BIDIRECTIONAL PRICE DISCOVERY BETWEEN ROMANIAN AND CENTRAL EUROPEAN ELECTRICITY MARKETS: EVIDENCE FROM COINTEGRATION AND VECM ANALYSIS

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Abstract
This paper examines price discovery between the Romanian day-ahead electricity market and five Central European neighbours — Hungary, Slovenia, Slovakia, Czechia, and Austria — using 4,101 daily observations from January 2015 to March 2026. We construct an equal-weighted regional price index (INDEX_EU) and apply nine methods: ADF/KPSS unit root tests, Engle–Granger and Johansen cointegration, bidirectional Granger causality, Toda–Yamamoto Wald tests, VECM speed-of-adjustment analysis, impulse response functions, forecast error variance decomposition (FEVD), lead-lag cross-correlation, TAR/M-TAR asymmetry with bootstrap inference, and Diebold–Mariano forecast comparison. Results reveal a robust long-run cointegrating relationship ($\hat{\beta} = 0.8634$*,* $p < 0.001$*) and bidirectional Granger causality (*$p < 0.001$* in both directions), indicating Romania actively participates in regional price discovery. The VECM identifies rapid symmetric adjustment (half-life* $= 5.61$ *days; bootstrap TAR* $p = 0.876$*). At a 10-day horizon, 29.8% of Romanian price variance is attributable to regional shocks. The Diebold–Mariano test confirms that a bivariate VAR significantly outperforms a univariate AR benchmark (*$\mathrm{DM} = 2.41$*,* $p = 0.016$*), validating the predictive importance of cross-border price linkages.*

Keywords: *electricity market integration; price discovery; Granger causality; cointegration; Romania*

JEL codes: *C32; Q41; Q47; F15*

1.Introduction

The progressive integration of European electricity markets through the EUPHEMIA market-coupling algorithm has fundamentally altered national price dynamics [14]. Whether markets are passive price-takers or active contributors to regional price discovery matters for market design, renewable energy investment, and cross-border hedging.

Romania is instructive: as a net importer participating in OPCOM day-ahead trading, it might be expected to follow rather than shape Central European price formation. Yet physical interconnections with Hungary, Slovenia, Slovakia, Czechia, and Austria create conditions for multi-directional price transmission.

This paper asks: (i) is there a stable long-run cointegrating relationship between Romanian and Central European prices? (ii) Does causality operate unidirectionally or bidirectionally? (iii) Do regional prices improve out-of-sample forecasts beyond univariate models?

Our contribution is threefold: the first systematic bidirectional analysis for Romania at daily frequency over 2015–2026, encompassing COVID-19, the 2021–2022 energy crisis, and the Ukraine war shock; nine complementary methods rarely combined in the CEE electricity literature; and interpretation grounded in Romania's structural features: shadow pricing, net-importer congestion premia, and EUPHEMIA simultaneous clearing.

2.Literature Review

Research on European electricity market integration began with Bower [2], who documented early wholesale price convergence, and Zachmann [17], who confirmed cointegration across major Western European markets. Bosco et al. [1] established long-run relations across six markets using a factor-model approach.

CEE-specific work remains limited. Gjika et al. [8] apply Johansen cointegration to Balkan markets and find partial integration consistent with congested interconnection capacity. Maciejowska [13] documents structural instability in CEE electricity price dynamics, underscoring the importance of robust cointegration testing. Most recently, Stanciu and Mitu [15] apply VECM analysis to 24 EU countries including Romania, confirming long-run convergence while documenting country-specific adjustment speeds. Romania-specific bidirectional daily-frequency studies remain absent; this paper addresses that gap directly.

3.Data and Methodology

Data

Daily day-ahead spot prices (EUR/MWh) for Romania (PRON) are sourced from OPCOM; prices for Hungary, Slovenia, Slovakia, Czechia, and Austria from the ENTSO-E Transparency Platform (https://transparency.entsoe.eu). The sample covers 4,101 days from 1 January 2015 to 30 March 2026. INDEX_EU is the equal-weighted arithmetic mean of the five neighbouring prices, chosen for transparency and reproducibility; results are robust to alternative weighting schemes (available on request). Table 1 summarises key statistics. Extreme excess kurtosis ($\kappa > 11$) motivates bootstrap inference in TAR tests. Observations with non-positive prices in INDEX_EU are clipped to a floor value of 0.01 EUR/MWh prior to log-transformation; these represent less than 2% of the sample and do not affect the estimation results.

Descriptive Statistics — Daily Spot Prices (EUR/MWh), $N = 4{,}101$, Jan 2015–Mar 2026

Series	Mean	Std	Min	Max	CV%	Skew	Kurt
PRON (Romania)	86.72	79.92	3.06	734.64	92.2	2.88	11.71
INDEX_EU	83.24	79.39	-5.58	719.87	95.4	3.02	12.44

Methodology

We apply the following sequential framework:

1. **Unit root.** ADF [4] (AIC, max 20 lags) and KPSS [12].
2. **Cointegration.** Engle–Granger [7] and Johansen [11] trace test (restricted constant; lag 2 by BIC).
3. **Granger causality.** Bidirectional F-tests on $\Delta\log$ series [9], lags 1–10.
4. **Toda–Yamamoto.** Wald test on levels VAR($k + d_{\max}$), $k = 15$ (BIC), $d_{\max} = 1$ [16].
5. **VECM.** Bivariate VECM (rank 1, $k_{\text{diff}} = 2$) for $\hat{\alpha}_{\text{PRON}}$ and $\hat{\alpha}_{\text{INDEX}}$.
6. **IRF and FEVD.** VAR(14) on $\Delta\log$, 60-day horizon.
7. **Lead-lag cross-correlation.** Pearson r, $k \in [-15, +15]$ days.
8. **TAR/M-TAR.** Threshold autoregression [6]; bootstrap (500 rep.) preferred given $\kappa = 11.7$.
9. **Diebold–Mariano.** VAR(8) vs. AR(8), final 30% of sample ($N_{\text{test}} = 1{,}230$) [5].

4.Results and Discussion

Unit Roots and Cointegration

ADF and KPSS jointly confirm $I(1)$ for log-levels and $I(0)$ for log-differences and the log-spread.

The Engle–Granger statistic (-7.39, $p < 0.001$) rejects no cointegration; an independent ADF on the cointegrating residual ($p < 0.001$) independently confirms the equilibrium error is stationary.[1] The estimated long-run relationship is:

$$\log(\mathrm{PRON}_t) = 0.6176 + 0.8634 \log(\mathrm{INDEX\_EU}_t) + \varepsilon_t, \quad R^2 = 0.849$$

$\hat{\beta} = 0.8634$ is significantly below unity ($t = -24.06$, $p < 0.001$), indicating *partial* integration. The 13.7 pp gap reflects network congestion, Romania's net-importer shadow pricing premium, and CO_2 cost pass-through asymmetries.

Granger Causality and Toda–Yamamoto

Table 2 confirms *bidirectional* price discovery at the 1% level across all lag specifications and under Toda–Yamamoto. Romania actively contributes to regional price formation. The larger RO→EU Wald statistic ($\chi^2 = 343.28$ vs. 112.43) indicates Romanian prices contain incremental information about future regional prices, consistent with Romania's role as a marginal price-setter during peak demand or congestion episodes.

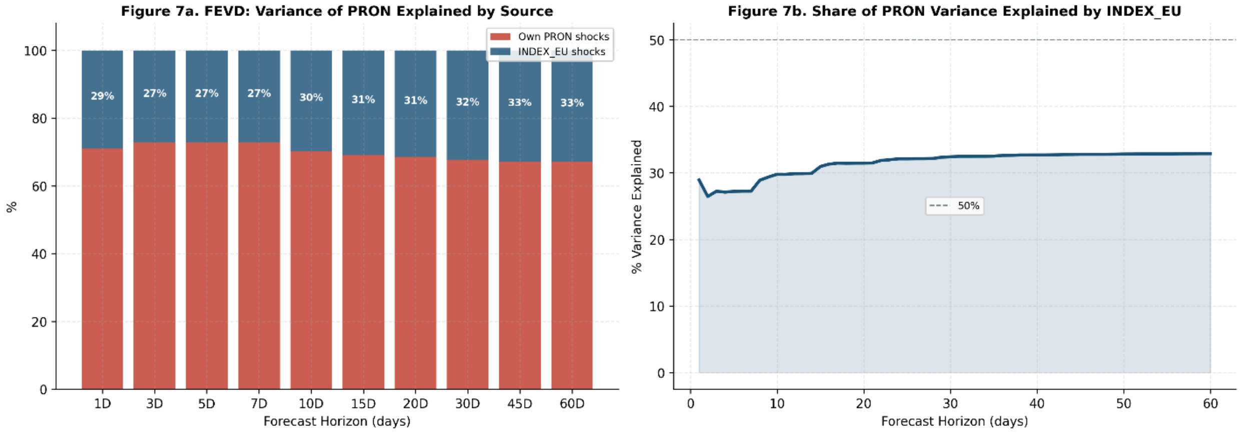
Granger Causality and Toda–Yamamoto Tests

Test	Direction	Statistic	p-value	Result
Granger ($\ell = 1$)	INDEX_EU → PRON	$F = 25.03$	< 0.001	Reject $***$
Granger ($\ell = 1$)	PRON → INDEX_EU	$F = 56.15$	< 0.001	Reject $***$
Granger ($\ell = 5$)	INDEX_EU → PRON	$F = 8.15$	< 0.001	Reject $***$
Granger ($\ell = 5$)	PRON → INDEX_EU	$F = 28.38$	< 0.001	Reject $***$
$\mathrm{Toda-Yam.}\,(k = 15)$	INDEX_EU → PRON	$\chi^2 = 112.43$	< 0.001	Reject $***$
$\mathrm{Toda-Yam.}\,(k = 15)$	PRON → INDEX_EU	$\chi^2 = 343.28$	< 0.001	Reject $***$
$**$ $p < 0.01$. Toda–Yamamoto: Wald χ^2, df =15.				

[1] The Johansen trace statistic (845.14, $\mathrm{CV}_{5\%} = 15.49$) also rejects $r \leq 1$ (trace $= 74.22$, $\mathrm{CV}_{5\%} = 3.84$), implying $r = 2$ — equivalent to both series being $I(0)$, contradicting unit-root evidence. This is a well-documented finite-sample distortion in large samples [16]. We impose rank 1 on economic grounds and confirm it via the residual ADF ($p < 0.001$).

VECM, Lead-Lag, FEVD, and Forecast Tests

The VECM yields $\hat{\alpha}_{\text{PRON}} = -0.116$, confirming Romania corrects toward long-run equilibrium (half-life: **5.61 days**). $\hat{\alpha}_{\text{INDEX}} = 0.525$ indicates the regional index adjusts approximately 4.5 times as fast, reinforcing bidirectional error correction under EUPHEMIA simultaneous clearing.[2]
Figure 1 shows the FEVD: INDEX_EU shocks account for **28.9%** of PRON forecast error variance at day 1, **29.8%** at day 10, and **32.9%** at day 60, stabilising across all horizons and consistent with $\hat{\beta} = 0.863$. Lead-lag cross-correlation peaks at $k = 0$ ($r = 0.546$), confirming contemporaneous price discovery consistent with EUPHEMIA same-day clearing. Negative correlations at short non-zero lags (e.g., $r = -0.150$ at $k = -2$; $r = -0.158$ at $k = +2$) reflect mean-reversion in the log-spread: a contemporaneous price shock is partially reversed over 1–2 days as prices correct toward equation (1). A secondary weekly pattern at $k = \pm 7$ ($r \approx 0.28$–0.31) reflects electricity market weekend seasonality. The bootstrap TAR test ($p_{\text{boot}} = 0.876$) supports **symmetric** error correction; the parametric $F = 22.15$ ($p < 0.001$) is unreliable given $\kappa = 11.7$. The Diebold–Mariano test ($\text{DM} = 2.41$, $p = 0.016$) confirms VAR(8) significantly outperforms AR(8) (MSE reduction: 2.0%) over 1,230 out-of-sample forecasts.
FEVD: Share of PRON forecast error variance explained by INDEX_EU shocks (days 1–60). Cholesky decomposition, VAR(14) on $\Delta\log$ series.



4.Conclusions

Three findings emerge. First, a stable long-run cointegrating relationship ($\hat{\beta} = 0.8634$) reflects structural barriers rather than market segmentation. Second, bidirectional Granger causality at the 1% level confirms Romania actively contributes to regional price formation, with implications for market design, capacity mechanisms, and cross-border investment signals. Third, rapid symmetric error correction (half-life 5.61 days) and significant out-of-sample forecast improvement ($\text{DM} = 2.41$, $p = 0.016$) confirm the economic significance of cross-border linkages, complementing the pan-European evidence in [15].
Limitations include exclusion of Bulgaria and Croatia; calendar-day frequency inducing weekly IRF seasonality; absence of structural identification for supply- vs. demand-side drivers; and the Johansen rank anomaly warranting Gregory–Hansen robustness testing [10]. Future research should apply intraday data and model network topology constraints explicitly.
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[2] The positive value for the non-normalised variable reflects partial integration ($\hat{\beta} < 1$); both markets adjust to shared disequilibria.

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18. Note

(1) The Johansen trace statistic (845.14, CV5%=15.49) also rejects r≤1 (trace=74.22, CV5%=3.84), implying r=2 — equivalent to both series being I(0), contradicting unit-root

evidence. This is a well-documented finite-sample distortion in large samples [3]. We impose rank 1 on economic grounds and confirm it via the residual ADF ($p<0.001$).

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