

Time-Series modeling of supply chain disruption drivers in ASEAN agri-food logistics networksSalang Musikasuwan¹⁾, Nguyen Tuong Chau^{*2)} and Tran Văn Bình³⁾¹⁾Faculty of Science and Technology, Prince of Songkla University, Pattani Campus, Pattani, Thailand²⁾University of Economics and Law, Ho Chi Minh City, Vietnam and Vietnam National University, Ho Chi Minh City, Vietnam³⁾Independent Researcher, Ho Chi Minh City, Vietnam

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Abstract

Disruptions in agri-food supply chains pose logistical and operational challenges for ASEAN member economies, whose agricultural sectors are simultaneously exposed to fluctuations in freight costs and climate-related production shocks. Prior time-series applications in shipping markets, agricultural commodity co-movement, and supply chain performance have generally examined these channels separately, and the joint transmission of these channels into ASEAN agri-food commodity logistics outcomes remains largely unexamined. This study applies a Vector Autoregression (VAR) time-series modeling framework to identify and quantify the principal drivers of disruption in ASEAN agri-food logistics networks, using 4,108 daily observations spanning January 2015 to March 2026. Seven variables are jointly modeled: Baltic Dry Index daily change (D_BDI), Brent crude oil log-return (R_Brent), Geopolitical Risk Index daily change (D_GPR), Oceanic Niño Index anomaly change (D_ONI), ASEAN aggregate agricultural production return (R_ASEAN_Production), and daily price changes of Robusta and Arabica coffee. Stationarity is verified by the Augmented Dickey-Fuller (ADF) tests. The lag order $p = 2$ is selected based on BIC and HQIC. GPR shocks exert statistically significant lagged effects on Arabica price ($p = 0.007$) and Robusta price ($p = 0.021$); ONI anomaly changes significantly propagate into Robusta prices ($p = 0.021$). A cross-domain pathway from ONI to GPR ($p = 0.010$) is consistent with climate disruption signals coinciding with subsequent geopolitical risk movements. BDI first-order persistence coefficient is 0.596 ($p < 0.001$). Forecast Error Variance Decomposition (FEVD) shows Robusta-to-Arabica cross-variance at 44.03% at horizon 10. Durbin-Watson statistics (1.958–2.061) confirm residual white noise across all equations. These results provide quantitative inputs for engineering early-warning systems for disruption and logistics resilience planning in ASEAN agri-food supply networks.

Keywords: Supply chain disruption, Agri-food logistics, VAR model, ASEAN, Climate anomaly, Geopolitical risk**1. Introduction**

Agri-food supply chains in the ASEAN region operate under compounding pressures from two structurally distinct yet dynamically interacting engineering domains: freight logistics cost dynamics and climate-related variability in agricultural production. The ASEAN bloc collectively accounts for approximately 20% of global rice production, 85% of palm oil output, and a dominant share of Robusta coffee exports, commodities whose logistics chains are inherently dependent on bulk shipping capacity and climate-sensitive cultivation conditions [1, 2]. The Baltic Dry Index (BDI), which tracks daily freight rates across 23 dry bulk shipping routes, serves as a proxy for per-unit transportation costs at the port-to-market stage of the supply network [1, 3]. Simultaneously, ocean temperature anomalies, as indicated by the Oceanic Niño Index (ONI), signal impending El Niño or La Niña episodes that alter precipitation patterns, soil moisture levels, and ultimately crop yields across the region [4-6]. When freight costs and climate conditions deteriorate simultaneously, the compounding effect on supply chain throughput, inventory lead times, and commodity price stability can be severe and difficult to anticipate using single-channel monitoring approaches [7, 8].

The engineering challenge of disruption transmission modeling lies in capturing not only the individual effects of each disruption driver, but the dynamic interdependencies among them as they propagate through the multi-stage logistics network. From a systems engineering perspective, an agri-food supply chain is a network of interdependent subsystems: production, storage, transportation, processing, and distribution, each with its own throughput capacity, inventory buffer, and vulnerability profile [9, 10]. Disruption signals entering the system at one node propagate through structural linkages to affect performance at downstream nodes, often with time delays associated with inventory transit times, contract adjustment windows, and market price discovery mechanisms [7]. Quantifying these propagation delays and their magnitudes supports the design of early-warning systems for disruptions, inventory safety-stock policies, and logistics capacity buffers [8, 11].

Prior quantitative approaches in supply chain engineering have predominantly addressed disruption propagation through simulation-based methods, discrete-event simulation, system dynamics, and agent-based models, which require detailed structural specification of the supply network topology [9, 10]. While these approaches provide rich operational detail, they are difficult to calibrate at the macro level of regional commodity networks where detailed node-level data is unavailable. Time-series econometric frameworks, particularly the Vector Autoregression (VAR) model, provide a complementary approach for identifying dynamic

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pathways of disruption transmission directly from observed market and logistics data without imposing a priori structural constraints [12, 13]. The VAR framework has been applied in shipping market analysis [14], agricultural commodity co-movement studies [15], and supply chain performance modeling [16], but its application to the simultaneous multivariate identification of disruption transmission in the ASEAN agri-food logistics context remains limited.

Geopolitical risk (GPR), as measured by the index of Caldara and Iacoviello [17], represents a third disruption channel that has grown in operational significance for ASEAN agri-food logistics following the Russia-Ukraine conflict (2022), the Red Sea shipping disruptions (2023–2024), and escalating trade policy uncertainty in major importing markets. GPR affects supply chain performance through multiple mechanisms: export-restriction announcements, insurance-cost surges along shipping routes, currency depreciation in commodity-exporting nations, and import-demand uncertainty from major buyers [9, 18]. The interaction between climate-related ONI signals and GPR is particularly relevant for ASEAN agri-food networks, where governments frequently impose export restrictions during drought or flood events to stabilize domestic food prices, a policy response that co-occurs with elevated geopolitical risk signals following climate disruptions.

This study addresses these gaps by developing and estimating a VAR(2) model using 4,108 daily observations from January 2015 to March 2026. The model jointly estimates dynamic interdependencies among seven supply chain system variables spanning logistics cost (BDI, Brent oil), climate disruption (ONI), geopolitical risk (GPR), and agri-food commodity performance (ASEAN production return, Robusta and Arabica coffee prices). Three specific engineering objectives are pursued: (1) to identify statistically significant lagged disruption transmission pathways from climate and geopolitical risk drivers to agri-food commodity logistics outcomes, suitable for integration into early-warning indicator systems; (2) to quantify the magnitude and temporal persistence of each transmission pathway through Impulse Response Function (IRF) analysis; and (3) to quantify the proportional variance contribution of each disruption driver through Forecast Error Variance Decomposition (FEVD), enabling risk-stratified logistics capacity planning under correlated disruption scenarios [19–21].

2. Materials and Methods

2.1 Dataset construction and variable definitions

The dataset comprises 4,108 daily observations covering 1 January 2015 to 31 March 2026, assembled from multiple publicly available institutional data sources. January 2015 was chosen as the start date to ensure the sample captures a complete ENSO cycle, beginning with the strong 2015–2016 El Niño event and extending through the 2023–2024 El Niño, thereby encompassing structurally complete climate cycles for model identification [4, 5]. The sample also spans the COVID-19 supply chain disruption (2020–2021), the onset of the Russia-Ukraine conflict (February 2022), and the post-pandemic freight market normalization (2022–2023), providing rich heterogeneity in disruptions. Each of the seven source series (Baltic Exchange BDI, EIA Brent crude, the Caldara-Iacoviello GPR index, NOAA ONI, FAO agricultural production, and ICO Robusta and Arabica prices) is available in the underlying raw dataset from January 2010 onwards; the 2015–2026 estimation window used here is a subset of this longer record, selected for the ENSO-cycle coverage rationale stated above rather than by data availability. Table 1 presents descriptive statistics for all modeled variables.

Baltic Dry Index daily change (D_BDI_Index): Sourced from the Baltic Exchange, D_BDI measures the daily first-difference of the BDI composite index, which aggregates freight rates across 23 routes for Capesize, Panamax, and Supramax bulk carriers. The BDI is the most widely used operational indicator of dry bulk shipping cost conditions serving the direct basis for the per-tonne transportation cost of rice, palm oil, and coffee shipped from ASEAN ports to import markets in Europe, the Middle East, and East Asia [1, 3]. The first difference removes the non-stationary trend while preserving day-to-day volatility in the signal, which is relevant for detecting supply chain disruptions [14].

Brent crude oil log-return (R_Brent_Price_Master): The natural logarithm of the daily price ratio captures proportional Brent crude oil price change, which governs bunker fuel costs, the dominant variable operating cost in bulk shipping, typically representing 50–70% of total voyage costs [3]. Rising Brent returns are associated with higher maritime transport costs for ASEAN agricultural exports, consistent with a channel through which logistics costs are transmitted from energy markets to commodity supply chain economics.

Geopolitical Risk Index daily change (D_GPR_Index): The GPR index of Caldara and Iacoviello [17] is constructed from automated text-frequency analysis of 11 major international newspapers, counting references to geopolitical tensions, conflicts, and threats. The daily first-difference captures net innovations in perceived geopolitical disruption risk. For ASEAN agri-food logistics, GPR shocks manifest as trade-restriction announcements, shipping-route diversions, port congestion, cargo-insurance surcharges, and demand uncertainty among importing nations [11, 18].

Oceanic Niño Index daily anomaly change (D_ONI_Anom): The ONI is the primary operational indicator of ENSO state, defined as the three-month running average of sea surface temperature anomaly in the Niño 3.4 region. The daily first difference of the ONI anomaly captures transitions between warming and cooling states, signaling impending disruptions to agricultural production in ASEAN. During positive ONI (El Niño) episodes, below-normal rainfall reduces crop yields in Indonesia, Malaysia, the Philippines, and southern Vietnam; during negative ONI (La Niña) episodes, above-normal precipitation is associated with elevated risk of flooding-related harvest losses [4, 5].

ASEAN aggregate agricultural production return (R_ASEAN_Production): Derived from FAO annual production statistics for agricultural output in ASEAN member states (rice, maize, palm oil, sugar, and coffee). The FAO does not publish these production statistics on a monthly basis; the variable is expressed as a year-over-year log-return applied as of 1 January of each year, when the prior year's FAO figure becomes available, and held at zero for the remaining days of that year. This variable serves as a supply-side logistics throughput proxy for the ASEAN agri-food network, capturing the realized production-shock channel through which climate and input-cost disruptions affect the volume of commodities available for export logistics handling [2, 4].

R_ASEAN_Production is constructed from FAO production statistics, which the FAO publishes annually; no monthly production series exists at the organization for this purpose. The variable is therefore a step function with a single non-zero log-return value on 1 January of each sample year and a value of zero on the remaining days of that year; it is not a cubic-spline interpolation of a monthly source, and its daily variation is not smoother than that of the other six series but is, for 364 of every 365 days, exactly constant. This is a limitation of the dataset rather than an economic finding, and it materially constrains the interpretation of any lagged relationship estimated for this variable: the coefficients and Granger causality results involving R_ASEAN_Production are each identified from eleven non-zero observations concentrated on 1 January of each sample year, rather than from a continuously varying daily signal. Readers should treat these specific results as indicative of an association between the annual FAO production release and subsequent

BDI and GPR movements around the turn of each year, which may, in part, coincide with other new-year seasonal effects in shipping and geopolitical risk reporting, rather than as evidence of a continuous day-to-day transmission channel. The observation dated 1 January 2025 could not be independently verified against publicly available FAOSTAT data at the time of this revision, since the most recent production year published by FAOSTAT at the time of writing is 2024; this figure should be checked against the specific data vintage used during original data assembly before the manuscript is finalized.

Coffee commodity price changes (D_Robusta_Price, D_Arabica_Price): Daily price changes for Robusta coffee (USD/tonne, sourced from the International Coffee Organization) and Arabica coffee (USD/lb, ICO) are supply chain performance indicators for the ASEAN export agri-food logistics network. Vietnam is the world's largest Robusta producer, contributing approximately 40% of global supply, while Indonesia is the fourth-largest coffee producer overall [22, 23]. These price series integrate information on climate conditions, freight costs, geopolitical risk, and global demand into a single observable performance metric that is closely linked to ASEAN agri-food exporters' revenues and logistics contract values.

Table 1 Descriptive statistics of modeled variables (January 2015–March 2026)

Variable	N	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
D_BDI_Index	4,108	0.313	43.225	-353.000	305.000	0.211	11.099
R_Brent_Price	4,108	0.000	0.022	-0.280	0.463	1.326	63.704
D_GPR_Index	4,108	0.060	45.688	-362.990	350.240	0.272	9.780
GEPU_current	3,987	225.12	85.355	100.978	623.352	1.440	3.394
D_ONI_Anomaly	4,108	-0.000	0.044	-0.690	0.470	-3.129	93.522
R_ASEAN_Production	4,108	0.000	0.004	-0.098	0.105	1.512	531.502
D_Robusta_Price	4,108	0.423	44.838	-571.000	358.000	-0.819	20.508
D_Arabica_Price	4,108	0.034	3.492	-33.700	24.400	-0.458	10.881

The distributional characteristics in Table 1 are consistent with known properties of logistics cost and commodity price series. Most variables exhibit leptokurtic distributions (kurtosis $\gg 3$), particularly R_ASEAN_Production (kurtosis = 531.50) and D_ONI_Anomaly (kurtosis = 93.52), indicating infrequent but large disruption events within a lower-volatility baseline regime, a characteristic pattern of supply chain shock series [7, 8]. The Robusta price change standard deviation (44.84 USD/tonne) reflects higher intrinsic volatility associated with concentration in fewer producing countries. The Robusta-Arabica price change correlation of 0.666 indicates structural co-movement between these coffee commodity series, consistent with commodity substitution dynamics in the global coffee logistics network [22, 23].

2.2 Stationarity testing

Pre-estimation stationarity testing is a prerequisite for valid VAR inference, as non-stationary series produce spurious regression results and invalid standard errors [12]. The Augmented Dickey-Fuller (ADF) test was performed on each variable in its transformed form. The ADF test regression is specified as follows:

$$\Delta y_t = \alpha + \beta y_{t-1} + \sum_{j=1}^p \gamma_j \Delta y_{t-j} + \varepsilon_t \quad (1)$$

where y_t is the series tested, α is an intercept constant, p is the lag length selected by AIC, and ε_t is white noise. The null hypothesis $H_0: \beta = 0$ (unit root present) is rejected at the 5% level when the ADF statistic falls below the 5% critical value. Results are reported in Table 2.

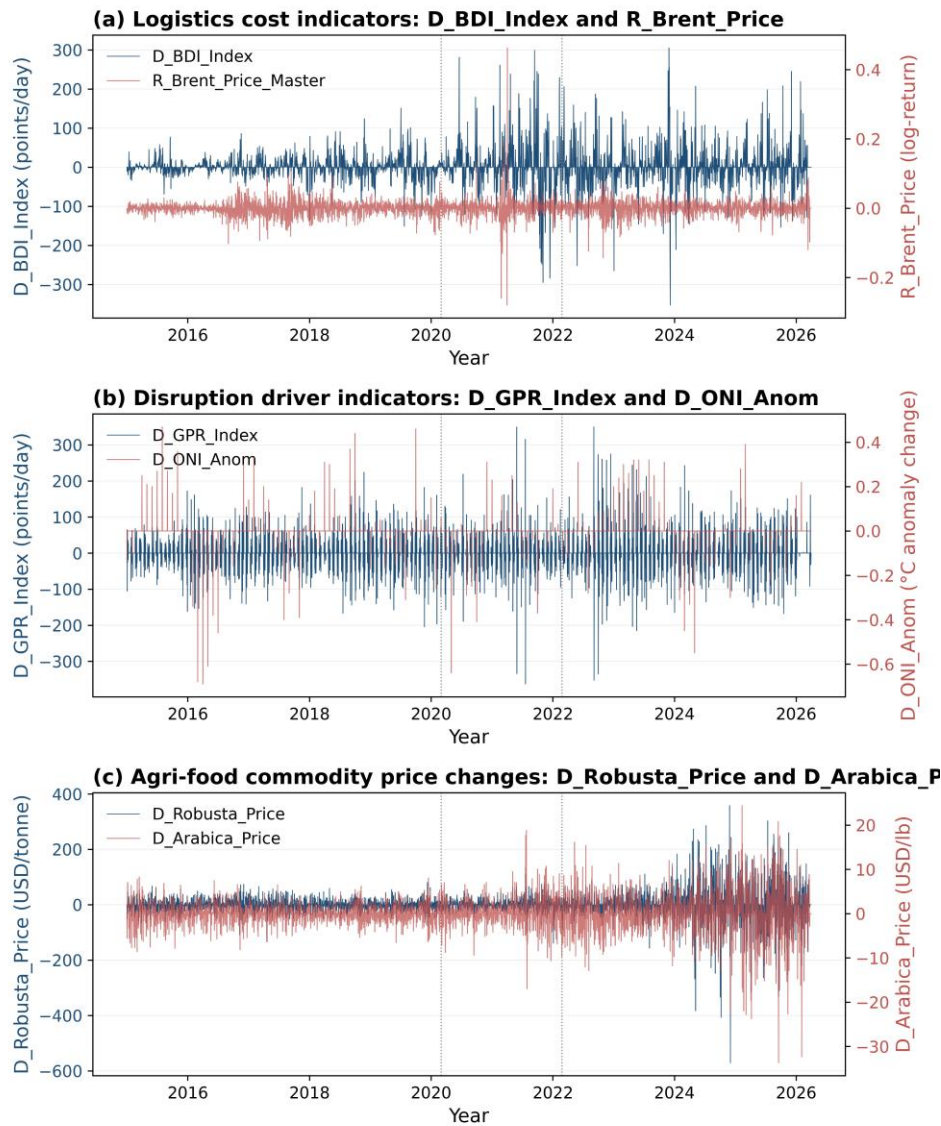
Table 2 Augmented Dickey-Fuller (ADF) unit root test results

Variable	ADF Statistic	p-value	CV 1%	CV 5%	Stationary (5%)
D_BDI_Index	-13.4379	0.0000	-3.4320	-2.8622	Yes
R_Brent_Price	-13.9942	0.0000	-3.4320	-2.8622	Yes
D_GPR_Index	-16.8526	0.0000	-3.4320	-2.8622	Yes
GEPU_current*	-2.6723	0.0790	-3.4320	-2.8623	No
D_ONI_Anomaly	-5.8757	0.0000	-3.4320	-2.8622	Yes
R_ASEAN_Production	-66.9461	0.0000	-3.4319	-2.8622	Yes
D_Robusta_Price	-22.0487	0.0000	-3.4319	-2.8622	Yes
D_Arabica_Price	-66.5388	0.0000	-3.4319	-2.8622	Yes

Note: * GEPU_current: non-stationary at 5% level; first-difference (D_GEPU) used in robustness checks. CV = critical value. ADF regression includes an intercept; lag length selected by AIC.

Table 2 confirms stationarity of seven of the eight tested variables at the 5% level. The GEPU_current level series (ADF = -2.67, $p = 0.079$) is non-stationary; its first difference (D_GEPU) becomes stationary and is used in robustness checks. Figure 1 displays the time-series behavior of the six core variables across the full sample, illustrating the characteristic high-frequency oscillation pattern of a stationary disruption series.

In Figure 1, time-series plots of core model variables. (a) Logistics cost indicators: Baltic Dry Index daily change (D_BDI_Index, left axis) and Brent crude oil log-return (R_Brent_Price, right axis). (b) Disruption driver indicators: Geopolitical Risk Index change (D_GPR_Index, left axis) and Oceanic Niño Index anomaly change (D_ONI_Anom, right axis). (c) Agri-food commodity price changes: Robusta coffee price change in USD/tonne (D_Robusta_Price, left axis) and Arabica coffee price change in USD/lb (D_Arabica_Price, right axis). Sample: January 2015–March 2026; $N = 4,108$.



Note: All series are in stationary form (first differences or log returns).

Source: Baltic Exchange (D_BDI_Index); U.S. Energy Information Administration (R_Brent_Price); Caldara and Iacoviello [17] (D_GPR_Index); NOAA Climate Prediction Center (D_ONI_Anom); Food and Agriculture Organization (FAO) ($R_ASEAN_Production$); International Coffee Organization (ICO) ($D_Robusta_Price$, $D_Arabica_Price$). Authors' own calculations.

Figure 1 Time-series plots of core model variables (January 2015–March 2026)

Several structural features in Figure 1 merit attention. In panel (a), BDI change shows a sharp negative spike in early 2020 corresponding to the COVID-19 pandemic-induced shipping demand collapse, followed by extreme positive volatility in 2021 reflecting the post-pandemic freight crisis. Brent oil returns exhibit large negative excursions in 2020 and large positive spikes in 2022 following the onset of the Russia-Ukraine conflict. In panel (b), GPR change shows discrete large-amplitude events corresponding to COVID-19 (2020), the Ukraine invasion (February 2022), and the Middle East escalation (2023–2024). The ONI anomaly change shows a smooth ENSO transition from the 2015–2016 El Niño through the 2020–2021 La Niña to the 2023–2024 El Niño. Panel (c) shows the marked upward shift in both coffee price volatility beginning in 2022–2023, coinciding with El Niño-related stress on the Vietnamese Robusta crop and sustained global demand exceeding supply capacity.

2.3 VAR model specification

A Vector Autoregression (VAR) model of order p is specified as the primary framework for identifying pathways of disruption transmission. The system equation is:

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \dots + A_p Y_{t-p} + \varepsilon_t \quad (2)$$

where $Y_t = [D_BDI_t, R_Brent_t, D_GPR_t, D_ONI_t, R_ASEAN_t, D_Robusta_t, D_Arabica_t]^T$ is the (7×1) vector of endogenous variables; c is a (7×1) constant vector; A_i ($i = 1, \dots, p$) are (7×7) coefficient matrices; and ε_t is a (7×1) white noise innovation vector with covariance matrix Σ_ε . The model is estimated equation by equation using OLS [12, 13]. The Cholesky ordering follows a conceptual exogeneity hierarchy: logistics cost indicators (BDI, Brent) are placed first as global market conditions exogenous to ASEAN production;

disruption drivers (GPR, ONI) are placed second; commodity performance variables (ASEAN production, Robusta, Arabica) are placed last as realized supply chain outcomes [13, 16].

2.3.1 Lag order selection

Four criteria are used to select a lag order ranging from 1 to 10. BIC (-0.949 at $p = 2$) and HQIC (-1.054 at $p = 2$) both achieve global minima at lag 2. AIC (-1.153 at $p = 5$) and FPE suggest a longer lag. The discrepancy between BIC/HQIC and AIC/FPE is typical for large daily datasets where AIC tends to overfit. VAR(2) is selected based on BIC/HQIC parsimony, avoiding parameter proliferation in the $7 \times 2 \times 7 + 7 = 105$ -parameter system, consistent with prior VAR applications in daily shipping and commodity research [14, 16].

2.3.2 Post-estimation diagnostics

Impulse Response Functions (IRFs) trace the response of each endogenous variable to a one-standard-deviation structural shock over a 10-period horizon, with Cholesky decomposition identifying orthogonal shocks and ± 1.96 standard-error (95% asymptotic) confidence bands, following the small-sample inference convention for VAR impulse responses [24]. The sensitivity of the orthogonalized IRF and FEVD to the Cholesky ordering assumption was assessed by re-estimating the system under alternative variable orderings (Section 3.3.1). Forecast Error Variance Decomposition (FEVD) decomposes h-step-ahead forecast error variance into contributions from each structural shock at $h = 1, 5$, and 10 periods [12, 13]. Residual diagnostics include Durbin-Watson (DW) statistics for each equation; DW values near 2.0 confirm the absence of residual serial autocorrelation. The residual cross-correlation matrix verifies contemporaneous independence across equations.

3. Results

3.1 Model diagnostics

The VAR(2) model is estimated on $N = 4,106$ observations. Model fit: AIC = -1.120 , BIC = -0.958 , HQIC = -1.063 , log-likelihood = $-38,378.76$. Durbin-Watson statistics range from 1.958 (D_BDI_Index) to 2.061 (D_GPR_Index) across the seven equations, all within $[1.8, 2.2]$, confirming that the two-lag specification adequately removes residual serial autocorrelation [12]. The residual cross-correlation matrix shows near-zero off-diagonal elements for all equation pairs except D_Robusta_Price and D_Arabica_Price ($p = 0.665$), which reflects structural commodity co-movement between these two series that persists in contemporaneous innovations after controlling for lagged dynamics and is accounted for in the Cholesky decomposition.

3.2 VAR(2) estimation results

Table 3 presents significant coefficient estimates ($p \leq 0.10$) for all seven system equations, along with equation-level R^2 values. The complete VAR(2) system comprises 105 estimated parameters; only those with empirical significance are reported to facilitate interpretation of the disruption transmission structure.

Table 3 VAR(2) significant coefficient estimates ($p \leq 0.10$): supply chain disruption transmission model

Dependent Variable	Predictor (Lag)	Coeff.	t-stat	p-value	R ²
D_BDI_Index	L1.D_BDI_Index	0.5961	38.490	0.0000	0.2936
	L2.D_BDI_Index	-0.1299	-8.384	0.0000	
	L2.R_ASEAN_Prod.	571.004	3.658	0.0003	
	L1.R_Brent_Price	44.014	1.696	0.0898	
R_Brent_Price	L2.R_Brent_Price	-0.0898	-5.763	0.0000	0.0110
	L1.D_GPR_Index	0.0000	1.923	0.0544	
D_GPR_Index	L1.D_GPR_Index	-0.5308	-35.552	0.0000	0.2451
	L2.D_GPR_Index	-0.2924	-19.602	0.0000	
	L1.R_ASEAN_Prod.	-500.689	-2.814	0.0049	
	L2.D_ONI_Anomaly	36.347	2.565	0.0103	
	L1.D_Arabica_Price	-0.4023	-1.686	0.0919	
D_ONI_Anomaly	L1.R_Brent_Price	-0.0714	-2.277	0.0228	0.0021
R_ASEAN_Prod.	L2.R_Brent_Price	0.0043	1.725	0.0845	0.0015
D_Robusta_Price	L1.D_ONI_Anomaly	36.831	2.311	0.0208	0.0098
	L1.D_BDI_Index	-0.0317	-1.666	0.0957	
	L2.D_GPR_Index	0.0386	2.302	0.0213	
	L1.D_Robusta_Price	0.0598	2.858	0.0043	
	L1.D_Arabica_Price	-0.8262	-3.080	0.0021	
D_Arabica_Price	L2.D_Arabica_Price	0.6376	2.373	0.0177	0.0061
	L2.D_GPR_Index	0.0035	2.705	0.0068	
	L1.D_ONI_Anomaly	2.1379	1.720	0.0854	
	L1.D_Robusta_Price	0.0035	2.117	0.0343	
	L1.D_Arabica_Price	-0.0667	-3.188	0.0014	

Note: Significant and near-significant coefficients ($p \leq 0.10$) reported. VAR(2): $N = 4,106$; AIC = -1.120 ; BIC = -0.958 ; HQIC = -1.063 ; log-likelihood = $-38,378.76$. Durbin-Watson statistics: 1.958–2.061 across all equations.

3.2.1 BDI logistics cost dynamics

The BDI equation achieves the highest explanatory power ($R^2 = 0.294$). The dominant dynamic is a two-component mean-reverting process: strong first-order positive persistence ($L1.D_BDI = 0.596$, $p < 0.001$) representing freight rate momentum, combined with a significant negative second-order correction ($L2.D_BDI = -0.130$, $p < 0.001$) representing mean reversion over a two-day horizon.

Lagged ASEAN agricultural production return is a significant positive predictor of BDI change at lag 2 ($L2.R_ASEAN_Production = 571.00$, $p < 0.001$).

3.2.2 Geopolitical risk and climate cascade

The GPR equation indicates a significant cross-domain transmission pathway: a lagged change in ONI anomaly positively predicts GPR fluctuations ($L2.D_ONI_Anom = 36.35$, $p = 0.010$).

3.2.3 Commodity price disruption transmission

In the Robusta price equation, the ONI anomaly at lag 1 ($L1.D_ONI_Anom = 36.83$, $p = 0.021$) represents the primary climate-to-logistics outcome transmission pathway: a one-unit increase in the ONI anomaly is associated with a 36.83 USD/tonne increase in Robusta price the following trading day.

For Arabica price, GPR transmission is indicated at lag 2 ($L2.D_GPR = 0.004$, $p = 0.007$), alongside a marginally significant same-channel association with ONI anomaly at lag 1 ($L1.D_ONI_Anom = 2.138$, $p = 0.085$).

3.2.4 Granger causality and structural stability

The lagged coefficients reported in Table 3 are complemented by pairwise Wald-type Granger causality tests on all 42 ordered variable pairs, jointly testing both lags of each predictor. Five pairs are significant at the 5% level: $D_Arabica_Price$ on $D_Robusta_Price$ ($F = 15.44$, $p < 0.001$), $R_ASEAN_Production$ on D_BDI_Index ($F = 13.65$, $p = 0.001$), $R_ASEAN_Production$ on D_GPR_Index ($F = 8.96$, $p = 0.011$), D_GPR_Index on $D_Arabica_Price$ ($F = 7.32$, $p = 0.026$), and D_ONI_Anom on D_GPR_Index ($F = 6.62$, $p = 0.037$), corroborating the climate-to-geopolitical-risk cascade and the ASEAN production feedback into logistics cost and geopolitical risk discussed above. Two pathways emphasized in Sections 3.2.2 and 3.2.3 based on individual lag coefficients are only marginal under the joint Wald test: D_GPR_Index on $D_Robusta_Price$ ($F = 5.71$, $p = 0.058$) and D_ONI_Anom on $D_Robusta_Price$ ($F = 5.34$, $p = 0.069$).

Parameter stability across the sample is assessed with a three-regime Chow test, splitting the sample into a pre-pandemic period (January 2015 to December 2019), a COVID-19 disruption period (January 2020 to February 2022), and a post-invasion period (February 2022 to March 2026), and testing whether each equation's coefficients differ across regimes. Coefficient instability is detected in the D_BDI_Index ($F = 2.29$, $p < 0.001$), $R_Brent_Price_Master$ ($F = 2.58$, $p < 0.001$), and D_GPR_Index ($F = 2.60$, $p < 0.001$) equations, but not in D_ONI_Anom ($F = 0.67$, $p = 0.913$), $R_ASEAN_Production$ ($F = 0.46$, $p = 0.995$), $D_Robusta_Price$ ($F = 1.35$, $p = 0.097$), or $D_Arabica_Price$ ($F = 1.28$, $p = 0.143$).

3.3 Impulse response analysis

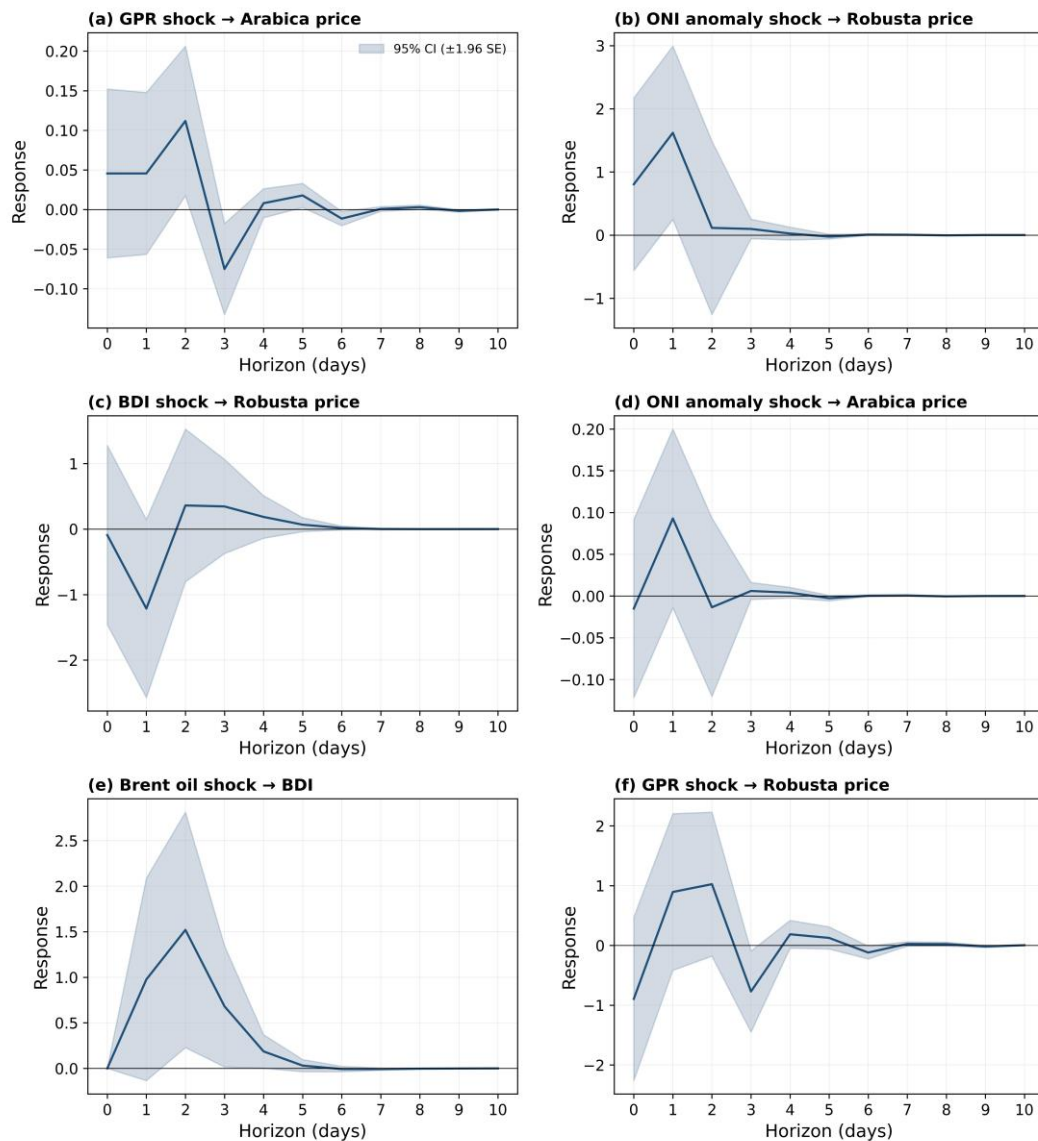
Figure 2 presents the Impulse Response Functions for six disruption transmission pathways over a 10-day forecast horizon, with ± 1.96 standard error (95%) confidence bands [24]. Under this stricter convention, several responses previously read as significant at earlier horizons now include zero for part of the tracked window: the GPR-to-Arabica response (panel a) is distinguishable from zero at periods 2, 3, 5, 6, 8 and 9 but not at every intervening period, and the BDI-to-Robusta response (panel c) does not exclude zero at any horizon. The ONI-to-Robusta response (panel b) is distinguishable from zero only at period 1; the Brent-to-BDI response (panel e) is distinguishable from zero at periods 2 through 4; and the ONI-to-Arabica response (panel d) does not exclude zero at any horizon within the 95% band.

Figure 2 Impulse Response Functions (IRF) for supply chain disruption transmission pathways from the VAR(2) model. Each panel shows the response of a target variable to a one-standard-deviation structural shock over 10 periods (days). Shaded bands: 95% confidence interval (± 1.96 standard error). (a) GPR shock $\rightarrow$ Arabica price; (b) ONI anomaly shock $\rightarrow$ Robusta price; (c) BDI shock $\rightarrow$ Robusta price; (d) ONI anomaly shock $\rightarrow$ Arabica price; (e) Brent oil shock $\rightarrow$ BDI; (f) GPR shock $\rightarrow$ Robusta price.

Panel (c) shows the BDI-to-Robusta IRF fluctuating in sign across the first three periods before settling near zero from period 5 onward, with the 95% band excluding zero at no horizon, indicating that any indirect pathway from freight cost shocks to commodity prices via capitalization of export logistics costs is not statistically distinguishable from noise in this specification.

3.3.1 Sensitivity of orthogonalized responses to Cholesky ordering

Because the Cholesky decomposition imposes a recursive contemporaneous structure, orthogonalized IRF and FEVD estimates are not invariant to variable ordering [25]. To assess this dependence, the VAR(2) system is re-estimated under two alternative orderings: one placing the climate and geopolitical indicators (D_ONI_Anom , D_GPR_Index) ahead of the logistics-cost block (D_BDI_Index , $R_Brent_Price_Master$), and a fully reversed ordering placing the commodity price variables first. The horizon-10 FEVD contributions attributed to the external disruption drivers are close to invariant across the first two orderings: the GPR contribution to Arabica variance changes from 0.19% to 0.19%, the ONI contribution to Robusta variance from 0.16% to 0.16%, and the ASEAN production contribution to BDI variance from 0.34% to 0.34%. Under the fully reversed ordering, these external-driver contributions remain within 0.05 percentage points of the baseline values. By contrast, the Robusta-to-Arabica cross-variance share, reported at 44.03% under the baseline ordering in Section 4.1, falls to 0.12% under the reversed ordering, since the two coffee series are contemporaneously correlated ($\rho = 0.665$) and the Cholesky factorization attributes their shared innovation to whichever series is placed first.



Note: Structural shocks identified by Cholesky decomposition with ordering: $D_BDI \rightarrow R_Brent \rightarrow D_GPR \rightarrow D_ONI \rightarrow R_ASEAN_Production \rightarrow D_Robusta \rightarrow D_Arabica$. Response is statistically significant when the confidence band excludes zero.

Source: Baltic Exchange; U.S. EIA; Caldara and Iacoviello [17]; NOAA Climate Prediction Center; FAO; ICO. Authors' own calculations.

Figure 2 Impulse Response Functions (IRF) from the VAR(2) model (10-day horizon; shaded bands: 95%, ± 1.96 SE)

4. Discussion

4.1 BDI logistics cost dynamics

This two-component structure is consistent with the friction-adjusted mean-reversion model of bulk freight markets, where short-term momentum from voyage-commitment decisions gives way to equilibrating corrections as new vessel capacity is deployed [1, 14].

A one-standard-deviation positive innovation in ASEAN production return (0.0037 log-return units) is associated with an expected BDI increase of approximately 2.11 points two days later, consistent with agricultural output conditions co-moving with forward-loading demand pressure on dry bulk shipping capacity [3]. This coefficient, like the corresponding GPR relationship discussed below, is estimated from eleven non-zero $R_ASEAN_Production$ observations concentrated on 1 January of each sample year (see Section 2.1); this pattern is interpreted as an association with the annual FAO production release rather than evidence of continuous day-to-day transmission. The Brent oil return at lag 1 ($L1.R_Brent = 44.01$, $p = 0.090$) reflects the fuel cost pass-through: a 1% increase in Brent returns is associated with a 44-point BDI increase the following day, consistent with short-run fuel surcharge adjustments in bulk charter contracts [3].

4.2 Geopolitical risk and climate cascade

This finding, that ENSO climate signals significantly predict geopolitical risk conditions two days later, implies that climate disruption cascades into systemic risk signals affecting trade and logistics policy environments. The mechanism is operationally plausible: El Niño-related agricultural shortfalls tend to coincide with government export restriction announcements (as Vietnam imposed on rice in 2023 and Indonesia on palm oil in 2022), with corresponding increases in GPR signals captured by the text-analysis index [17]. From a supply chain engineering standpoint, this is consistent with a second-order disruption amplification pattern: climate

disruption is associated not only with production volume variation but also with geopolitical-risk movements that co-occur with further constraints on logistics network operations [9, 11, 18].

The GPR equation also shows a negative association with ASEAN agricultural production ($L1.R_ASEAN_Production = -500.69$, $p = 0.005$); above-normal agricultural output is associated with lower geopolitical tensions, consistent with an easing of food security pressures [17]. A weaker, marginally significant negative association with lagged Arabica price is also present ($L1.D_Arabica_Price = -0.402$, $p = 0.092$), consistent with commodity market conditions carrying a secondary association with the geopolitical risk signal alongside the climate and production channels discussed above. Strong oscillatory autocorrelation in GPR ($L1.D_GPR = -0.531$; $L2.D_GPR = -0.292$; both $p < 0.001$) reflects the index's news-frequency construction, which decays rapidly after disruption events as media attention shifts.

4.3 Commodity price disruption transmission

This rapid, one-day propagation reflects the responsiveness of spot Robusta markets to real-time updates of climate signals, as traders and logistics planners incorporate El Niño forecast revisions into procurement pricing and futures hedging [22]. A marginally significant negative association with lagged BDI change is also present ($L1.D_BDI_Index = -0.032$, $p = 0.096$), consistent with freight-cost movements carrying a small indirect association with Robusta pricing alongside the climate channel. GPR at lag 2 ($L2.D_GPR = 0.039$, $p = 0.021$) operates through a two-day propagation channel, consistent with the decision horizon required for procurement contract adjustments and shipping route reallocations following geopolitical disruption events [9, 11].

The cross-commodity Robusta-to-Arabica transmission ($L1.D_Robusta = 0.004$, $p = 0.034$) is consistent with logistics-level price movements in one market co-moving with the other within one day, reflecting the integrated buyer and shipping capacity pools serving both coffee varieties in the global agri-food export logistics network [23]. The cross-price interaction ($L1.D_Arabica = -0.826$ on Robusta, $p = 0.002$) acts as a partial substitution effect, pulling buyers away from Robusta and exerting downward pressure on Robusta price adjustments. This same-day substitution effect reverses sign at the two-day lag, where Arabica price change is instead positively associated with Robusta price change ($L2.D_Arabica_Price = 0.638$, $p = 0.018$). The two coefficients together describe an oscillating rather than a monotonic relationship: a negative same-day co-movement consistent with short-run buyer substitution between the two coffee varieties, followed by a positive association two days later consistent with both markets adjusting towards shared demand and logistics-cost conditions once the initial substitution effect has passed. This pattern is reported without a settled structural interpretation, since distinguishing an overshoot-correction dynamic from two independent channels operating at different lags is beyond what the reduced-form VAR(2) coefficients alone can establish.

4.4 Granger causality and structural stability

This divergence between individual-coefficient significance and joint-test significance indicates that the climate and geopolitical influence on Robusta price operates primarily through a single lag rather than through a jointly significant two-lag structure, and the corresponding language in Sections 3.2.2 and 3.2.3 is read with this qualification. Consistent with established cautions regarding the interpretation of Granger-type evidence in commodity market research, statistical precedence in this sense is treated as evidence of predictive association rather than proof of an underlying causal mechanism [26].

Parameter instability is therefore concentrated in the logistics-cost and geopolitical-risk block of the system, consistent with the regime shifts documented in freight and energy markets during the COVID-19 disruption and the Russia-Ukraine conflict, the climate and coffee-price equations exhibit more stable dynamics across the full sample. This asymmetry indicates that the single-regime VAR(2) coefficients for the BDI, Brent, and GPR equations should be read as sample-average relationships rather than as fixed structural parameters applicable uniformly to all subperiods, a qualification consistent with the broader structural-break literature on macroeconomic time series [27].

4.5 Impulse response analysis

These qualifications align with the emphasis on the two-day GPR and ONI propagation windows reported in Table 3, rather than a claim of persistent multi-day significance across all six pathways.

Panel (a) shows the GPR-to-Arabica IRF: an initial positive response peaking around period 2 and decaying toward zero by period 5–6, consistent with an initial price spike coinciding with accelerated forward procurement as buyers seek to secure supply, followed by market equilibration [17]. Panel (b) shows the ONI-to-Robusta IRF with an immediate positive response peaking at period 1 and declining sharply thereafter, distinguishable from zero only at that first period, consistent with the rapid incorporation of weather forecast updates into Robusta spot pricing in Vietnam and Indonesia [4, 22].

Panel (e) presents the Brent-to-BDI IRF, showing a response that is zero on impact by construction of the Cholesky ordering, rises to a peak at period 2, and is distinguishable from zero at periods 2 through 4 before reverting toward zero by period 5, consistent with short-run fuel surcharge pass-through followed by vessel supply equilibration [3, 14]. Panel (f) shows the GPR-to-Robusta IRF turning positive in point estimates from period 2 onward, though the response is distinguishable from zero under the 95% band only at periods 3, 6, and 9. This wider band is consistent with the more conservative joint Granger test result for this pathway reported in Section 3.2.4 ($F = 5.71$, $p = 0.058$).

The external disruption pathways (GPR, ONI, ASEAN production) are therefore ordering-robust. Conversely, the magnitude, though not the direction, of the Robusta-Arabica cross-variance contribution is an ordering-dependent artifact of the identification scheme rather than a stable structural estimate, and is interpreted with this qualification in Section 4.1.

4.6 Forecast error variance decomposition

The FEVD results at horizons 1, 5, and 10 quantify the proportional contribution of each structural shock to the forecast error variance of the supply chain outcome. $R_ASEAN_Production$ variance is explained by own innovations at 99.41% at horizon 10, with ONI anomaly representing the largest external contribution (0.40%), stabilizing by horizon 5, consistent with full incorporation of climate-related variance within five days [4, 5]. $D_Robusta_Price$ is explained by own innovations at 99.09% at horizon 10, with GPR contributing 0.16%, ONI contributing 0.16%, and BDI contributing 0.09%.

D_Arabica_Price exhibits the most diversified variance structure: own innovations explain 55.58%, while Robusta price shocks explain 44.03%, the largest cross-variable contribution in the system, reflecting the structural commodity co-movement identified in the residual correlation matrix ($\rho = 0.665$). As shown in Section 3.3.1, this particular share is sensitive to the Cholesky ordering assumption, falling from 44.03% to 0.12% under a reversed ordering, so the 44.03% figure is read as an upper bound attributable to shared contemporaneous innovation between the two coffee series rather than as a directional estimate of Robusta's influence on Arabica. GPR is associated with 0.19% of Arabica variance, a magnitude consistent with the geopolitical channel carrying more of the ordering-robust external variance than the freight cost channel for Arabica. D_BDI_Index FEVD shows ASEAN production return contributing 0.34% of BDI variance at horizon 10, consistent with the ASEAN production-BDI feedback association discussed above.

Although absolute FEVD shares for external disruption drivers are modest (0.10–0.40% per driver per outcome), they reflect systematic rather than idiosyncratic transmission channels. Systematic channels generate correlated disruption signals simultaneously across multiple logistics network nodes in response to common shock events, such as the 2023–2024 El Niño episode or a geopolitical escalation, undermining diversification-based buffering strategies that rely on supply source portfolio correlation near zero [7, 8, 21].

These findings complement prior engineering research on ASEAN agri-food logistics. Chuyen and Rajagopal [19] showed, through bibliometric analysis, that freight disruption propagation pathways are a central concern in logistics network design, identifying quantitative disruption modeling as a gap that this study directly addresses. Wiangkarn et al. [20] demonstrated that supplier disruption risk characteristics have a significant impact on cold-chain logistics provider selection within the food industry. These risk characteristics link to the GPR and ONI transmission coefficients estimated here, providing quantitative inputs for supplier risk scoring in cold chain network design. Saengsathien et al. [21] found that cold chain system configuration has measurable effects on supply chain performance stability, consistent with the BDI–ASEAN production feedback loop identified in the VAR(2) system.

4.7 Out-of-sample forecast accuracy

The predictive value of the VAR(2) system is assessed with a rolling-origin, expanding-window out-of-sample forecast evaluation over the final 750 observations of the sample, re-estimating the model every 10 origins and generating forecasts at horizons of 1, 5, and 10 days. Forecast accuracy is benchmarked against two naive alternatives: a zero-change persistence forecast, appropriate for a differenced series, and a univariate AR(1) model estimated separately for each variable. At the one-day horizon, the VAR(2) forecast reduces RMSE relative to the persistence benchmark by 4.5% for D_BDI_Index, while RMSE is 3.7% higher than the persistence benchmark for R_Brent_Price_Master and 4.2% higher for D_GPR_Index; the remaining variables exhibit differences of less than 1% in either direction. At 5- and 10-day time horizons, RMSE differences between the VAR(2) model and both benchmarks are less than 0.5% for six of the seven variables. R_ASEAN_Production is excluded from this comparison in relative terms because its near-zero daily variation, discussed in Section 2.1, makes percentage RMSE comparisons uninformative at this frequency.

These results indicate that the VAR(2) system offers a measurable, though modest, one-day-ahead forecast improvement for the logistics cost indicator (D_BDI_Index) relative to naive benchmarks, while for the geopolitical risk indicator and for the remaining variables the model does not outperform a simple persistence or univariate autoregressive forecast at any horizon tested. This pattern is consistent with the joint Wald test results in Section 3.2.4, where only a subset of the lagged relationships in Table 3 remain jointly significant, and it tempers the interpretation of the VAR(2) system as a general-purpose forecasting tool. As discussed below, the practical value of the estimated system lies less in multi-step point forecasting and more in identifying of short-lag transmission pathways and generating threshold-based signal for specific variables such as D_BDI_Index and D_GPR_Index.

4.8 Application to disruption early-warning and logistics decision-making

Three of the estimated relationships are structured in a form suitable for embedding in a rule-based disruption early-warning indicator system, following the approach outlined by Yongsheng and Li [28]. The two-day lag from D_GPR_Index to both coffee price series (Table 3, Section 3.2.3) implies that a sustained rise in the geopolitical risk index, observable from automated news-based indices in near real time, provides an approximately 48-hour window before an associated price movement is expected in Robusta and Arabica markets, within which a logistics planner could bring forward procurement or adjust forward-contract exposure. Similarly, the two-day lag from D_ONI_Anom to D_GPR_Index (Section 3.2.4) suggests that sustained ENSO anomaly readings could be monitored as a leading indicator of subsequent geopolitical-risk index movements, ahead of their downstream effect on commodity prices. The structural-break results in Section 3.2.4 indicate that any such indicator system built on the BDI, Brent, or GPR equations would need periodic re-estimation, since the underlying coefficients are not stable across the pre-pandemic, COVID-19, and post-invasion regimes identified in this sample, whereas the coefficients feeding the ONI and coffee-price equations are comparatively stable and would tolerate a longer re-estimation interval. Given the modest and horizon-limited forecast gains documented in Section 4.2, the practical role envisaged for this system is threshold-based signal generation, flagging when GPR or ONI innovations exceed a specified magnitude, rather than multi-day point forecasting of commodity prices or freight costs.

5. Conclusions

This study developed and estimated a VAR(2) time-series model to identify and quantify the transmission of disruptions in ASEAN agri-food logistics networks, using 4,108 daily observations from January 2015 to March 2026. Model validity is confirmed by Durbin-Watson statistics (1.958–2.061), indicating adequate white-noise residuals. Three principal engineering findings emerge.

Geopolitical risk (GPR) is significantly associated with both Arabica (coefficient = 0.004, $p = 0.007$) and Robusta (coefficient = 0.039, $p = 0.021$) coffee price movements, with a two-day lag. This two-day propagation delay represents a tractable early-warning window: GPR signals, observable in real time through automated news monitoring, provide a 48-hour advance indicator of commodity price disruption in ASEAN export markets, suitable for embedding in procurement decision algorithms that initiate safety-stock replenishment or forward contracting when GPR exceeds predefined thresholds.

Climate anomaly signals (ONI) are significantly associated with Robusta prices at a one-day lag (coefficient = 36.83, $p = 0.021$) and with GPR conditions at a two-day lag (coefficient = 36.35, $p = 0.010$), consistent with a compound association linking climate stress, geopolitical risk, and commodity logistics outcomes. Single-variable climate impact models that exclude GPR would be expected to understate the variance associated with supply chain disruption by omitting this second-order amplification channel.

In price-level terms, a one-standard-deviation ONI anomaly shock (0.044, Table 1) is associated with an approximate 1.6 USD/tonne change in Robusta price at a one-day lag, and a one-standard-deviation GPR shock (45.7, Table 1) is associated with an approximate 1.8 USD/tonne change in Robusta price at a two-day lag. Both magnitudes are small relative to the 44.84 USD/tonne daily standard deviation of Robusta price changes reported in Table 1, consistent with the modest FEVD shares documented in Section 4.1, and indicate that the economic value of these coefficients lies primarily in early-warning signal timing rather than in the share of daily price variance explained.

BDI autoregressive persistence (0.596, $p < 0.001$), together with its association with ASEAN agricultural production returns (571.00, $p < 0.001$), is consistent with a feedback pattern in which agricultural production variation and logistics cost variation co-move, compounding the direct supply-side association and unfolding over multiple days through dynamic bulk shipping allocation adjustments.

Three engineering applications follow from these results. The GPR and ONI transmission coefficient estimates can serve as indicator weights in a quantitative disruption early-warning system, enabling automated alert generation when predefined thresholds are exceeded. FEVD results provide risk-stratified variance attribution for logistics safety-stock sizing. The Robusta-Arabica cross-variance, 44.03% under the baseline Cholesky ordering and subject to the ordering caveat in Section 3.3.1, indicates that operators managing both coffee varieties face correlated price risk that may warrant proportionally larger safety-stock buffers than single-commodity operators. The VAR(2) framework is computationally efficient and scalable for real-time streaming data environments, making it suitable for integration into automated logistics monitoring platforms with daily data ingestion.

Study limitations include the annual publication frequency of FAO agricultural production statistics, which restricts *R_ASEAN_Production* to a step-function variable taking non-zero values on exactly eleven observations in the sample, one per calendar year, rather than a continuously varying daily series, precluding inference on within-year production dynamics from the estimated coefficients, and the Cholesky identification assumption, which imposes a recursive ordering. The out-of-sample evaluation in Section 4.2 indicates that multi-step forecast gains from the VAR(2) system relative to naive benchmarks are limited to a small subset of variables at the shortest horizon, so the system is positioned here as a tool for identifying short-lag transmission pathways rather than as a general-purpose forecasting model. The structural-break results in Section 3.2.4 indicate that the estimated coefficients are not stable over the full 2015–2026 sample for the logistics-cost and geopolitical-risk equations, and the ordering-sensitivity check in Section 3.3.1 indicates that the FEVD share attributed to Robusta-Arabica co-movement is not invariant to the Cholesky ordering, so this figure is not read as a directional structural estimate. Future research should incorporate port-level logistics throughput data for higher operational resolution and extend to nonlinear threshold VAR or time-varying parameter VAR specifications to detect asymmetries in disruption transmission across high- and low-disruption regimes.

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