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Horizon-Dependent Price Transmission and Market Leadership in Thailand–Vietnam Rice Markets, 2018–2024

Angky Dwi Seffyanto [a,*], Yusman Syaukat [a], Sri Hartojo [a], Ahmad Faroby Falatehan [a]

[a] Department of Agricultural Economics, Faculty of Economics and Management, IPB University, Bogor, Indonesia

Abstract. *Thailand and Vietnam are major rice exporters whose price signals became increasingly relevant during and after the COVID-19 disruption. Using 336 sequential within-month observations for 2018–2024, this study distinguishes short-run predictive information, conditional long-run adjustment, and medium-term shock influence. The analysis combines ADF tests, lag-order selection, Johansen cointegration, a Vector Error Correction Model (VECM), Granger predictive-causality tests, forecast error variance decomposition (FEVD), structural-break tests, and residual diagnostics. The raw analysis file confirms 84 month-year identifiers with exactly four ordered observations per month and no missing price observations. Under the BIC/HQ benchmark VAR(2)/VECM specification, one cointegrating relation is identified, but this result disappears under longer lag structures, including AIC/FPE-preferred VAR(5). Vietnam-to-Thailand predictive content is more robust, remaining significant across lags 1–4 in first-difference checks, whereas the reverse direction is less persistent. Orthogonalized FEVD shows substantial cross-market influence at a 12-period horizon, but the directional shares change materially when the Cholesky ordering is reversed. Formal Chow tests reject parameter stability at both regime transitions. The main contribution is therefore a qualified, horizon- and regime-dependent interpretation of price leadership in which the short-run predictive result is more robust than the full-sample long-run and FEVD directional results. These findings support monitoring both exporters in regional rice-price early-warning and trade-risk systems.*

Keywords: *rice export prices; price transmission; market leadership; Granger causality; VECM.*

Type of the Paper: Regular Article.

1. Introduction

Rice is a strategic commodity in Asia because changes in its price affect food security, inflation, rural welfare, and trade stability. Thailand and Vietnam are particularly important because both are major exporters, and their quotations are widely observed by buyers and policymakers in regional and international rice markets [1–3].

The 2018–2024 period provides a useful setting for studying exporter-to-exporter price transmission because it spans a relatively stable pre-pandemic phase, the COVID-19 disruption, and a post-pandemic period of renewed trade-policy uncertainty. COVID-19 affected food prices, processing margins, policy responses, trade flows, and supply-chain conditions [4–11]. The central empirical question is therefore whether the Thailand–Vietnam pricing relationship remained stable and whether the apparent leader depends on the horizon used to measure influence. Broader

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* Corresponding author
Email: angkydwi@apps.ipb.ac.id
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evidence on cereal-price pass-through, food-industry price transmission, and geopolitical food-security shocks likewise underscores the importance of international market linkages [12–14].

Vietnam's expanding export role also makes the bilateral relationship economically relevant. Existing studies show that international rice prices and exporter policies transmit across markets rather than remaining country-specific [15–19]. Recent evidence further identifies Vietnam as an influential price leader in the non-aromatic long-grain segment and shows that transmission can vary across products, locations, and horizons [20–23].

A specific gap remains between two strands of literature. Ghoshray [18] examined asymmetric adjustment between Thailand and Vietnam, whereas Mottaleb and Durand-Morat [20] examined leader–follower relationships across a broader set of exporters using different empirical models. This study differs by using a bilateral 2018–2024 sequence that explicitly spans pre-COVID, COVID-19, and post-COVID regimes and by evaluating leadership simultaneously through short-run predictive content, long-run error correction, medium-term FEVD influence, formal structural breaks, and lag-sensitivity checks. The novelty therefore lies in testing whether the identity and strength of leadership change with the analytical horizon and market regime, not in the econometric tools themselves.

In this study, market leadership is defined operationally as an information role that may differ by horizon. Short-run predictive leadership refers to whether lagged prices in one market improve forecasts of the other market in the Granger sense; long-run adjustment refers to responses to deviations from an estimated cointegrating relation; and medium-term influence refers to the share of forecast variance associated with cross-market shocks. This definition is distinct from export volume, market size, price dominance, or permanent benchmark status [24–29]. This interpretation is also consistent with the spatial-market integration literature, which allows price co-movement and arbitrage to remain incomplete when transaction costs and market frictions are present [30–32].

Because the sample spans major disruptions, the full-period VECM is used as a common benchmark rather than assumed to represent an invariant structure. Formal Chow tests, rolling correlations, and alternative-lag Johansen tests are used to evaluate that assumption. Accordingly, any full-sample long-run relation is interpreted conditionally and is not treated as evidence that the same equilibrium parameters held unchanged in every regime.

This framework allows apparently competing findings to coexist: one exporter can contain more short-run predictive information, while the other accounts for a larger accumulated share of forecast uncertainty at longer horizons. It also permits structural breaks and specification sensitivity to become substantive qualifications of market-leadership claims rather than secondary diagnostics.

The purpose of this study is to: (1) test whether Thailand and Vietnam rice export prices share a long-run equilibrium relationship under alternative lag specifications; (2) estimate the speed and direction of adjustment toward that relation when cointegration is supported; (3) identify the direction and robustness of short-run predictive transmission; (4) compare cross-market shock contributions across forecast horizons; and (5) assess how structural breaks, lag choice, and residual diagnostics qualify the substantive conclusions.

The empirical contribution is therefore centered on horizon-dependent leadership, regime change, and the relative robustness of short-run versus long-run evidence. Particular weight is placed on whether conclusions survive alternative lag structures rather than on a single preferred specification.

2. Materials and Methods

2.1. Data

This study uses 336 sequential observations of Thailand and Vietnam rice export prices covering a period from January 2018 to December 2024. The research file was compiled and harmonized from the official rice-market information used during data preparation, including FAO material [2] and supporting official sources cited in the study. The replication file supplied for this revision contains six fields: observation number, month-year identifier, sequential period number, Thailand price, Vietnam price, and a COVID-period dummy. The price series are analyzed in USD/kg as recorded in the research dataset and are transformed to natural logarithms ($\mathrm{Ln}P_{\mathrm{TH}}$ and $\mathrm{Ln}P_{\mathrm{VN}}$) for econometric estimation. Importantly, the analysis file itself does not retain the exact quotation date, rice-grade/benchmark label, or an observation-level source identifier. Those items therefore cannot be independently reconstructed from the analysis file alone and should be documented from the original source records in a supplementary provenance table if available.

Direct inspection of the raw file confirms 84 distinct month-year identifiers from January 2018 through December 2024, with exactly four ordered observations attached to every month ($84 \times 4 = 336$). The sequential index runs without gaps from 1 to 336, and neither price series contains missing values. The month-year field identifies the calendar month rather than an exact weekly quotation date; consequently, the four observations within each month form a standardized sequential within-month index rather than ISO-calendar weeks. Months with five calendar weeks do not create a fifth observation. The COVID dummy equals one for observations 97–240, corresponding to January 2020 to December 2022 (144 observations), and zero for the 96 pre-COVID and 96 post-COVID observations. Forecast horizons and adjustment speeds are therefore interpreted in sequential periods that are approximately weekly within the constructed four-observations-per-month index, not as exact dated calendar weeks.

2.2. Unit Root Test

The Augmented Dickey–Fuller (ADF) test is used to determine whether each logarithmic price series is stationary. If a series is non-stationary in levels but stationary after first differencing, it is treated as integrated of order one, I(1), which is the required integration order for the cointegration framework applied here [33,34].

2.3. Lag Order Selection

Lag order is evaluated using the Akaike Information Criterion (AIC), Schwarz/Bayesian Information Criterion (SIC/BIC), Hannan–Quinn criterion (HQ), and Final Prediction Error (FPE). Replication from the raw data confirms that AIC and FPE select VAR lag $p = 5$, whereas BIC/SC and HQ select $p = 2$. Because the criteria disagree and the Johansen rank changes with lag length, no lag order is treated as empirically dominant. VAR $p = 2$ is retained as the BIC/HQ benchmark for the conditional VECM because two independent penalized criteria select it, while VAR $p = 5$ is treated as an equally important competing specification because AIC/FPE selects it. The disagreement itself is part of the substantive evidence: cointegration is supported under $p = 2$ and $p = 3$ but not under $p = 4$ or $p = 5$. Accordingly, long-run conclusions are explicitly conditional on lag choice, whereas short-run predictive evidence is evaluated separately across several lags in first differences.

2.4. Structural Break and Stability Tests

Because the 2018–2024 sample spans major disruptions, structural stability is tested formally rather than inferred only from regime correlations. Chow breakpoint tests are applied at the two pre-specified transitions: after observation 96 (entry into the COVID-19 period) and after observation 240 (entry into the post-COVID period). The null hypothesis is parameter stability. Rejection indicates that the bilateral price relationship changed across regimes. The full-sample model is retained only as a common benchmark for comparability. To examine the implication of the breaks more directly, supplementary Johansen rank tests are also reported for the pre-COVID, COVID-19, and post-COVID subsamples under a $k = 1$ lagged difference. The full regime-specific VECM is not used as the principal model because the 96/144/96-observation subsamples reduce precision, but regime rank tests provide an additional check on whether the full-sample long-run relation is stable across periods.

2.5. Johansen Cointegration Test

The Johansen procedure is used to determine whether Thailand and Vietnam rice prices share a long-run equilibrium relationship. Trace and maximum-eigenvalue statistics are used jointly to determine the cointegration rank [27–29].

2.6. Vector Error Correction Model, Granger Causality, and FEVD

When cointegration is identified, the VECM describes short-run dynamics and adjustment

toward the estimated long-run relation. Granger causality is used only in its predictive sense: rejection of the null hypothesis means that lagged values of one price series add forecasting information for the other, conditional on the model, not that an economic or structural causal mechanism has been identified. FEVD measures the model-based contribution of each innovation to forecast uncertainty at different horizons [24–29].

2.7. Diagnostic and Robustness Evaluation

Model adequacy is evaluated using residual autocorrelation and normality diagnostics. Robustness is examined by comparing lag-selection criteria, re-estimating Johansen rank results under alternative lagged-difference specifications, comparing pairwise predictive tests on first-differenced log prices across lags 1–4, conducting supplementary regime-specific Johansen tests, and testing FEVD sensitivity to Cholesky ordering. The VECM standard errors are conventional model-based asymptotic standard errors; no HAC/robust covariance adjustment is applied. The baseline Granger results in Table 8 are system-level F tests from the fitted VECM, whereas Panel B of Table 11 reports separate pairwise OLS Granger checks in first differences. Because residual autocorrelation and non-normality remain, p-values are interpreted cautiously and greater weight is placed on results that persist across specifications. Residual normality is assessed using the Jarque–Bera framework [35].

2.8. Econometric Model Specification

Let $P_{TH,t}$ and $P_{VN,t}$ denote the sequential within-month rice export prices for Thailand and Vietnam at period t. The logarithmic price vector is $y_t = [\mathrm{Ln}P_{TH,t}, \mathrm{Ln}P_{VN,t}]'$, where $\mathrm{Ln}P_{TH,t} = \ln(P_{TH,t})$ and $\mathrm{Ln}P_{VN,t} = \ln(P_{VN,t})$. The logarithmic form permits proportional interpretation and reduces scale differences. The period index advances four times per calendar month and should not be interpreted as an exact ISO-week date.

First, stationarity is assessed using the Augmented Dickey–Fuller specification shown in Eq. (1).

$$\Delta y_{i,t} = \mu_i + \rho_i y_{i,t-1} + \Sigma_{(j=1 \text{ to } k)} \psi_{i,j} \Delta y_{i,t-j} + \varepsilon_{i,t}, \; i = \mathrm{TH}, \mathrm{VN} \quad (1)$$

The null hypothesis is $\rho_i = 0$, indicating a unit root. If both log-price series are non-stationary in levels but stationary in first differences, they are treated as I(1) [33,34].

Second, the unrestricted VAR representation is specified as shown in Eq. (2). Lag-order selection is mixed: AIC and FPE select $p = 5$, whereas BIC/SC and HQ select $p = 2$. Rather than designating one criterion set as uniquely correct, the analysis uses VAR $p = 2$ as the BIC/HQ benchmark and treats the AIC/FPE-preferred VAR $p = 5$ as a co-equal sensitivity specification. A VAR(p) corresponds to a VECM with $p - 1$ lagged differences; therefore, VAR $p = 2$ corresponds to VECM $k = 1$, while VAR $p = 5$ corresponds to $k = 4$. This mapping is shown explicitly in Table

11. The fact that the cointegration rank changes across these competing specifications is treated as a limitation on the full-sample long-run conclusion rather than as a reason to suppress the higher-order result.

$$y_t = c + \mathrm{A}_1 y_{t-1} + \mathrm{A}_2 y_{t-2} + \cdots + \mathrm{A}_p y_{t-p} + u_t \quad (2)$$

If the variables are I(1), the VAR can be reparameterized as the Johansen VECM shown in Eqs. (3) and (4) [26–29].

$$\Delta y_t = \mu + \Pi y_{t-1} + \Sigma_{(i=1\ \mathrm{to}\ p-1)} \Gamma_i \Delta y_{t-i} + \varepsilon_t \quad (3)$$

$$\Pi = \alpha\beta' \quad (4)$$

In this specification, β contains the long-run cointegrating vector, and α contains the adjustment coefficients. The rank of Π determines the number of cointegrating relations. A rank of one implies a single long-run equilibrium relationship between the two export-price series.

Based on the estimated cointegrating vector in the specification, the long-run error-correction term is shown in Eq. (5).

$$\mathrm{ECT}_{t-1} = \mathrm{Ln}P_{\mathrm{TH},t} - 1 - 0.8246\ \mathrm{Ln}P_{\mathrm{VN},t-1} + 0.0980 \quad (5)$$

The short-run VECM system is then expressed in Eqs. (6) and (7).

$$\Delta\mathrm{Ln}P_{\mathrm{TH},t} = \alpha_{\mathrm{TH}}\mathrm{ECT}_{t-1} + \Sigma_{(i=1\ \mathrm{to}\ p-1)}\gamma_{11,i}\,\Delta\mathrm{Ln}P_{\mathrm{TH},t-i} + \Sigma_{(i=1\ \mathrm{to}\ p-1)}\gamma_{12,i}\Delta\mathrm{Ln}P_{\mathrm{VN},t-\mathrm{i}} + \varepsilon_{\mathrm{TH},t} \quad (6)$$

$$\Delta\mathrm{Ln}P_{\mathrm{VN},t} = \alpha_{\mathrm{VN}}\mathrm{ECT}_{t-1} + \Sigma_{(i=1\ \mathrm{to}\ p-1)}\gamma_{21,i}\,\Delta\mathrm{Ln}P_{\mathrm{TH},t-i} + \Sigma_{(i=1\ \mathrm{to}\ p-1)}\gamma_{22,i}\Delta\mathrm{Ln}P_{\mathrm{VN},t-i} + \varepsilon_{\mathrm{VN},t} \quad (7)$$

The coefficients α_{TH} and α_{VN} measure how each market responds to a deviation from long-run equilibrium. The cross-market short-run coefficients capture lagged price transmission between Vietnam and Thailand.

Third, predictive Granger causality is tested within the fitted VECM system. Replication from the raw data confirms the originally reported system-level statistics: Vietnam-to-Thailand $F = 8.3639$ ($p = 0.000259$) and Thailand-to-Vietnam $F = 4.3237$ ($p = 0.013633$), with $df = (2,652)$ in both directions. The denominator 652 is not the residual degrees of freedom of a single OLS equation. It arises because the VECM Granger procedure evaluates restrictions in the bivariate system and reports the denominator as two equations multiplied by 326 residual degrees of freedom per equation ($2 \times 326 = 652$). For transparency, Table 11 separately reports conventional pairwise Granger tests on first-differenced log prices, whose single-equation degrees of freedom are correspondingly smaller. In both implementations, 'Granger causality' is interpreted strictly as incremental predictive content, not structural or economic causation [24,25].

Fourth, FEVD is used to distinguish predictive content from the cumulative contribution of model innovations across forecast horizons. Table 9 reports an orthogonalized Cholesky decomposition with $\mathrm{Ln}P_{\mathrm{TH}}$ ordered before $\mathrm{Ln}P_{\mathrm{VN}}$, reproducing the original 12-period shares of

18.77% for Vietnam innovations in Thailand's forecast variance and 30.10% for Thailand innovations in Vietnam's variance. Because Cholesky FEVD is identification-order dependent, Table 11 also reports a reverse-order sensitivity check. Reversing the ordering materially changes the 12-period cross-market shares to 41.15% for Vietnam innovations in Thailand's variance and 10.49% for Thailand innovations in Vietnam's variance. FEVD is therefore interpreted as evidence of medium-horizon interdependence, not as an ordering-invariant measure of structural leadership. FEVD confidence intervals were not estimated.

3. Results and Discussion

The results are reported from descriptive price behavior to stationarity, lag selection, cointegration, error correction, Granger causality, FEVD, and diagnostics. The interpretation emphasizes economic mechanisms and horizon-dependent leadership rather than repeating numerical results.

3.1. Price Dynamics and Regime Synchronization

Table 1 shows that Thailand has a slightly higher mean export price, whereas Vietnam has the higher coefficient of variation. The difference suggests that Vietnam quotations were relatively more variable over the sample, which is economically relevant because a more responsive export market can incorporate supply, demand, and policy information quickly even when its average price remains below Thailand's.

Table 1. Descriptive statistics of Thailand and Vietnam rice export prices.

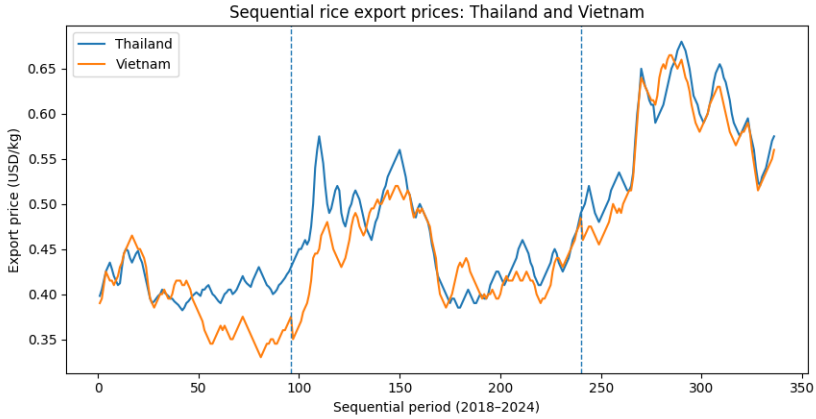
Variable	Obs	Mean	Median	Max	Min	Std. Dev.	CV
$P_{THAILAND}$	336	0.4803	0.4550	0.6800	0.3820	0.0805	0.1676
$P_{VIETNAM}$	336	0.4625	0.4425	0.6650	0.3300	0.0858	0.1854

Table 2. Regime-based descriptive statistics and Thailand–Vietnam price correlation.

Regime	Obs	Mean TH	Mean VN	SD TH	SD VN	Correlation
Pre-COVID 2018–2019	96	0.4102	0.3868	0.0161	0.0356	0.3864
COVID 2020–2022	144	0.4596	0.4416	0.0482	0.0419	0.7480
Post-COVID 2023–2024	96	0.5816	0.5694	0.0558	0.0635	0.9584

Table 2 shows a marked increase in price co-movement across regimes: the correlation rises from 0.3864 before COVID-19 to 0.7480 during the pandemic and 0.9584 after COVID-19. This pattern is consistent with tighter post-disruption synchronization, although correlation alone is not a formal structural-break test. The post-COVID increase is therefore interpreted as descriptive evidence of stronger common pricing forces, not as proof of a statistically dated structural break.

Fig. 1 shows the full price path rather than repeating Table 1. The visual comparison highlights the shift from relatively low and weakly synchronized prices in the early sample toward much tighter co-movement in the later period, providing direct context for the regime-correlation results.



(source: authors' calculations from the harmonized multi-source dataset compiled from FAO, USDA, the Ministry of Trade of the Republic of Indonesia, and other official sources)

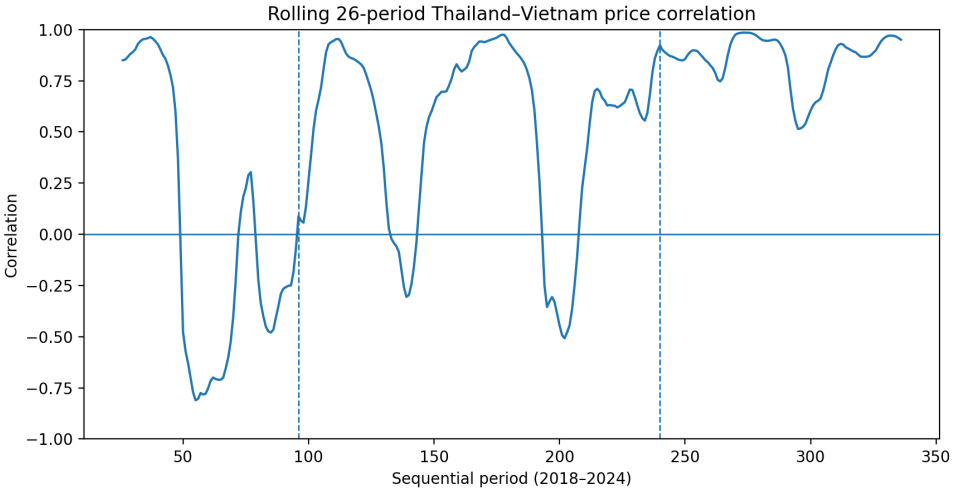
Fig. 1. Sequential Thailand and Vietnam rice export-price movements, 2018–2024 (four ordered observations per calendar month)

3.2. Stationarity and Lag Selection

Table 3 confirms that $\text{Ln}P_{\text{TH}}$ and $\text{Ln}P_{\text{VN}}$ are non-stationary in levels but stationary after first differencing ($p < 0.001$ for both first differences). Both variables are therefore I(1), supporting the use of cointegration methods rather than an unrestricted regression in levels [27–29,33,34].

Table 3. ADF unit root test results.

Variable	Transformation	ADF Statistic	*p*-value	Lag	5% Critical Value	Conclusion
$\text{Ln}P_{\text{TH}}$	Level	−1.2053	0.6713	4	−2.8703	Non-stationary
$\text{Ln}P_{\text{TH}}$	First difference	−9.6427	<0.001	3	−2.8703	Stationary
$\text{Ln}P_{\text{VN}}$	Level	−1.4562	0.5551	1	−2.8702	Non-stationary
$\text{Ln}P_{\text{VN}}$	First difference	−9.6492	<0.001	0	−2.8702	Stationary



(source: authors' calculations from the harmonized study dataset)

Fig. 2. Rolling 26-period correlation between Thailand and Vietnam rice export prices (correlation coefficient on vertical axis; sequential observation index on horizontal axis)

Fig. 2 provides a time-varying view of co-movement and is more informative than a bar chart of ADF statistics. Sustained increases in rolling correlation indicate periods in which common regional shocks or competitive repricing became more important.

Table 4. Lag order selection criteria.

Criterion	Selected lag
AIC	5
BIC/SC	2
HQ	2
FPE	5

Table 4 confirms a substantive split between criteria: AIC and FPE prefer $p = 5$, whereas BIC/SC and HQ prefer $p = 2$. The analysis therefore does not treat $p = 2$ as empirically dominant. Instead, $p = 2$ serves as the BIC/HQ benchmark and $p = 5$ as the AIC/FPE competing benchmark. Because the Johansen rank changes across this range, long-run findings are conditional on lag choice; results that survive alternative lag choices are given greater evidential weight.

3.3. Structural Breaks and Long-Run Integration

Table 5 shows that the Thailand–Vietnam log-price relationship was not structurally stable across the full sample. Parameter stability is rejected at both pre-specified regime transitions, with a particularly large break at the shift into the COVID-19 regime ($F = 70.5308$, $p < 0.001$) and a second significant break at the post-COVID transition ($F = 21.9579$, $p < 0.001$). These breaks are treated as a substantive result: they imply that a single full-sample equilibrium relation, if estimated, summarizes an evolving relationship and should not be interpreted as invariant across the 2018–2024 period.

Table 5. Structural break tests for the Thailand–Vietnam log-price relationship.

Regime transition	Breakpoint	*F*-statistic	*p*-value	Decision
Pre-COVID to COVID	After observation 96	70.5308	<0.001	Reject parameter stability
COVID to post-COVID	After observation 240	21.9579	<0.001	Reject parameter stability

Table 6. Johansen cointegration test results.

Hypothesis	Trace Statistic	Trace 5% CV	Trace Decision	Max-Eigen Statistic	Max-Eigen 5% CV	Max-Eigen Decision
None	21.6067	15.4943	Reject	18.9326	14.2639	Reject
At most 1	2.6741	3.8415	Do not reject	2.6741	3.8415	Do not reject

Table 6 rejects no cointegration under the BIC/HQ benchmark VAR(2)/VECM($k = 1$) specification: the trace statistic is 21.6067, and the maximum-eigenvalue statistic is 18.9326. Table 11 shows, however, that full-sample cointegration is not supported at $k = 3$ or $k = 4$, including $k = 4$ in correspondence with the AIC/FPE-preferred VAR(5). The long-run result is therefore specification-sensitive. The supplementary regime tests reinforce the structural-break qualification: under $k = 1$, no cointegration is detected in the pre-COVID subsample (trace = 13.5839; max-eigen = 10.8522), whereas one vector is supported in the COVID (22.4383; 16.1585) and post-COVID (19.7388; 15.0943) subsamples. These smaller-sample results are treated as supportive rather than definitive evidence that the long-run relationship changed across regimes.

3.4. Error Correction and Horizon-Dependent Market Leadership

As reported in Table 7, the normalized benchmark relation is $\mathrm{Ln}P_{TH} - 0.8246\ \mathrm{Ln}P_{VN} + 0.0980 = 0$. Because both prices are in logarithms, the coefficient describes the proportional association implied by this normalization; the magnitude below one is not interpreted as direct evidence of incomplete economic transmission without additional restrictions and explicit modeling of market frictions [36–39].

Table 7. VECM long-run equation and error-correction terms. Note: reported standard errors are conventional model-based asymptotic estimates.

Panel	Variable/Equation	Coefficient	Std. Error	*p*-value
Cointegration equation	$\mathrm{Ln}P_{TH}$	1.0000	-	-
Cointegration equation	$\mathrm{Ln}P_{VN}$	−0.8246	0.0788	0.0000
Cointegration equation	Constant	0.0980	0.0637	0.1240
ECT	$\Delta\mathrm{Ln}P_{TH}$	−0.0334	0.0101	0.0010
ECT	$\Delta\mathrm{Ln}P_{VN}$	0.0242	0.0122	0.0468

Thailand's error-correction coefficient is −0.0334 ($p = 0.0010$), implying adjustment of about 3.34% of disequilibrium per sequential period; Vietnam's coefficient is 0.0242 ($p = 0.0468$). Because the research index contains four ordered observations per calendar month, this is a per-period rather than exact calendar-week rate. These ECTs describe conditional adjustment in the benchmark VECM and do not establish permanent leadership.

Table 8. Granger causality test results.

Direction	*F*-statistic	*p*-value	*df*	Interpretation
$\mathrm{Ln}P_{VN} \rightarrow \mathrm{Ln}P_{TH}$	8.3639	0.0003	(2, 652)	Vietnam helps predict Thailand (VECM system test)
$\mathrm{Ln}P_{TH} \rightarrow \mathrm{Ln}P_{VN}$	4.3237	0.0136	(2, 652)	Thailand helps predict Vietnam (VECM system test)

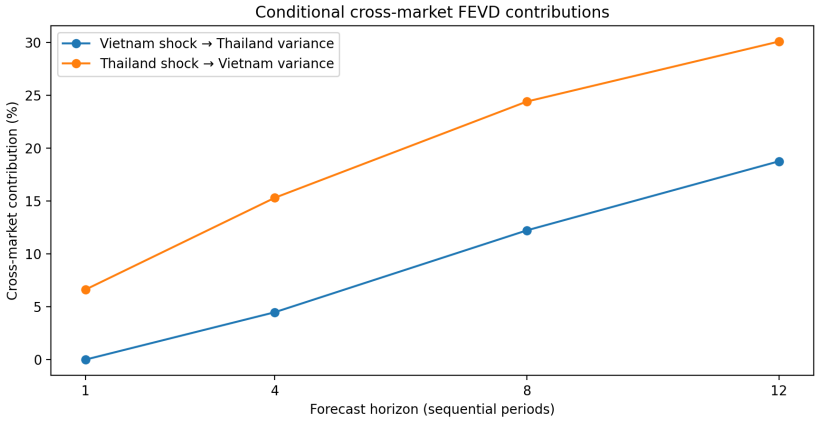
Table 8 reproduces the original VECM system results: Vietnam-to-Thailand $F = 8.3639$ ($p = 0.0003$; $df = 2,652$) and Thailand-to-Vietnam $F = 4.3237$ ($p = 0.0136$; $df = 2,652$). The denominator 652 reflects the stacked two-equation system rather than a single-equation OLS test. The results are predictive, not structural; separate first-difference checks in Table 11 show Vietnam-to-Thailand significance at lags 1–4 and Thailand-to-Vietnam significance only at lags 1–2.

Table 9. Forecast error variance decomposition results.

Period	TH explained by TH	TH explained by VN	VN explained by TH	VN explained by VN
1	100.00	0.00	6.63	93.37
4	95.52	4.48	15.31	84.69
8	87.77	12.23	24.42	75.58
12	81.23	18.77	30.10	69.90

The FEVD results in Table 9 reproduce the original baseline decomposition. With $\mathrm{Ln}P_{TH}$ ordered first, Vietnam innovations account for 18.77% of Thailand's forecast variance at period 12, while Thailand innovations account for 30.10% of Vietnam's. However, the reverse-order robustness check in Table 11 changes these shares to 41.15% and 10.49%, respectively. The medium-horizon finding is therefore robust only in the broad sense that cross-market innovations

matter increasingly over time; the directional ranking of which market contributes more is not robust to Cholesky identification. FEVD is consequently interpreted as conditional evidence of interdependence rather than as proof that either exporter is the structural medium-term leader.



(source: authors' calculations from Table 9)

Fig. 3. Conditional cross-market FEVD contributions across forecast horizons (Cholesky ordering: LnP_{TH} before LnP_{VN}; vertical axis = contribution to forecast-error variance, %; horizontal axis = forecast horizon in periods)

Fig. 3 displays the conditional cross-market FEVD shares across horizons. Vietnam's contribution to Thailand rises from 0% at period 1 to 18.77% at period 12, while Thailand's contribution to Vietnam rises from 6.63% to 30.10%. The horizontal axis reports forecast horizon in sequential periods, and the vertical axis reports the cross-market contribution to forecast-error variance (%). The figure should be read together with the stated Cholesky ordering and diagnostic limitations.

3.5. Diagnostics and Robustness Checks

Table 10 indicates residual autocorrelation (Portmanteau statistic = 65.6662, $p = 0.0112$) and strong rejection of residual normality (statistic = 443.7595, $p < 0.001$). These failures limit the reliability of conventional small-sample inference. Table 7 therefore reports conventional model-based asymptotic standard errors without HAC adjustment, and Table 8 reports the conventional system-level VECM F test. No claim is made that these p-values are robust to the diagnostic failures. Instead, inference is triangulated using first-difference Granger checks across lags, alternative Johansen lag structures, regime-specific rank checks, structural-break tests, and FEVD ordering sensitivity.

Table 10. Diagnostic test results.

Test	Statistic	p-value	Interpretation
Portmanteau whiteness test, nlags = 12	65.6662	0.0112	Residual autocorrelation remains.
Normality test	443.7595	<0.001	Residuals are not normally distributed.

The expanded robustness analysis produces four central qualifications. First, full-sample cointegration is supported at $k = 1$ and $k = 2$ but not at $k = 3$ or $k = 4$; the AIC/FPE-preferred VAR(5) therefore does not support the baseline long-run rank. Second, regime-specific $k = 1$ tests

detect no cointegration before COVID but support one vector during and after COVID, consistent with the Chow evidence that the relationship changed across regimes. Third, pairwise Granger tests on first-differenced log prices show Vietnam-to-Thailand predictive content at lags 1–4, whereas the reverse direction is significant only at lags 1–2. Fourth, reversing Cholesky ordering materially changes the FEVD directional shares. The most robust empirical statement is therefore the short-run Vietnam-to-Thailand predictive pattern; the full-sample long-run relation and the direction of medium-horizon FEVD influence are more specification- and identification-sensitive.

Table 11. Robustness checks across lag specifications, market regimes, and FEVD identification.

Panel/specification	Statistic 1	Statistic 2	Inference
A. Johansen: $k = 1$ (VAR $p = 2$; BIC/HQ benchmark)	Trace $r = 0$: 21.6067	Max-Eigen $r = 0$: 18.9326	One cointegrating vector
A. Johansen: $k = 2$ (VAR $p = 3$)	Trace $r = 0$: 17.8760	Max-Eigen $r = 0$: 15.6767	One cointegrating vector
A. Johansen: $k = 3$ (VAR $p = 4$)	Trace $r = 0$: 13.7377	Max-Eigen $r = 0$: 11.9445	No cointegration at 5%
A. Johansen: $k = 4$ (VAR $p = 5$; AIC/FPE benchmark)	Trace $r = 0$: 11.1684	Max-Eigen $r = 0$: 9.2283	No cointegration at 5%
B. Pairwise Granger on Δlog prices, lag 1	TH → VN $p = 0.0110$	VN → TH $p = 0.0008$	Both significant; VN → TH stronger
B. Pairwise Granger on Δlog prices, lag 2	TH → VN $p = 0.0473$	VN → TH $p = 0.0017$	Both significant; VN → TH stronger
B. Pairwise Granger on Δlog prices, lag 3	TH → VN $p = 0.0881$	VN → TH $p = 0.0014$	Only VN → TH significant
B. Pairwise Granger on Δlog prices, lag 4	TH → VN $p = 0.1454$	VN → TH $p = 0.0004$	Only VN → TH significant
C. Regime Johansen: Pre-COVID, $k = 1$ ($n = 96$)	Trace $r = 0$: 13.5839	Max-Eigen $r = 0$: 10.8522	No cointegration at 5%
C. Regime Johansen: COVID, $k = 1$ ($n = 144$)	Trace $r = 0$: 22.4383	Max-Eigen $r = 0$: 16.1585	One cointegrating vector
C. Regime Johansen: Post-COVID, $k = 1$ ($n = 96$)	Trace $r = 0$: 19.7388	Max-Eigen $r = 0$: 15.0943	One cointegrating vector
D. FEVD order LnP_{TH}, LnP_{VN}; horizon 12	VN → TH: 18.77%	TH → VN: 30.10%	Baseline allocation
D. FEVD order LnP_{VN}, LnP_{TH}; horizon 12	VN → TH: 41.15%	TH → VN: 10.49%	Directional allocation is ordering-sensitive.

3.6. Economic Interpretation and Policy Implications

Taken together, the results do not support a single time-invariant definition of market leadership. A long-run adjustment mechanism appears under the shorter full-sample specifications and in the COVID/post-COVID regime checks, but it is absent under longer full-sample lags and in the pre-COVID subsample. The more stable directional result is short-run predictive asymmetry: Vietnam prices contain forecasting information for Thailand across a wider set of lag choices.

At medium horizons, both markets contribute to each other's forecast uncertainty, but the relative FEVD shares are sensitive to Cholesky ordering. Under the baseline ordering, Thailand appears to contribute more to Vietnam at period 12; under the reverse ordering, Vietnam

contributes more to Thailand. The model therefore supports medium-term interdependence but does not identify an ordering-invariant structural leader. Economic explanations involving competitiveness, rapid quotation adjustment, policy responses, or common shocks remain plausible interpretations from the cited literature [7,15–20,40–42] rather than mechanisms directly identified here.

The structural-break results are integral to this interpretation. Rejection of parameter stability at both regime transitions indicates that the bilateral pricing relationship changed during 2018–2024. The rising post-COVID correlation may reflect stronger common shocks, competitive repricing, policy responses, or other shared forces, but the present model does not separately identify these channels. The breaks also help explain why the full-sample cointegration result is sensitive to lag specification: one stable parameterization must approximate relationships that changed across major disruptions [43].

This study has four principal limitations. First, it covers only Thailand and Vietnam rather than the full network of rice exporters. Second, exchange rates, freight costs, explicit trade-policy interventions, and verified time-varying rice-grade differentials are not modeled directly. Third, although the complete 336-observation analysis file is now available for replication and has been checked for continuity and missing values, it does not itself contain exact quotation dates, grade labels, or observation-level source identifiers; full provenance therefore still depends on the original source documentation. Fourth, residual autocorrelation, non-normality, structural breaks, lag-sensitive cointegration, and Cholesky-order sensitivity of FEVD limit strong causal or structural interpretation. These limitations do not remove the repeated Vietnam-to-Thailand predictive pattern, but they require caution in interpreting the long-run relation and medium-horizon directional shares.

4. Conclusions

Four findings summarize the replicated evidence. First, one full-sample cointegrating relation is supported under the BIC/HQ benchmark VAR(2)/VECM(k = 1) and the next-shorter alternative, but not under the longer VAR(4)–VAR(5) structures; supplementary regime tests also show no cointegration before COVID but one vector during and after COVID under k = 1. Second, Vietnam-to-Thailand predictive content is the more stable short-run result, remaining significant across lags 1–4 in first-difference checks, whereas the reverse direction is less persistent. Third, cross-market FEVD contributions increase with horizon, but their directional ranking changes when the Cholesky ordering is reversed. Fourth, Chow tests reject parameter stability at both the COVID-19 and post-COVID transitions.

The combined evidence therefore supports a horizon- and regime-dependent interpretation

of price leadership without identifying a single permanent structural leader. Vietnam provides the more robust short-run predictive signal in this dataset. Evidence about a stable full-sample long-run equilibrium is conditional on lag choice, and evidence about which exporter exerts greater medium-horizon shock influence is conditional on FEVD identification. These qualifications are central to the conclusion rather than secondary robustness notes.

For policy and market monitoring, regional institutions and rice-importing countries should track both exporters simultaneously. An ASEAN-oriented monitoring system could combine rice-price early warning, transparent notification of export restrictions and stock-policy changes, coordination with regional food-reserve mechanisms, and importer risk management. These implications are best used for risk monitoring rather than as evidence of structural causality.

Abbreviations

ADF	Augmented Dickey-Fuller
CV	coefficient of variation
ECT	error correction term
FEVD	forecast error variance decomposition
I(1)	integrated of order one
VECM	Vector Error Correction Model.

Data Availability Statement

The complete 336-observation analysis file used for the reported results is available from the corresponding author and should accompany the revised submission as supplementary data. The file contains the observation number, month-year identifier, sequential period number, Thailand price, Vietnam price, and COVID-period dummy. Inspection confirms 84 month-year identifiers with four observations per month, a continuous 1-336 period index, and no missing price observations. The current analysis file does not contain exact quotation dates, rice-grade/benchmark labels, or observation-level source identifiers. Those provenance fields should be added from the original source records if available, and the absence of such metadata from the analysis file is acknowledged as a reproducibility limitation rather than inferred or reconstructed.

CRediT Authorship Contribution Statement

Angky Dwi Seffyanto: Conceptualization, data curation, formal analysis, methodology, visualization, writing - original draft, writing - review and editing. **Yusman Syaukat**: Conceptualization, supervision, validation, writing - review and editing. **Sri Hartojo**: Methodology, supervision, validation, writing - review and editing. **Ahmad Faroby Falatehan**: Conceptualization, policy analysis, supervision, validation, writing - review and editing.

Declaration of Competing Interest

The authors declare that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Use of AI in the Writing Process

During the preparation of this manuscript, generative AI tools were used to support language editing, structural formatting, and journal-template adjustment. The authors reviewed and edited the content and take full responsibility for the final manuscript.

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