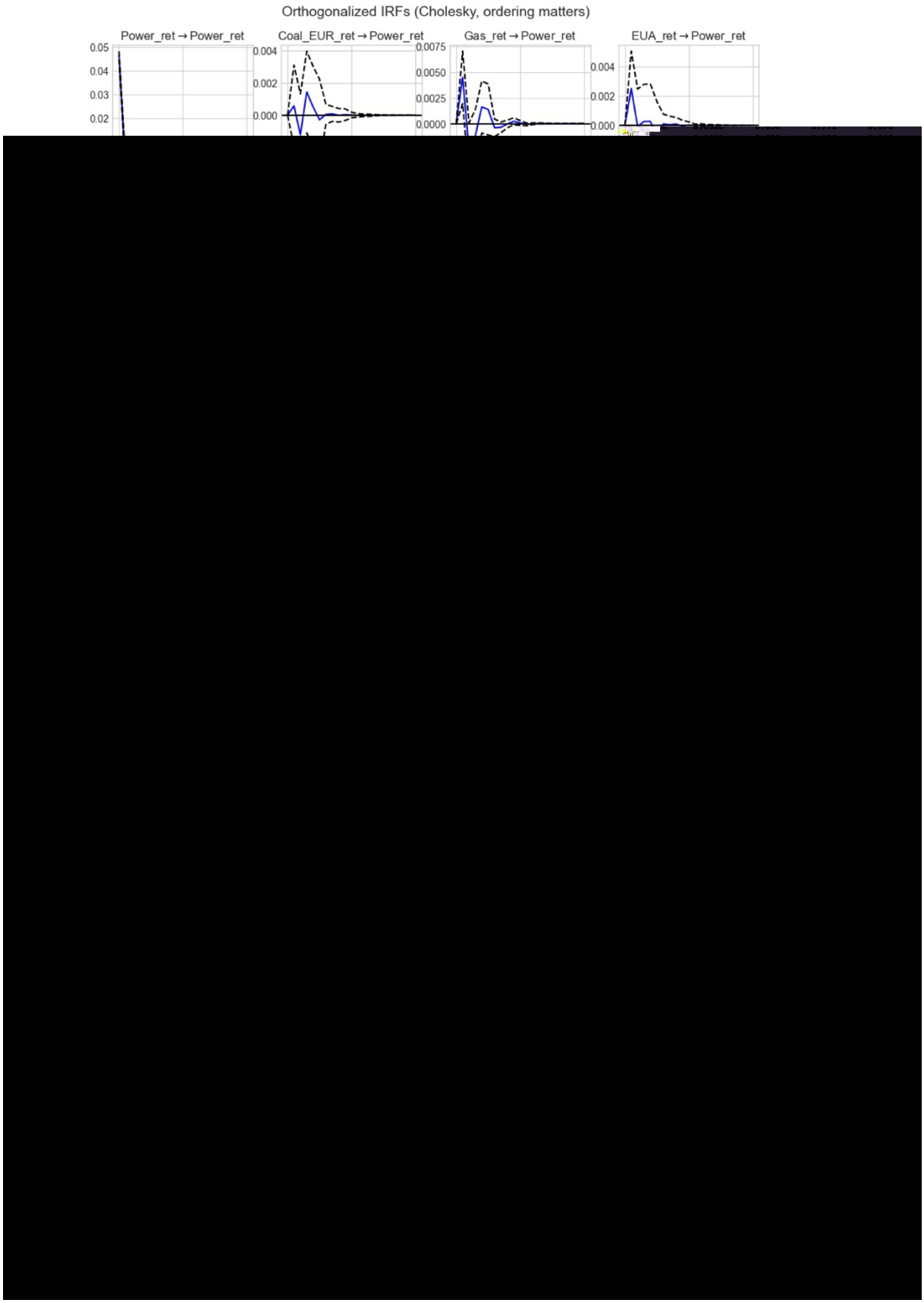
	Variable	ADF (levels)	ADF p-value	KPSS (levels)	KPSS p-value	ADF (diff/ret)	ADF diff p-value	KPSS (diff/ret)	KPSS diff p-value
0	EUA	-0.400	0.910	5.366	0.01	-12.971	0.0	0.136	0.1
1	Coal_EUR	-1.449	0.559	1.330	0.01	-42.236	0.0	0.167	0.1
2	Gas	-2.438	0.131	2.928	0.01	-6.458	0.0	0.062	0.1
3	Power	-3.051	0.030	0.876	0.01	-46.516	0.0	0.074	0.1
4	Brent_EUR	-2.040	0.269	2.833	0.01	-7.870	0.0	0.090	0.1
5	CDS	-2.582	0.097	1.935	0.01	-10.010	0.0	0.046	0.1
6	CSS	-1.760	0.401	5.592	0.01	-28.737	0.0	0.043	0.1

In [ ]:
```
stationarity_tbl(df_des_phase4)
```


Orthogonalized IRFs (Cholesky, ordering matters)
Power_ret → Power_ret
Coal_EUR_ret → Power_ret
Gas_ret → Power_ret
EUA_ret → Power_ret
Power_ret → Coal_EUR_ret
Coal_EUR_ret → Coal_EUR_ret
Gas_ret → Coal_EUR_ret
EUA_ret → Coal_EUR_ret
Power_ret → Gas_ret
Coal_EUR_ret → Gas_ret
Gas_ret → Gas_ret
EUA_ret → Gas_ret
Power_ret → EUA_ret
Coal_EUR_ret → EUA_ret
Gas_ret → EUA_ret
EUA_ret → EUA_ret
Bootstrapping IRFs...


IRFs: Response of EUA_ret to shocks
Shock to Power_ret
EUA_ret
0.06
0.04
0.02
0.00
−0.02
−0.04

[redacted]


Orthogonalized IRFs (Cholesky, ordering matters)
Power_ret → Power_ret
Coal_EUR_ret → Power_ret
Gas_ret → Power_ret
EUA_ret → Power_ret
0.05
0.04
0.03
0.02
0.004
0.002
0.000
0.0075
0.0050
0.0025
0.0000
0.004
0.002
0.000

L5.Power_ret	-0.045025	0.043341	-1.039	0.299
L5.Coal_EUR_ret	0.006903	0.038870	0.178	0.859
L5.Gas_ret	0.045478	0.042249	1.076	0.282
L5.EUA_ret	0.009941	0.059302	0.168	0.867

Results for equation EUA_ret

	coefficient	std. error	t-stat	prob
const	0.001094	0.000654	1.673	0.094
L1.Power_ret	0.025787	0.021707	1.188	0.235
L1.Coal_EUR_ret	-0.064439	0.019502	-3.304	0.001
L1.Gas_ret	-0.024113	0.021013	-1.148	0.251
L1.EUA_ret	-0.031117	0.029495	-1.055	0.291
L2.Power_ret	0.029012	0.022232	1.305	0.192
L2.Coal_EUR_ret	0.018214	0.019546	0.932	0.351
L2.Gas_ret	-0.023346	0.021581	-1.082	0.279
L2.EUA_ret	0.019962	0.029561	0.675	0.500
L3.Power_ret	0.023361	0.022275	1.049	0.294
L3.Coal_EUR_ret	-0.024348	0.019546	-1.246	0.213
L3.Gas_ret	-0.037616	0.021739	-1.730	0.084
L3.EUA_ret	-0.003903	0.029661	-0.132	0.895
L4.Power_ret	0.014425	0.022182	0.650	0.515
L4.Coal_EUR_ret	-0.032754	0.019403	-1.688	0.091
L4.Gas_ret	-0.023957	0.021530	-1.113	0.266
L4.EUA_ret	0.034455	0.029667	1.161	0.245
L5.Power_ret	0.018799	0.021566	0.872	0.383
L5.Coal_EUR_ret	0.016251	0.019341	0.840	0.401
L5.Gas_ret	-0.016294	0.021023	-0.775	0.438
L5.EUA_ret	-0.050122	0.029508	-1.699	0.089

Correlation matrix of residuals

	Power_ret	Coal_EUR_ret	Gas_ret	EUA_ret
Power_ret	1.000000	0.262148	0.747797	0.328486
Coal_EUR_ret	0.262148	1.000000	0.274502	0.139882
Gas_ret	0.747797	0.274502	1.000000	0.282004
EUA_ret	0.328486	0.139882	0.282004	1.000000

			1.846	0.065	-0.002	0.051
L2.EUA	-0.0398	0.015	-2.741	0.006	-0.068	-0.011
L2.Power	0.0503	0.014	3.585	0.000	0.023	0.078



```
L5.Power_ret          -0.044906         0.024279           -1.850           0.064
L5.Coal_EUR_ret       -0.027867         0.031288           -0.891           0.373
L5.Gas_ret             0.014053         0.023195            0.606           0.545
L5.EUA_ret             0.016667         0.025164            0.662           0.508
===============================================================================

Results for equation EUA_ret
===============================================================================
                     coefficient       std. error           t-stat            prob
-------------------------------------------------------------------------------
const                  0.000781         0.000523            1.493           0.135
L1.Power_ret           0.030955         0.017174            1.802           0.071
L1.Coal_EUR_ret       -0.088660         0.022171           -3.999           0.000
L1.Gas_ret            -0.032385         0.016390           -1.976           0.048
L1.EUA_ret            -0.008861         0.017866           -0.496           0.620
L2.Power_ret           0.025533         0.017488            1.460           0.144
L2.Coal_EUR_ret        0.020852         0.022226            0.938           0.348
L2.Gas_ret            -0.006789         0.016672           -0.407           0.684
L2.EUA_ret            -0.058747         0.017843           -3.292           0.001
L3.Power_ret           0.017499         0.017523            0.999           0.318
L3.Coal_EUR_ret       -0.007279         0.022237           -0.327           0.743
L3.Gas_ret            -0.047257         0.016769           -2.818           0.005
L3.EUA_ret            -0.021034         0.017853           -1.178           0.239
L4.Power_ret           0.014473         0.017525            0.826           0.409
L4.Coal_EUR_ret       -0.022881         0.022188           -1.031           0.302
L4.Gas_ret            -0.008339         0.016693           -0.500           0.617
L4.EUA_ret             0.069921         0.017833            3.921           0.000
L5.Power_ret          -0.004996         0.017180           -0.291           0.771
L5.Coal_EUR_ret        0.032634         0.022140            1.474           0.140
L5.Gas_ret            -0.011842         0.016413           -0.721           0.471
L5.EUA_ret            -0.003088         0.017807           -0.173           0.862
===============================================================================

Correlation matrix of residuals
               Power_ret  Coal_EUR_ret   Gas_ret   EUA_ret
Power_ret       1.000000      0.246004  0.647656  0.227141
Coal_EUR_ret    0.246004      1.000000  0.289649  0.101526
Gas_ret         0.647656      0.289649  1.000000  0.178530
EUA_ret         0.227141      0.101526  0.178530  1.000000



Companion roots (abs): [2.20695764 2.20695764 2.1654645  2.1654645  2.15463487 2.15463487
 2.14088901 2.14088901 1.94583471 1.94583471 1.91080808 1.91080808
 1.84150473 1.72029979 1.72029979 1.69996654 1.69996654 1.68144525
 1.68144525 1.57997771]
WARNING: VAR is not stable (roots >= 1). IRF/FEVD may be unreliable.

=== RESIDUAL DIAGNOSTICS ===

Durbin-Watson (per equation):
[2.00223897 1.99569121 2.00034172 2.00094778]

Ljung-Box Q-test (lags 5 & 10):

Residual series: Power_ret
Lag 5:
    lb_stat  lb_pvalue
5  0.071474   0.999929
Lag 10:
      lb_stat  lb_pvalue
10  11.395179    0.32757

Residual series: Coal_EUR_ret
Lag 5:
    lb_stat  lb_pvalue
5  0.080528   0.999905
Lag 10:
     lb_stat  lb_pvalue
10  8.620025   0.568504

Residual series: Gas_ret
Lag 5:
    lb_stat  lb_pvalue
5  0.068805   0.999926
```



```
=== VAR sample: 2 to 3339, n=3338 ===
Lag order selection (lower = better):
 VAR Order Selection (* highlights the minimums)
=================================================
       AIC         BIC         FPE         HQIC
-------------------------------------------------
0       -27.71      -27.70   9.224e-13      -27.71
1       -27.76     -27.72*   8.831e-13      -27.74
2       -27.77      -27.71   8.660e-13     -27.75*
3       -27.78      -27.69   8.606e-13      -27.75
4       -27.79      -27.66   8.552e-13      -27.74
5      -27.79*      -27.64  8.527e-13*      -27.74
6       -27.79      -27.60   8.558e-13      -27.72
7       -27.78      -27.57   8.585e-13      -27.71
8       -27.78      -27.54   8.629e-13      -27.69
9       -27.78      -27.50   8.644e-13      -27.68
10      -27.78      -27.48   8.645e-13      -27.67
-------------------------------------------------
Using lag = 5 (forced for stability and comparability)
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Sun, 23, Nov, 2025
Time:                     12:48:02
--------------------------------------------------------------------
No. of Equations:         4.00000    BIC:                   -27.6397
Nobs:                     3333.00    HQIC:                  -27.7386
Log likelihood:           27485.0    FPE:                8.49822e-13
AIC:                     -27.7938    Det(Omega_mle):     8.28737e-13
--------------------------------------------------------------------
Results for equation Power_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                  0.000186         0.000704            0.265           0.791
L1.Power_ret          -0.100218         0.023102           -4.338           0.000
L1.Coal_EUR_ret        0.043387         0.029823            1.455           0.146
L1.Gas_ret             0.095666         0.022047            4.339           0.000
L1.EUA_ret             0.046365         0.024032            1.929           0.054
L2.Power_ret           0.008630         0.023523            0.367           0.714
L2.Coal_EUR_ret        0.051783         0.029897            1.732           0.083
L2.Gas_ret            -0.031910         0.022426           -1.423           0.155
L2.EUA_ret            -0.013863         0.024001           -0.578           0.564
L3.Power_ret          -0.045319         0.023570           -1.923           0.055
L3.Coal_EUR_ret        0.097288         0.029912            3.253           0.001
L3.Gas_ret            -0.005703         0.022556           -0.253           0.800
L3.EUA_ret             0.024486         0.024014            1.020           0.308
L4.Power_ret           0.015141         0.023573            0.642           0.521
L4.Coal_EUR_ret        0.034663         0.029846            1.161           0.245
L4.Gas_ret             0.051441         0.022454            2.291           0.022
L4.EUA_ret            -0.005462         0.023988           -0.228           0.820
L5.Power_ret          -0.054525         0.023109           -2.359           0.018
L5.Coal_EUR_ret        0.018640         0.029781            0.626           0.531
L5.Gas_ret             0.022302         0.022077            1.010           0.312
L5.EUA_ret             0.031506         0.023952            1.315           0.188
================================================================================

Results for equation Coal_EUR_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                  0.000005         0.000429            0.011           0.991
L1.Power_ret           0.010640         0.014065            0.757           0.449
L1.Coal_EUR_ret        0.026848         0.018157            1.479           0.139
L1.Gas_ret             0.026709         0.013423            1.990           0.047
L1.EUA_ret            -0.021904         0.014631           -1.497           0.134
L2.Power_ret           0.053358         0.014321            3.726           0.000
L2.Coal_EUR_ret       -0.001850         0.018202           -0.102           0.919
L2.Gas_ret             0.005309         0.013653            0.389           0.697
L2.EUA_ret            -0.043212         0.014613           -2.957           0.003
L3.Power_ret          -0.005212         0.014350           -0.363           0.716
L3.Coal_EUR_ret       -0.022377         0.018211           -1.229           0.219
L3.Gas_ret             0.004412         0.013733            0.321           0.748
L3.EUA_ret             0.014710         0.014620            1.006           0.314
L4.Power_ret           0.030625         0.014352            2.134           0.033
L4.Coal_EUR_ret        0.017966         0.018171            0.989           0.323
L4.Gas_ret             0.011212         0.013670            0.820           0.412
L4.EUA_ret            -0.026722         0.014604           -1.830           0.067
L5.Power_ret           0.053774         0.014069            3.822           0.000
L5.Coal_EUR_ret       -0.032946         0.018131           -1.817           0.069
L5.Gas_ret            -0.024412         0.013441           -1.816           0.069
L5.EUA_ret             0.017980         0.014583            1.233           0.218
================================================================================

Results for equation Gas_ret
================================================================================
                    coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------------
const                  0.000034         0.000740            0.046           0.963
L1.Power_ret           0.121586         0.024271            5.010           0.000
L1.Coal_EUR_ret        0.007599         0.031332            0.243           0.808
L1.Gas_ret            -0.100055         0.023163           -4.320           0.000
L1.EUA_ret            -0.020160         0.025248           -0.798           0.425
L2.Power_ret           0.111544         0.024714            4.513           0.000
L2.Coal_EUR_ret        0.083031         0.031410            2.643           0.008
L2.Gas_ret            -0.153183         0.023561           -6.502           0.000
L2.EUA_ret            -0.018066         0.025216           -0.716           0.474
L3.Power_ret           0.028127         0.024763            1.136           0.256
L3.Coal_EUR_ret        0.036235         0.031426            1.153           0.249
L3.Gas_ret            -0.080205         0.023697           -3.385           0.001
L3.EUA_ret             0.030358         0.025229            1.203           0.229
L4.Power_ret           0.045033         0.024766            1.818           0.069
L4.Coal_EUR_ret        0.048716         0.031357            1.554           0.120
L4.Gas_ret             0.020949         0.023590            0.888           0.375
L4.EUA_ret            -0.044773         0.025202           -1.777           0.076
```

```
    })

    return df_out.round(4)


table_energy = var_summary_table(df_sub1, df_sub2, df_w,
                                 var_vars=['Power_ret','Coal_EUR_ret','Gas_ret','EUA_ret'])

display(table_energy)
```

```
c:\Users\Barkn\OneDrive - Norwegian School of Economics\3. semester-Barks_Yoga\FIN11\Faktisk databehandling final paper\Regressions\.venv\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As a result, forecasts cannot be generated. To use the model for forecasting, use one of the supported classes of index.
  self._init_dates(dates, freq)
c:\Users\Barkn\OneDrive - Norwegian School of Economics\3. semester-Barks_Yoga\FIN11\Faktisk databehandling final paper\Regressions\.venv\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As a result, forecasts cannot be generated. To use the model for forecasting, use one of the supported classes of index.
  self._init_dates(dates, freq)
c:\Users\Barkn\OneDrive - Norwegian School of Economics\3. semester-Barks_Yoga\FIN11\Faktisk databehandling final paper\Regressions\.venv\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As a result, forecasts cannot be generated. To use the model for forecasting, use one of the supported classes of index.
  self._init_dates(dates, freq)
```

	Phase 3	Phase 4	Full
n	2019.0000	1318.0000	3338.0000
lag	5.0000	5.0000	5.0000
max_root	7.9411	2.5929	5.6135
DW	1.9977	1.9983	2.0004
LB_p	0.9882	0.9998	0.9976
ARCH_p	0.0000	0.0000	0.0000
JB_p	0.0000	0.0000	0.0000
GC_Power_ret	0.3458	0.5819	0.2655
GC_Coal_EUR_ret	0.1006	0.0062	0.0072
GC_Gas_ret	0.2373	0.4526	0.1009
FEVD1_Power_ret	0.0910	0.1071	0.0842
FEVD1_Coal_EUR_ret	0.0093	0.0124	0.0073
FEVD1_Gas_ret	0.0209	0.0034	0.0080
FEVD1_EUA_ret	0.8788	0.8771	0.9005
FEVD5_Power_ret	0.0944	0.1078	0.0843
FEVD5_Coal_EUR_ret	0.0114	0.0169	0.0080
FEVD5_Gas_ret	0.0219	0.0060	0.0093
FEVD5_EUA_ret	0.8722	0.8693	0.8984
FEVD10_Power_ret	0.0945	0.1078	0.0844
FEVD10_Coal_EUR_ret	0.0115	0.0170	0.0080
FEVD10_Gas_ret	0.0219	0.0063	0.0093
FEVD10_EUA_ret	0.8721	0.8689	0.8983

In [24]:
```
# VAR on full sample for unwinzorized data
runvar2(df, ['Power_ret','Coal_EUR_ret','Gas_ret','EUA_ret'])
```

```
c:\Users\Barkn\OneDrive - Norwegian School of Economics\3. semester-Barks_Yoga\FIN11\Faktisk databehandling final paper\Regressions\.venv\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As a result, forecasts cannot be generated. To use the model for forecasting, use one of the supported classes of index.
  self._init_dates(dates, freq)
```

```
    else:
        return ''

# Function for exctracting model info
def extract_vecm_info(model, label, lag_order, rank):
    k = model.k_ar
    variables = model.names  # ['EUA','Power','Coal_EUR','Gas']

    # alpha: (n_variables x rank)
    alpha = model.alpha
    alpha_p = model.pvalues_alpha

    # beta: (n_variables x rank)
    beta = model.beta
    beta_p = model.pvalues_beta

    rows_alpha = []
    rows_beta = []

    # Panel B: ALPHA
    for i, var in enumerate(variables):
        for r in range(rank):
            coef = alpha[i, r]
            pval = alpha_p[i, r]
            rows_alpha.append([
                label,
                f"α{r+1}({var})",
                coef,
                pval,
                star(pval)
            ])

    # Panel C: BETA
    for j, var in enumerate(variables):
        for r in range(rank):
            coef = beta[j, r]
            pval = beta_p[j, r]
            rows_beta.append([
                label,
                f"β{r+1}({var})",
                coef,
                pval,
                star(pval)
            ])

    # Panel A summary row
    summary_row = pd.DataFrame({
        "Sample": [label],
        "Rank": [rank],
        "Lag order": [lag_order],
        "N variables": [len(variables)]
    })

    df_alpha = pd.DataFrame(rows_alpha, columns=["Sample", "Coefficient", "Estimate", "p-value", "Sig"])
    df_beta  = pd.DataFrame(rows_beta,  columns=["Sample", "Coefficient", "Estimate", "p-value", "Sig"])

    return summary_row, df_alpha, df_beta


summary_full, alpha_full, beta_full = extract_vecm_info(vecm_full,    "Full sample", lag_order=2, rank=1)
summary_p3,   alpha_p3,   beta_p3   = extract_vecm_info(vecm_phase3,  "Phase 3",     lag_order=2, rank=1)
summary_p4,   alpha_p4,   beta_p4   = extract_vecm_info(vecm_phase4,  "Phase 4",     lag_order=2, rank=2)

# Panel A
panel_A = pd.concat([summary_full, summary_p3, summary_p4]).reset_index(drop=True)

# Panel B
panel_B = pd.concat([alpha_full, alpha_p3, alpha_p4]).re
```

					Coal_EUR	1.1519***	-0.0025***
5	Phase 3	EUA	1.0000***	0.0008			
6	Phase 3	Gas	1.1885***	-0.0024			
7	Phase 3	Power	-3.4981***	0.0055***			
8	Phase 4	Coal_EUR	-9.2597***	0.0009	-1.6262***	-0.0008	
9	Phase 4	EUA	1.0000***	-0.0020*	-0.0000***	0.0084	
10	Phase 4	Gas	6.3211***	-0.0029	0.2289	-0.0001	
11	Phase 4	Power	0.0000***	0.0047*	1.0000***	-0.0398***	

In [ ]:
```python
# stationarity tests table

def run_adf(series):
    result = adfuller(series.dropna(), autolag='AIC')
    return result[0], result[1]

def run_kpss_test(series):
    result = kpss(series.dropna(), regression='c', nlags='auto')
    return result[0], result[1]

def stationarity_tbl(df):
    # List all relevant variables
    level_vars = [
        'EUA', 'Coal_EUR', 'Gas', 'Power', 'CDS', 'CSS'
    ]

    diff_vars = [
        'EUA_ret', 'Coal_EUR_ret', 'Gas_ret', 'Power_ret',
        'CDS_change', 'CSS_change'
    ]

    rows = []

    for lv, dv in zip(level_vars, diff_vars):
        adf_lv, p_lv = run_adf(df[lv])
        kpss_lv, p_kpss_lv = run_kpss_test(df[lv])

        adf_dv, p_dv = run_adf(df[dv])
        kpss_dv, p_kpss_dv = run_kpss_test(df[dv])

        rows.append([
            lv,
            adf_lv, p_lv,
            kpss_lv, p_kpss_lv,
            adf_dv, p_dv,
            kpss_dv, p_kpss_dv
        ])

    stationarity_table = pd.DataFrame(
        rows,
        columns=[
            'Variable',
            'ADF (levels)', 'ADF p-value',
            'KPSS (levels)', 'KPSS p-value',
            'ADF (diff/ret)', 'ADF diff p-value',
            'KPSS (diff/ret)', 'KPSS diff p-value'
        ]
    )
    stationarity_table = stationarity_table.round({
    'ADF (levels)': 3,
    'ADF p-value': 3,
    'KPSS (levels)': 3,
    'KPSS p-value': 3,
    'ADF (diff/ret)': 3,
    'ADF diff p-value': 3,
    'KPSS (diff/ret)': 3,
    'KPSS diff p-value': 3
    })
    return stationarity_table

stationarity_tbl(df_des_phase3)
```

	Phase 3	Phase 4	Full
n	2019.0000	1318.0000	3338.0000
lag	3.0000	3.0000	3.0000
max_root	2.9853	3.2511	4.4008
DW	1.9960	1.9959	1.9976
LB_p	0.4602	0.9801	0.5128
ARCH_p	0.0000	0.0000	0.0000
JB_p	0.0000	0.0000	0.0000
GC_CSS_change	0.2197	0.0248	0.0290
GC_CDS_change	0.4728	0.2610	0.3025
FEVD1_CSS_change	0.0012	0.0035	0.0013
FEVD1_CDS_change	0.0195	0.0047	0.0027
FEVD1_EUA_ret	0.9794	0.9918	0.9960
FEVD5_CSS_change	0.0020	0.0084	0.0031
FEVD5_CDS_change	0.0210	0.0080	0.0038
FEVD5_EUA_ret	0.9770	0.9836	0.9931
FEVD10_CSS_change	0.0020	0.0085	0.0031
FEVD10_CDS_change	0.0210	0.0080	0.0038
FEVD10_EUA_ret	0.9770	0.9835	0.9931

In [ ]:
```
# Descriptive statistics
cols = ['EUA_ret','Coal_EUR_ret','Gas_ret','Power_ret','CDS_change','CSS_change', 'Power', 'Coal_EUR', 'Gas', 'EUA', 'CSS', 'CDS']

df_des_phase3 = df.loc[:'2020-12-31', cols]
df_des_phase4 = df.loc['2021-01-01':, cols]

df_des_phase3[['Power', 'Coal_EUR', 'Gas', 'EUA']] = np.log(df_des_phase3[['Power', 'Coal_EUR', 'Gas', 'EUA']])
df_des_phase4[['Power', 'Coal_EUR', 'Gas', 'EUA']] = np.log(df_des_phase4[['Power', 'Coal_EUR', 'Gas', 'EUA']])
# Levels data (Phase 3 and Phase 4)
desc_phase3_levels = descriptive_table(df_des_phase3[cols])
desc_phase4_levels = descriptive_table(df_des_phase4[cols])

desc_phase3_levels
```

Out[ ]:

	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis
EUA_ret	0.000709	0.033520	-0.432077	0.238234	-1.107998	17.838370
Brent_EUR_ret	-0.000531	0.024865	-0.280314	0.181057	-0.968248	18.181118
Coal_EUR_ret	-0.000265	0.014617	-0.181348	0.171610	-0.002849	37.239508
Gas_ret	-0.000356	0.029129	-0.210721	0.381368	2.332044	26.455012
Power_ret	-0.000094	0.028646	-0.239059	0.259893	0.345247	15.487659
CDS_change	0.002435	1.062087	-7.981005	9.978015	0.740959	17.060267
CSS_change	0.007494	1.005944	-9.450520	8.073740	-0.697570	19.479562
Power	3.559160	0.220468	2.836150	4.154185	0.168648	0.611166
Coal_EUR	4.389129	0.287096	3.727985	4.787519	-0.320944	-1.310057
Gas	2.842047	0.381092	1.289233	3.379293	-1.257886	1.817339
Brent_EUR	4.321424	0.423122	3.043791	5.073385	0.231131	-0.586472
EUA	2.204070	0.662937	1.011601	3.416743	0.545566	-1.252406
CSS	-2.814412	9.352081	-23.167900	17.990920	-0.067073	-0.774707
CDS	-3.636395	6.849174	-18.256275	12.683756	-0.100078	-0.930331

In [ ]:
```
desc_phase4_levels
```

Out[ ]:

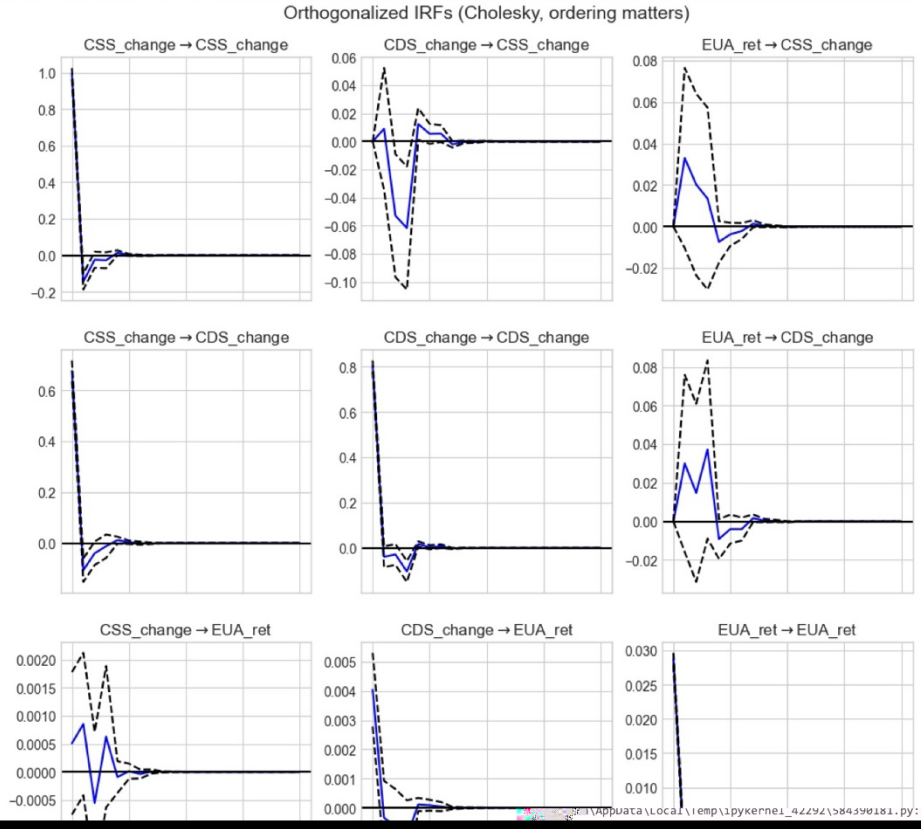
	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis
EUA_ret	0.000838	0.024823	-0.177347	0.161378	-0.406663	4.899736
Brent_EUR_ret	0.000314	0.021979	-0.125064	0.089441	-0.573240	2.722556
Coal_EUR_ret	0.000373	0.035300	-0.532995	0.325766	-2.525028	55.806950
Gas_ret	0.000633	0.058354	-0.385446	0.478866	0.309748	10.562379
Power_ret	0.000680	0.054582	-0.277732	0.329984	0.522466	6.511069
CDS_change	0.017754	11.787466	-82.658628	102.061853	0.931014	19.324637
CSS_change	0.010145	8.683155	-83.153220	79.959580	1.240662	29.915540
Power	4.665846	0.596939	3.437208	6.453625	0.699524	-0.019251
Coal_EUR	4.970468	0.440096	4.081725	6.185038	0.791926	0.065256
Gas	3.809805	0.649400	2.561096	5.739793	0.640091	-0.019565
Brent_EUR	4.452323	0.163411	3.775737	4.937960	-0.561895	2.600743
EUA	4.210081	0.292247	3.136798	4.608564	-1.652663	2.603805
CSS	1.324197	15.242760	-48.777460	133.615380	2.027678	11.347442
CDS	37.603967	66.897618	-26.113550	447.546857	2.536880	6.861747

```
Residual series: CDS_change
Lag 5:
    lb_stat  lb_pvalue
5  3.524315   0.619712
Lag 10:
      lb_stat  lb_pvalue
10  11.205882   0.341705

Residual series: EUA_ret
Lag 5:
    lb_stat  lb_pvalue
5  7.176689   0.207828
Lag 10:
     lb_stat  lb_pvalue
10  9.777679    0.46021

ARCH LM tests (per equation):
CSS_change: ARCH LM stat=65.7794, p=2.875e-10
CDS_change: ARCH LM stat=47.9350, p=6.379e-07
EUA_ret: ARCH LM stat=275.8675, p=1.938e-53

Jarque-Bera normality (per equation):
CSS_change: JB stat=23599.5460, p=0
CDS_change: JB stat=20605.5196, p=0
EUA_ret: JB stat=79.4343, p=5.637e-18
c:\Users\Barkn\OneDrive - Norwegian School of Economics\3. semester-Barks_Yoga\FIN11\Faktisk databehandling final paper\Regressions\.venv\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As a result, forecasts cannot be generated. To use the model for forecasting, use one of the supported classes of index.
  self._init_dates(dates, freq)
```



```
Det. terms outside the coint. relation & lagged endog. parameters for equation EUA
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
L1.EUA        -0.0372      0.028     -1.312      0.189      -0.093       0.018
L1.Power       0.0140      0.019      0.739      0.460      -0.023       0.051
L1.Coal_EUR   -0.0915      0.020     -4.485      0.000      -0.131      -0.051
L1.Gas        -0.0052      0.018     -0.295      0.768      -0.040       0.029
L2.EUA         0.0138      0.028      0.488      0.626      -0.042       0.069
L2.Power       0.0122      0.019      0.657      0.511      -0.024       0.049
L2.Coal_EUR    0.0122      0.021      0.594      0.553      -0.028       0.052
L2.Gas         0.0083      0.017      0.474      0.636      -0.026       0.042
Det. terms outside the coint. relation & lagged endog. parameters for equation Power
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
L1.EUA         0.0730      0.062      1.171      0.241      -0.049       0.195
L1.Power      -0.0925      0.041     -2.230      0.026      -0.174      -0.011
L1.Coal_EUR    0.0154      0.045      0.343      0.731      -0.072       0.103
L1.Gas         0.1013      0.039      2.610      0.009       0.025       0.177
L2.EUA        -0.0504      0.062     -0.814      0.415      -0.172       0.071
L2.Power       0.0680      0.041      1.660      0.097      -0.012       0.148
L2.Coal_EUR    0.0524      0.045      1.165      0.244      -0.036       0.141
L2.Gas        -0.0806      0.038     -2.102      0.036      -0.156      -0.005
Det. terms outside the coint. relation & lagged endog. parameters for equation Coal_EUR
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
L1.EUA        -0.0930      0.040     -2.306      0.021      -0.172      -0.014
L1.Power       0.0107      0.027      0.399      0.690      -0.042       0.063
L1.Coal_EUR    0.0259      0.029      0.895      0.371      -0.031       0.083
L1.Gas         0.0281      0.025      1.118      0.263      -0.021       0.077
L2.EUA        -0.0911      0.040     -2.273      0.023      -0.170      -0.013
L2.Power       0.0802      0.026      3.028      0.002       0.028       0.132
L2.Coal_EUR    0.0003      0.029      0.009      0.993      -0.057       0.057
L2.Gas        -0.0025      0.025     -0.102      0.919      -0.051       0.046
Det. terms outside the coint. relation & lagged endog. parameters for equation Gas
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
L1.EUA        -0.0678      0.066     -1.025      0.305      -0.197       0.062
L1.Power       0.1742      0.044      3.955      0.000       0.088       0.261
L1.Coal_EUR   -0.0324      0.048     -0.682      0.495      -0.126       0.061
L1.Gas        -0.1234      0.041     -2.993      0.003      -0.204      -0.043
L2.EUA         0.0083      0.066      0.127      0.899      -0.121       0.137
L2.Power       0.1720      0.043      3.955      0.000       0.087       0.257
L2.Coal_EUR    0.0896      0.048      1.873      0.061      -0.004       0.183
L2.Gas        -0.2205      0.041     -5.416      0.000      -0.300      -0.141
                Loading coefficients (alpha) for equation EUA
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
ec1           -0.0020      0.001     -1.783      0.075      -0.004       0.000
ec2            0.0084      0.006      1.375      0.169      -0.004       0.020
               Loading coefficients (alpha) for equation Power
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
ec1            0.0047      0.002      1.916      0.055      -0.000       0.009
ec2           -0.0398      0.013     -2.972      0.003      -0.066      -0.014
              Loading coefficients (alpha) for equation Coal_EUR
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
ec1            0.0009      0.002      0.586      0.558      -0.002       0.004
ec2           -0.0008      0.009     -0.088      0.930      -0.018       0.016
               Loading coefficients (alpha) for equation Gas
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
ec1           -0.0029      0.003     -1.132      0.258      -0.008       0.002
ec2           -0.0001      0.014     -0.009      0.993      -0.028       0.028
        Cointegration relations for loading-coefficients-column 1
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
beta.1         1.0000          0          0      0.000       1.000       1.000
beta.2      8.579e-17          0          0      0.000    8.58e-17    8.58e-17
beta.3        -9.2597      2.361     -3.922      0.000     -13.887      -4.632
beta.4         6.3211      0.433     14.604      0.000       5.473       7.169
const         17.5786      1.601     10.979      0.000      14.440      20.717
        Cointegration relations for loading-coefficients-column 2
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
beta.1     -1.799e-17          0          0      0.000    -1.8e-17    -1.8e-17
beta.2         1.0000          0          0      0.000       1.000       1.000
beta.3        -1.6262      0.294     -5.540      0.000      -2.202      -1.051
beta.4         0.2289      6.579      0.035      0.972     -12.667      13.124
const          2.5269      1.206      2.095      0.036       0.163       4.891
================================================================================
c:\Users\Barkn\OneDrive - Norwegian School of Economics\3. semester-Barks_Yoga\FIN11\Faktisk databehandling final paper\Regressions\.venv\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As a result, forecasts cannot be generated. To use the model for forecasting, use one of the supported classes of index.
  self._init_dates(dates, freq)
```

In [ ]:
```python
# Code for making tables from VECM results

# Function for returning right significance star based on p-value
def star(p):
    if p < 0.01:
        return '***'
    elif p < 0.05:
        return '**'
    elif p < 0.10:
        return '*'
```

```
Det. terms outside the coint. relation & lagged endog. parameters for equation EUA
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
L1.EUA         0.0028      0.023      0.118      0.906      -0.043       0.048
L1.Power       0.0326      0.030      1.088      0.277      -0.026       0.091
L1.Coal_EUR   -0.0864      0.053     -1.637      0.102      -0.190       0.017
L1.Gas        -0.0479      0.029     -1.643      0.100      -0.105       0.009
L2.EUA        -0.0808      0.023     -3.469      0.001      -0.126      -0.035
L2.Power       0.0091      0.030      0.304      0.761      -0.049       0.068
L2.Coal_EUR   -0.0014      0.053     -0.027      0.979      -0.105       0.102
L2.Gas        -0.0015      0.029     -0.052      0.959      -0.059       0.056
Det. terms outside the coint. relation & lagged endog. parameters for equation Power
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
L1.EUA         0.0300      0.020      1.508      0.132      -0.009       0.069
L1.Power      -0.0653      0.026     -2.558      0.011      -0.115      -0.015
L1.Coal_EUR    0.0547      0.045      1.215      0.224      -0.034       0.143
L1.Gas         0.0492      0.025      1.978      0.048       0.000       0.098
L2.EUA        -0.0125      0.020     -0.630      0.528      -0.051       0.026
L2.Power      -0.0134      0.025     -0.525      0.599      -0.063       0.037
L2.Coal_EUR    0.0829      0.045      1.840      0.066      -0.005       0.171
L2.Gas        -0.0058      0.025     -0.233      0.816      -0.055       0.043
Det. terms outside the coint. relation & lagged endog. parameters for equation Coal_EUR
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
L1.EUA         0.0044      0.010      0.435      0.664      -0.016       0.024
L1.Power       0.0173      0.013      1.324      0.185      -0.008       0.043
L1.Coal_EUR    0.0464      0.023      2.017      0.044       0.001       0.091
L1.Gas         0.0098      0.013      0.774      0.439      -0.015       0.035
L2.EUA        -0.0125      0.010     -1.228      0.219      -0.032       0.007
L2.Power      -0.0011      0.013     -0.082      0.935      -0.027       0.024
L2.Coal_EUR    0.0107      0.023      0.465      0.642      -0.034       0.056
L2.Gas        -0.0095      0.013     -0.750      0.453      -0.034       0.015
Det. terms outside the coint. relation & lagged endog. parameters for equation Gas
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
L1.EUA        -0.0040      0.020     -0.198      0.843      -0.044       0.036
L1.Power       0.0534      0.026      2.051      0.040       0.002       0.104
L1.Coal_EUR    0.0711      0.046      1.547      0.122      -0.019       0.161
L1.Gas        -0.0666      0.025     -2.626      0.009      -0.116      -0.017
L2.EUA        -0.0249      0.020     -1.230      0.219      -0.065       0.015
L2.Power       0.0345      0.026      1.328      0.184      -0.016       0.085
L2.Coal_EUR    0.0161      0.046      0.350      0.726      -0.074       0.106
L2.Gas        -0.0325      0.025     -1.280      0.201      -0.082       0.017
                Loading coefficients (alpha) for equation EUA
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
ec1            0.0008      0.002      0.404      0.686      -0.003       0.005
               Loading coefficients (alpha) for equation Power
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
ec1            0.0055      0.002      3.385      0.001       0.002       0.009
             Loading coefficients (alpha) for equation Coal_EUR
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
ec1           -0.0025      0.001     -2.972      0.003      -0.004      -0.001
               Loading coefficients (alpha) for equation Gas
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
ec1           -0.0024      0.002     -1.471      0.141      -0.006       0.001
         Cointegration relations for loading-coefficients-column 1
================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
beta.1         1.0000          0          0      0.000       1.000       1.000
beta.2        -3.4981      0.377     -9.271      0.000      -4.238      -2.759
beta.3         1.1519      0.389      2.958      0.003       0.389       1.915
beta.4         1.1885      0.271      4.387      0.000       0.658       1.719
const          1.8538      1.279      1.449      0.147      -0.654       4.361
================================================================================
```

In [ ]:
```
# Fitting VECM for phase 4
r = 2    # Rank from above results
vecm_model = VECM(df_phase4, k_ar_diff=2, coint_rank=r, deterministic='ci')
vecm_phase4 = vecm_model.fit()
print(vecm_phase4.summary())
```