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EXECUTIVE SUMMARY OF THE THESIS

# Modelling price interdependencies between the European carbon and electricity markets: a Global Vector Autoregressive approach

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## 1. Introduction

Within the European Union's strategic framework for the energy sector, two primary objectives prevail: ensuring affordable energy costs and achieving decarbonisation. The main tool to accomplish the latter is the EU Emissions Trading System (EU ETS), a cap-and-trade mechanism that imposes a binding emissions ceiling on covered sectors and enables participants to trade emission allowances (EUAs).

Although this policy reinforces Europe's leadership in decarbonisation, it has the potential to exert upward pressure on prices, particularly in electricity markets, which represent the sector most exposed to carbon costs. Hence, although decarbonisation and energy affordability are distinct goals, current dynamics reveal their interdependence and potential trade-offs.

This consideration is reinforced by the recent evolution of the EU ETS. Its early phases were marked by weak price signals and limited influence on firms, making it more of a testing ground rather than a fully functional scheme. Only in recent years—after a sequence of reforms—has the EU ETS evolved into a truly active carbon market. Since 2018, allowance prices have risen sharply, supported also by the official designation of EUAs as financial instruments under the revised Markets in Financial Instruments Directive (MiFID II), which further enhanced the system's credibility [1].

These dynamics make it particularly relevant to assess the EU ETS's effects when its influence is at its highest, as such an investigation would not only capture the policy's potential impact but also foster a more comprehensive understanding of its implications.

## 2. Literature review

As production of electricity accounts for the largest share of regulated emissions, a considerable amount of the literature that focuses on studying the impact of the EU ETS narrows its attention to the power generation sector.

Among the most comprehensive European studies on this topic, P.-A. Jouvet and B. Solier (2013) [2] assess the impact of $CO_2$ price fluctuations on electricity prices across 13 countries and, while highlighting substantial changes in the electricity-carbon price relationship from Phase I to Phase II of the scheme, the study focuses less on disparities across Member States. Within cross-country comparative studies, P. Aatola et al. (2013) [3] analyse a set of mostly Western and Northern European countries using a VAR model. The authors conclude that the EU ETS has had a positive but uneven impact on electricity prices across nations and highlight how the increasing European market integration has shaped those price relationships over time. They also recommend future research to incorporate transmission capacity data into their models.

In fact, in pursuit of higher cost-effectiveness, reliability, and renewable penetration, the EU has long worked towards a single integrated electricity market. This is because price interdependencies between adjacent countries arise in proportion to their transmission capacity. But despite the considerable progress made over the last decade, full market integration has yet to be achieved, and congestion—exacerbated by the expansion of renewables—continues to drive cross-country price differences. It is thus clear that cross-border interconnections are a crucial factor to account for when studying EU ETS-electricity market interactions.

A slightly different perspective is adopted by G. Castagneto Gissey (2014) [4] where, on a smaller set of countries, directionality of impact is examined via Granger-causality tests after constructing VAR models. In this study, however, the author misinterpreted the p-values associated with these tests. After correcting for this oversight, results indicate, in general, a unidirectional effect from carbon prices to national electricity prices. This investigation also confirms the heterogeneous impacts reported by the aforementioned authors.

Similarly, this heterogeneity is also confirmed by more recent works. A few examples refer to I. Ahamada and D. Kirat (2018) [5] (who, however, focus solely on the French and German markets), and the 2023 study by Y. Bai and S. J. Okullo [6] (who adopt a broader perspective, analysing 10 Member States but using data only up to May 2018).

The relevant literature suggests that although changes in carbon-market design have reshaped EUA-electricity interactions across phases, carbon costs still influence wholesale electricity prices—albeit unevenly across Member States. Substantial cross-country heterogeneity is evident, and more specifically, some studies (e.g. I. Ahamada and D. Kirat (2018) [5]), also show that higher allowance prices intensify producers' behavioural shifts, amplifying this heterogeneity as carbon permits become more valuable. This is particularly relevant in light of the mentioned evolution of the EU ETS towards a more mature market and an increased carbon price in recent years.

In addition, market integration emerged as a key determinant of electricity-price dynamics, and lastly, while doubts have been cast on the electricity markets potentially having an impact on the carbon price, the reverse link is more plausible.

## 2.1. Identified gaps

Although many of the relevant studies are not explicitly included in this summary, the existing literature is dominated by single-country analyses or EU-wide aggregates. While comparative multi-country works are present, these are often dated, resulting in a lack of a comprehensive pan-European framework. In addition, several Member States—notably in Central and Eastern Europe—are frequently omitted.

The reviewed research confirms cross-country heterogeneity in the transmission from carbon to electricity prices, but its magnitude and geographical distribution remain unclear. Given the considerable increase in allowance price since 2018, and based on the previously drawn conclusions, it is reasonable to expect this heterogeneity to have grown more pronounced in recent years; yet the extant literature does not cover the post-2018 period.

Another gap lies in the omission in nearly all instances of cross-border transmission capacity features in spite of the acknowledged importance of electricity market integration within the EU.

In connection with this, while fuel price inputs are usually considered, other key drivers—such as climatic conditions, renewable output, and economic or financial indicators—are seldom incorporated jointly. Controlling simultaneously for these variables as well would allow for a more comprehensive assessment of the carbon market's influence on electricity prices.

## 2.2. Research question definition

Given the previous considerations, my work sets out to investigate the following issue: modelling and quantifying empirically how the price of GHG emissions set by the EU ETS affects country-specific electricity prices in Europe. Special attention will be given to examining the degree of cross-country heterogeneity of this effect, taking into account both specific national characteristics and the dynamics associated with cross-border interconnection. Moreover, the analysis covers the entire EU, thus including as many Member States as possible and spans from 2018 to the present.

In addition, this thesis focuses on the wholesale day-ahead electricity market, as this choice allows me to draw implications on both the impact on end consumers and on the system's effectiveness in shaping producers' decisions, in line with the dual European energy objective stated in the Introduction.

# 3. Data collection

In light of this thesis's objectives, the temporal scope spans from 1 January 2018 to 20 March 2025, for a total of 2636 daily observations. All European countries are considered except a few, which I excluded due to insufficient data or limited relevance, yielding a final sample of 23 Member States.

## 3.1. Global variables

I used the EUA continuation series based on futures settlement prices as the carbon price reference, since it closely reflects the price signal used by installations for input-cost assessment. I applied the same approach to fossil-fuel prices (coal, natural gas and oil), where I used European benchmarks, as country-specific data were not uniformly available. I included the STOXX Europe 600 index as an additional control to capture aggregate financial market sentiment. All these series were sourced from LSEG Workspace.

## 3.2. Country-specific variables

I obtained day-ahead electricity prices for each country from the ENTSO-E Transparency Platform [7]. It is important to notice that all other explanatory series were temporally aligned to the day-ahead auction cut-off since market participants could not rely on data released after the auction when bidding for delivery of electricity on the following day. For the same reason, I also introduced day-ahead forecasts for wind and solar generation rather than actual output.

As additional controls, because day-ahead weather forecast data are scarce, I considered actual meteorological observations as proxies and constructed national-level indicators. To do this, I computed the daily mean absolute deviation of temperature from 18 °C (to capture electricity demand variation from both cold and hot extremes) and total daily precipitation following Y. Bai and S. J. Okullo (2018) [6]. In light of the simplistic aggregation procedures oftentimes implemented throughout the literature [8]—such as averages weighted over major cities or selected weather stations in key regions [5]—I used climatic 0.25° x 0.25° gridded data from Copernicus ERA5 reanalysis [9]. I assigned each grid cell to a country if located within its borders, and I computed national-level values as population-weighted averages using grid-cell population counts from NASA's GPWv4 dataset [10].

At last, to account for integration dynamics, the implemented model (that I will discuss shortly) requires weights that quantify the share of each country's openness to electricity trade with every other country in the sample. This involves accounting for interconnection strength (i.e., transfer capacities) between neighbouring countries. I therefore used net transfer capacity (NTC) data from ENTSO-E [7] to build a 23×23 matrix ($\boldsymbol{W}$) of pairwise weights, which feeds into the subsequent econometric specification.

Since day-ahead price volatility generally increased at higher price levels, to mitigate the issue of heteroscedasticity, I transformed all electricity price series as follows:

$$y_t = \ln(P_t) - \ln(P_{t-1}) \approx \frac{P_t - P_{t-1}}{P_{t-1}}. \tag{3.1}$$

This was applied to all other data except for climatic indices, which I instead first-differenced, as their properties did not push in favour of log transforming. These transformations were also implemented to ensure stationarity.

# 4. Methods

I chose to base this study on a Global Vector Autoregressive (GVAR) framework. This approach, initially proposed by M. H. Pesaran et al. (2004) [11], allows to model a geographically extensive system while simultaneously capturing interdependencies and feedback effects across regions. It also overcomes the curse of dimensionality inherent in large-scale models—where numerous countries and variables can lead to overparameterization. These features directly address the methodological requirements and contextual complexity of my research question.

To my knowledge, no existing study has applied this approach to the European energy sector. In addition, this thesis also departs from the standard GVAR practice in its treatment of endogeneity (especially from a country-specific perspective). Whereas much of the GVAR literature retains most series as jointly "endogenous", the characteristics of the data compel me to treat many controls inevitably as "exogenous"; climatic indicators or renewable output are, for instance, not plausibly influenced by electricity or commodity prices.

Few software packages offer pre-built GVAR estimation tools, and existing implementations favour convenience over flexibility. Since all the available solutions lacked the versatility required for this thesis, despite drawing on the econometric exposition provided by L. V. Smith and A. Galesi (2014) [12], I developed my GVAR model from scratch. Specifically, I coded the estimation of all country-specific models, their aggregation into a global system and the procedures to compute results and associated uncertainty measures.

## 4.1. Econometric modelling

The construction of the model begins from a collection of $N = 23$ country-specific ARX models. For each country $i$, consider the specification of a basic ARX$(p_i, k_i)$:

$$\begin{aligned} y_{it} = \mu_{i0} &+ \sum_{j=1}^{6} \delta_{ij} d_t^j + \sum_{j=1}^{p_i} \rho_{ij} y_{i,t-j} \\ &+ \sum_{j=0}^{k_i} \left( \lambda_{ij} y_{i,t-j}^* + \boldsymbol{\beta}_{ij}^{c\,\prime} \boldsymbol{x}_{i,t-j}^c + \boldsymbol{\beta}_{ij}^{g\,\prime} \boldsymbol{x}_{t-j}^g \right) + \varepsilon_{it}. \end{aligned} \tag{4.1}$$

$y_{it}$ denotes the electricity price returns (i.e., the domestic variable) for country $i$ at time $t$ and $d_t^j$ represents the seasonal dummy variables. The final summation is the exogenous block, which comprises the two groups of "purely" exogenous inputs (i.e., country-specific and global)—whose values and coefficients are included in the vectors $\boldsymbol{x}_{it}^c$, $\boldsymbol{\beta}_{ij}^c$ and $\boldsymbol{x}_t^g$, $\boldsymbol{\beta}_{ij}^g$ respectively—plus the foreign variable $y_{i,t}^*$. The latter captures spillover effects from the rest of the environment and is defined as

$$y_{it}^* = \sum_{j=1}^{N} w_{ij} y_{jt}, \quad \text{such that} \quad \sum_{j=1}^{N} w_{ij} = 1$$

$$\text{and} \quad w_{ii} = 0 \quad \forall i,$$

where $w_{ij}$ are the weights taken from the matrix $\boldsymbol{W}$ described in Subsection 3.2.

After selecting the optimal lags $p_i$ and $k_i$ and estimating each model, the global VAR is constructed as follows. By defining

$$\boldsymbol{y}_t = \begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{Nt} \end{bmatrix} \quad \text{and} \quad \boldsymbol{z}_{it} = \begin{bmatrix} y_{it} \\ y_{it}^* \end{bmatrix} = \boldsymbol{W}_i \boldsymbol{y}_t,$$

where $\boldsymbol{W}_i$ is the $2 \times N$ link matrix of country $i$ built starting from the entries $w_{ij}$ of the global weights matrix $\boldsymbol{W}$, Equation (4.1) can be written as

$$\begin{aligned} \boldsymbol{A}_{i0} \boldsymbol{W}_i \boldsymbol{y}_t = \mu_{i0} &+ \sum_{j=1}^{6} \delta_{ij} d_t^j + \sum_{j=1}^{q_i} \boldsymbol{A}_{ij} \boldsymbol{W}_i \boldsymbol{y}_{t-j} \\ &+ \sum_{j=0}^{k_i} \left( \boldsymbol{\beta}_{ij}^{c\,\prime} \boldsymbol{x}_{i,t-j}^c + \boldsymbol{\beta}_{ij}^{g\,\prime} \boldsymbol{x}_{t-j}^g \right) + \varepsilon_{it}. \end{aligned}$$

in which $q_i = \max(p_i, k_i)$, and

$$\boldsymbol{A}_{i0} = \begin{bmatrix} 1 & -\lambda_{i0} \end{bmatrix}, \quad \boldsymbol{A}_{ij} = \begin{bmatrix} \rho_{ij} & \lambda_{ij} \end{bmatrix} \quad \text{for } j = 1, \dots, q_i.$$

At this point, all the $N$ specifications are stacked on top of each other to obtain the following model.

$$\begin{aligned} \boldsymbol{G}_0 \boldsymbol{y}_t = \boldsymbol{\mu}_0 &+ \boldsymbol{\delta} \boldsymbol{d}_t + \sum_{j=1}^{p} \boldsymbol{G}_j \boldsymbol{y}_{t-j} \\ &+ \sum_{j=0}^{k} \left( \boldsymbol{B}_j^c \boldsymbol{\Upsilon}_{t-j}^c + \boldsymbol{B}_j^g \boldsymbol{x}_{t-j}^g \right) + \boldsymbol{\varepsilon}_t, \end{aligned} \tag{4.2}$$

where

$$\boldsymbol{G}_0 = \begin{bmatrix} \boldsymbol{A}_{10} \boldsymbol{W}_1 \\ \boldsymbol{A}_{20} \boldsymbol{W}_2 \\ \vdots \\ \boldsymbol{A}_{N0} \boldsymbol{W}_N \end{bmatrix} \quad \text{and} \quad \boldsymbol{G}_j = \begin{bmatrix} \boldsymbol{A}_{1j} \boldsymbol{W}_1 \\ \boldsymbol{A}_{2j} \boldsymbol{W}_2 \\ \vdots \\ \boldsymbol{A}_{Nj} \boldsymbol{W}_N \end{bmatrix} \quad \text{for } j = 1, \dots, p,$$

are $N \times N$ matrices and $\boldsymbol{B}_j^c$ and $\boldsymbol{B}_j^g$ denote the $N \times (N \times 4)$ and $N \times 5$ matrices respectively—4 being the number of country-specific exogenous inputs and 5 being the global exogenous variables in each individual ARX— built from the vectors $\boldsymbol{\beta}_{ij}^{c}$ and $\boldsymbol{\beta}_{ij}^{g}$ with $i = 1, \dots, N$. $\boldsymbol{\gamma}_t^c = [\boldsymbol{x}_{1t}^{c}{}', \boldsymbol{x}_{2t}^{c}{}', \dots, \boldsymbol{x}_{Nt}^{c}{}']'$ is the $(N \times 4) \times 1$ vector containing the values for the country-specific variables, while $\boldsymbol{\mu}_0$ (an $N \times 1$ vector of constants), $\boldsymbol{\delta}$ (an $N \times 6$ matrix of seasonal coefficients) and $\boldsymbol{d}_t$ (the $6 \times 1$ vector of seasonal dummies) form the deterministic components of the model. $\boldsymbol{\varepsilon}_t = [\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{Nt}]'$ contains each individual model's error. Finally, $p = \max_i q_i$ and $k = \max_i k_i$ denote the maximum lag orders.

Because $\boldsymbol{G}_0$ is a non-singular and known matrix (its elements being functions of the weights matrix $\boldsymbol{W}$ and the estimated ARX coefficients), premultiplying both sides of Equation (4.2) by $\boldsymbol{G}_0^{-1}$ yields to a GVARX$(p, k)$ which can be expressed as

$$\begin{aligned}\boldsymbol{y}_t = \boldsymbol{a}_0 + \boldsymbol{D}\boldsymbol{d}_t + \sum_{j=1}^{p} \boldsymbol{F}_j \boldsymbol{y}_{t-j} \\ + \sum_{j=0}^{k} \left( \boldsymbol{H}_j^c \boldsymbol{\gamma}_{t-j}^c + \boldsymbol{H}_j^g \boldsymbol{x}_{t-j}^g \right) + \boldsymbol{u}_t,\end{aligned} \tag{4.3}$$

where
$$\begin{aligned}&\boldsymbol{a}_0 = \boldsymbol{G}_0^{-1}\boldsymbol{\mu}_0,\\ &\boldsymbol{D} = \boldsymbol{G}_0^{-1}\boldsymbol{\delta},\\ &\boldsymbol{F}_j = \boldsymbol{G}_0^{-1}\boldsymbol{G}_j, \quad \text{for } j = 1, \dots, p,\\ &\boldsymbol{H}_j^c = \boldsymbol{G}_0^{-1}\boldsymbol{B}_j^c \text{ and } \boldsymbol{H}_j^g = \boldsymbol{G}_0^{-1}\boldsymbol{B}_j^g, \quad \text{for } j = 0, \dots, k,\\ &\boldsymbol{u}_t = \boldsymbol{G}_0^{-1}\boldsymbol{\varepsilon}_t.\end{aligned}$$

The resulting $N \times 1$ vector equation expresses each element of $\boldsymbol{y}_t$ also as a function of other countries' domestic variables since $\boldsymbol{y}_t$ collects the electricity prices of all $N$ regions. By exploiting the first-stage ARX estimates and the link matrices $\boldsymbol{W}_i$, it is possible to effectively sidestep the dimensionality challenge that would arise from direct estimation. In fact, the full GVARX is not estimated; it is calculated starting from a set of more parsimonious, individually estimated models.

The model in Equation (4.3) can be equivalently expressed in a more compact form. Starting from the obtained GVARX$(p, k)$ and defining

$$\boldsymbol{\Psi}_t = \begin{bmatrix} \boldsymbol{y}_t \\ \boldsymbol{y}_{t-1} \\ \vdots \\ \boldsymbol{y}_{t-p+1} \end{bmatrix}, \quad \boldsymbol{\Gamma}_t = \begin{bmatrix} \boldsymbol{\gamma}_t^c \\ \boldsymbol{\gamma}_{t-1}^c \\ \vdots \\ \boldsymbol{\gamma}_{t-k}^c \end{bmatrix}, \quad \text{and} \quad \boldsymbol{X}_t = \begin{bmatrix} \boldsymbol{x}_t^g \\ \boldsymbol{x}_{t-1}^g \\ \vdots \\ \boldsymbol{x}_{t-k}^g \end{bmatrix},$$

one can express (4.3) as

$$\boldsymbol{\Psi}_t = \boldsymbol{C} + \boldsymbol{S}\boldsymbol{d}_t + \boldsymbol{F}\boldsymbol{\Psi}_{t-1} + \boldsymbol{\Phi}^c\boldsymbol{\Gamma}_t + \boldsymbol{\Phi}^g\boldsymbol{X}_t + \boldsymbol{U}_t, \tag{4.4}$$

corresponding to a GVARX(1,0). In this specification $\boldsymbol{F}$ is the $(p \times N) \times (p \times N)$ companion coefficient matrix constructed from the $\boldsymbol{F}_1, \boldsymbol{F}_2, \dots, \boldsymbol{F}_p$ matrices and a set of $N \times N$ identity matrices. Similarly, $\boldsymbol{\Phi}^c$ and $\boldsymbol{\Phi}^g$ are built from the matrices $\boldsymbol{H}_0^c, \boldsymbol{H}_1^c, \dots, \boldsymbol{H}_k^c$ and $\boldsymbol{H}_0^g, \boldsymbol{H}_1^g, \dots, \boldsymbol{H}_k^g$ respectively. $\boldsymbol{C}$ accounts for the constant terms of the model and $\boldsymbol{S}$ for the seasonal coefficients, while $\boldsymbol{U}_t = [\boldsymbol{u}_t{}', \boldsymbol{0}', \dots, \boldsymbol{0}']'$ contains the error terms.

One of the advantages of the GVARX companion form in Equation (4.4) is the ease it provides in computing dynamic responses. To address this thesis's research question, I constructed impulse response functions of the EUA return series on each country's electricity price return $y_{it}$; the impact at each step $h$ following a one-off shock of magnitude $\eta$ can be derived from

$$\boldsymbol{\Psi}_h = \sum_{i=0}^{\min(k,h)} \boldsymbol{F}^{h-i}\boldsymbol{\Phi}^g \eta \boldsymbol{e}_{1+5i},$$

where $\boldsymbol{e}_i$ is the vector of the same dimensions as $\boldsymbol{X}_t$ containing all zeros except a 1 as the $i$-th entry. Extracting the first $N$ elements out of $\boldsymbol{\Psi}_h$, yields the vector $\boldsymbol{y}_h$ of impulse responses across all countries.

Since $y_{ih} = \ln(P_{ih}) - \ln(P_{i,h-1})$ (see Equation (3.1)), by calculating the cumulated impulse response function (CIRF) at step $h$, given by

$$\mathcal{CIRF}_i(h) = \sum_{j=0}^{h} y_{ij} = \ln(P_{ih}) - \ln(P_{i,-1}),$$

one can obtain the percentage difference of the day-ahead price at $h$ with respect to the pre-shock price level $P_{i,-1}$. Noting that an impulse of $100\eta\%$ in the first differences of the EUA logged prices is mathematically equivalent to a step function of size $100\eta\%$ in the non-differenced series, this approach allowed me to interpret the results as follows: "given a $100\eta\%$ sustained increase in the EUA price, what is the resulting percentage change in electricity prices across countries relative to their pre-shock levels?" And: "how does that percentage response evolve over time?"

Finally, to construct confidence intervals around the point estimates of the CIRFs, I implemented a bootstrap-based procedure as this nonparametric method allows not to rely on distributional assumptions. The critical interpretation of each country's response formed the basis of the following discussion.

## 5. Results

The observed heterogeneity of EUA prices impact is systematic rather than random, as it can be explained by countries' structural characteristics.

The main driver is the generation mix: high-emission systems exhibit larger price elasticities, whereas low-carbon mixes dampen this effect. Crucially, the proportion of time a technology is marginal often matters more than its total share in generation. However, the latter must not be neglected since frequent marginality does not imply strong dependence on a given source if its generation share is limited, national electricity demand is modest, and access to low-emission imports is present; in this case, marginal domestic bids risk being undercut, thereby reducing the technology's influence on EUA cost transmission.

Integration dynamics also modulate this impact: where interconnection is weak, domestic factors dominate the EUA-electricity price relationship; where integration is strong, imports can displace high-emission, price-setting units and thus attenuate the domestic effect. The degree of buffering depends on trading partners' emission profiles: low-emission neighbours have the potential to reduce cost transmissions, whereas similarly carbon-intensive partners cannot. In addition, assessing interconnection requires not only looking at the absolute transfer capacity values but also at their significance relative to national electricity demand. The number of partner countries matters too, since a larger supplier pool increases the chance that marginal supply originates from cheaper sources.

Market structure also matters. High market fragmentation strengthens competitive pressure and makes it harder for producers to pass through EUA cost shocks. Moreover, state-controlled incumbents—owing to objectives not restricted to profit maximisation—tend to attenuate the impact of increased EUA prices even where competition is weak, while predominantly private ownership is associated with stronger pass-through.

Finally, unique national features that can heavily alter EUA-electricity price transmissions are still present. Country-specific regulatory settings (including additional carbon taxes), idiosyncratic technological events, and atypical producers' behaviour may dominate structural determinants.

## 6. Conclusions

These findings have clear implications. If higher EUA costs are simply passed through to consumers without displacing high-emission units, a stricter ETS will mainly increase electricity bills and disproportionately affect vulnerable households, while doing little to accelerate decarbonisation. Conversely, when higher allowance prices imply a greater risk of displacement for carbon-intensive producers, a tighter ETS can promote the green transition without unduly burdening end consumers.

The factors identified in this thesis determine the relative likelihood of these outcomes, therefore indicating where to direct targeted subsidies, interconnection investments and modernisation efforts. As a consequence, the results clarify the trade-off between environmental stringency and energy affordability, offering guidance on how to achieve decarbonisation while limiting adverse consumer effects.

Moreover, the developed GVARX has multiple uses beyond assessing how shocks propagate through the system. The model is applicable to forecasting exercises, infrastructure planning and resilience analysis, making it valuable for energy regulators, public authorities, TSOs, infrastructure investors and energy traders.

### 6.1. Limitations and further research

This analysis is not without limitations. While European benchmarks provide a reasonable proxy for producers' fuel-input costs, future work should seek to incorporate country-specific fuel prices. In that case, these variables would be best treated as endogenous, converting each ARX specification into a VARX, thus allowing for mutual interactions between electricity and fuel prices.

Additional controls like national indicators of economic activity—such as the yield-curve spread—could mitigate weaker explanatory powers stemming from fluctuations in electricity prices that are merely a reflection of a country's economic strength during a given period.

Finally, applying this framework to the electricity futures market and extending the analysis to other sectors covered by the EU ETS could yield further understanding of the policy's effects.

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