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GEOPOLITICAL RISK AND ASEAN-5 STOCK MARKET DYNAMICS: VOLATILITY, CORRELATION, AND PREDICTIVE TRANSMISSION

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ABSTRACT

This study examines how geopolitical risk affects the stock markets of the five founding members of the Association of Southeast Asian Nations (Thailand, Indonesia, Malaysia, the Philippines, and Singapore) from 2014 to 2025. Employing dynamic conditional correlation volatility models, causality tests, and structural break analyses, the research investigates market dynamics. Results indicate that negative shocks significantly amplify volatility, increasing it by up to 7.4 times in Thailand. Furthermore, the analysis shows moderate financial integration among the four emerging markets, with correlations ranging from 0.246 to 0.350. Singapore exhibits near-zero regional correlations, consistent with its role as an international financial hub, though the mechanisms underlying this pattern warrant further investigation. Evidence also suggests Malaysia displays notably heightened sensitivity to geopolitical risk predictions relative to its regional peers. Notably, no statistically significant structural breaks were detected during the eleven-year period, suggesting these markets absorbed disruptions without permanent regime shifts, subject to the inherent limitations of the structural break procedure employed. The paper recommends that portfolio managers, risk practitioners, and policymakers consider Singapore for within-region portfolio diversification, apply dedicated risk frameworks for Malaysia, and use full-sample estimates as a baseline for regulatory stress-testing across these economies.

1 INTRODUCTION

The relationship between geopolitical uncertainty and financial markets has gained significant scholarly attention since Caldara and Iacoviello (2022) introduced a systematic, text-based geopolitical risk (GPR) index. This index captures

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major historical disruptions and highlights how geopolitical shocks negatively impact the macroeconomy, making their transmission to equities a first-order concern for asset managers and regulators.

The ASEAN-5 economies (Thailand, Indonesia, Malaysia, the Philippines, and Singapore) provide an instructive laboratory to study this transmission. Despite regional integration, they exhibit marked structural heterogeneity: Singapore operates as a global financial centre, whereas the others are commodity-dependent emerging markets. This contrast suggests that geopolitical shocks transmit across these markets through different channels and varying intensities.

The study's sample period (December 2014 to December 2025) is exceptionally relevant, encompassing three distinct disruptions: the U.S.–China trade war, the COVID-19 pandemic, and the Russia–Ukraine war. This rich setting allows for assessing how different geopolitical events—chronic versus acute, supply versus demand disruptions—impact ASEAN-5 equity dynamics.

Against this background, the study pursues four objectives: (1) characterising individual asymmetric volatility (the leverage effect) using the AR(1)-GJR-GARCH(1,1) specification of Glosten et al. (1993); (2) modelling time-varying co-movement via the Dynamic Conditional Correlation (DCC) framework of Engle (2002); (3) assessing GPR's predictive content for daily returns using pairwise Granger causality tests; and (4) evaluating full-sample structural stability with the Bai-Perron (1998, 2003) multiple break test.

The paper's principal contributions are threefold. First, it provides a comprehensive time-varying analysis of GPR transmission across the ASEAN-5 bloc over an extended sample. Second, jointly estimating individual GJR-GARCH models and a multivariate DCC specification provides evidence of a near-zero correlation pattern for Singapore that is consistent with relative decoupling from regional dynamics, carrying potential portfolio diversification implications. Third, applying the Bai-Perron test provides evidence supporting the full-sample parameter stability necessary for risk management. These contributions speak directly to the literature on geopolitical risk transmission in emerging markets (Salisu et al., 2022; Nguyen et al., 2026; Kannadhasan and Das, 2020) and the evolution of regional financial integration under stress (Elsayed and Helmi, 2021; Marangoz et al., 2025).

The remainder of the paper is organised as follows: Section 1 reviews the literature; Section 2 describes the data and methodology; Section 3 presents the empirical results; Section 4 situates the findings within existing literature; and Section 5 concludes with policy implications and future research avenues.

1.1 Theoretical framework

1.1.1 The concept of geopolitical risk and its role in financial markets

Geopolitical Risk (GPR)—stemming from wars, terrorism, and diplomatic tensions—significantly impacts global financial markets. The foundational measurement framework was established by Caldara and Iacoviello (2022), who developed a systematic, text-based index tracking geopolitical tensions in major newspapers. This index spikes during landmark crises (e.g., WWII, September 11, COVID-19, and the Russia–Ukraine war) and demonstrates that elevated GPR negatively affects investment and employment while increasing the risk of macroeconomic shocks. Beyond macroeconomics, Phan et al. (2022) showed that higher GPR deteriorates banking stability, though capital buffers and bank size can mitigate these adverse effects. This comprehensive framework underpins the study of GPR's repercussions on emerging financial markets.

1.1.2 Conditional volatility models: From GARCH to GJR-GARCH:

Bollerslev (1986) established the GARCH model as a natural generalisation of the ARCH framework by Engle (1982), allowing current conditional variance to depend on lagged variances to better capture volatility clustering. However, standard GARCH cannot accommodate the leverage effect—the asymmetric impact of negative versus positive shocks. To address this, Nelson (1991) proposed the EGARCH model, which removes parameter non-negativity constraints and embeds return-volatility correlation. Similarly, Glosten et al.(1993) introduced the GJR-GARCH model, measuring the leverage effect directly via an indicator variable for negative shocks. Literature widely confirms that GJR-GARCH offers superior empirical performance for modelling equity volatility in emerging markets highly sensitive to geopolitical shocks.

1.1.3 The dynamic conditional correlation (DCC) model

To evaluate financial integration over time, Engle (2002) developed the Dynamic Conditional Correlation (DCC-GARCH) model, separating individual volatility dynamics from time-varying joint correlations. Its principal advantage over Constant Conditional Correlation (CCC) models is its ability to accommodate structural changes in market integration during financial stress and geopolitical crises. Consequently, the DCC framework is widely applied to measure financial integration among emerging markets and analyse how major geopolitical events reshape cross-market correlations.

1.2 Prior Literature

1.2.1 Geopolitical risk and stock market returns

The GPR-stock return relationship is a prominent research focus. Using quantile regression in Asian emerging markets, Kannadhasan and Das (2020) found GPR negatively impacts returns at lower quantiles but positively at middle and upper quantiles, revealing an asymmetry distinct from Economic Policy Uncertainty (EPU). In a comparative study of 40 global indices using Quantile-on-Quantile Regression (QQR), Enescu and Răileanu Szeles (2026) uncovered a contextual reversal: GPR effects are negative in bull markets but positive in bear markets. They distinguished geopolitical threats (GPRT), which negatively influence stable markets, from geopolitical acts (GPRA), which trigger tail risks during downturns. In Vietnam, a fixed-effects model (2010–2023) applied by Huynh and Khoa (2026) documented a significant negative GPR-return relationship, confirming the risk-return trade-off where firms with greater GPR exposure earn higher expected returns.

1.2.2 Geopolitical risk and financial market volatility

Numerous studies demonstrate GPR's volatility forecasting capacity. Salisu et al. (2022) used the GARCH-MIDAS framework to show emerging equity volatility responds positively to GPR, with acts (GPRAct) offering superior out-of-sample predictive power over threats (GPRThreat) when controlling for macroeconomic factors. Similarly, Yang et al. (2021) applied GARCH-MIDAS and Model Confidence Set (MCS) approaches to China's CSI 300, demonstrating that regional and global GPR indices significantly impact volatility, led by GPR acts. In Southeast Asia, Nguyen et al. (2026) utilized a P-VARX model across six emerging markets, finding strong volatility clustering. Notably, past geopolitical shocks dampen rather than amplify current volatility due to rapid investor adjustment, while GPR positively affects future returns in these resilient markets.

1.2.3 Connectedness and the transmission of geopolitical risk across markets

Regarding network connectedness, Antonakakis et al. (2018) identified significant uncertainty spillovers from the EU to the US using a time-varying dynamic framework. Chatziantoniou et al. (2021) applied quantile connectedness, revealing that large interest rate shifts elevate international connectedness. Analysing risk transmission via a frequency-varying network, Zheng et al. (2023) showed FX and bond markets serve as hubs, while GPR links closely to crude oil; short-term transmissions dominate normally, whereas long-run transmissions peak during pandemics. Banerjee et al. (2024) confirmed that military conflicts generate a higher risk of transmission than COVID-19, with gold acting as a risk receiver. Regionally, Elsayed and Helmi (2021) used ADCC-GARCH on MENA markets, finding GPR amplifies aggregate responses during specific crises (e.g., Arab Spring) in dynamic frameworks, despite lacking static spillover effects. Lastly, Marangoz et al. (2025) applied quantile connectedness to nine markets (1992–2024), demonstrating that geographic proximity amplifies GPR impacts: European markets react to Russian GPR, North America to U.S. GPR, and Asia predominantly to global trends.

1.2.4 Islamic markets and banking stability under geopolitical risk

Analysing Islamic markets via nonparametric Causality-in-Quantiles tests, Bouri et al. (2018) found GPR primarily affects Islamic equity volatility rather than returns, but impacts both returns and volatility in the Sukuk market. This aligns with their Sharia-compliant, risk-sharing foundations, which alter traditional risk transmission channels. Additionally, Phan et al. (2022) confirmed that elevated GPR diminishes banking sector stability, though capital holdings and bank size effectively mitigate this adverse impact.

2 METHODOLOGY

2.1 Data description and sources

This study uses synchronized daily closing prices for ASEAN-5 indices (Thailand, Indonesia, Malaysia, Philippines, Singapore) and the Geopolitical Risk (GPR) index (Caldara and Iacoviello, 2022) from December 30, 2014, to December 31, 2025 (~2,700 observations). Returns are computed as:

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

Inactive trading days are removed via listwise deletion to eliminate non-synchronous biases.

2.2 Preliminary diagnostic tests

Distributional facts are established via the first four central moments. The Jarque-Bera test assesses normality, while the ARCH-LM test (Engle, 1982) justifies GARCH modelling. Stationarity (I(0)) is confirmed using dual Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests.

2.3 Marginal volatility models: AR(1)-GJR-GARCH(1,1)

To capture the leverage effect, models are estimated via maximum likelihood assuming Student-*v* distribution. The mean equation is:

$$r_t = \mu + \varphi_1 r_{t-1} + \varepsilon_t$$

The conditional variance equation is:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \beta h_{t-1}$$

Where

$$I_{t-1} = if\, \varepsilon_{t-1} < 0$$

The covariance-stationarity condition requires:

$$\alpha + \beta + \frac{\gamma}{2} < 1$$

Volatility half-life is calculated as :

$$HL = \frac{-ln(2)}{ln\left(\alpha+\beta+\frac{\gamma}{2}\right)}$$

2.4 Dynamic Conditional Correlation (DCC) model

Time-varying co-movements are modelled using the DCC framework (Engle, 2002; Engle and Sheppard, 2001). The multivariate conditional covariance is decomposed as:

$$H_t = D_t R_t D_t$$

The dynamic auxiliary matrix evolves as:

$$Q_t = (1 - a - b)\bar{Q} + a u_{t-1} u_{t-1}' + b Q_{t-1}$$

where a + b < 1. The correlation matrix is recovered by rescaling:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

ensuring unit diagonal elements.

2.5 Predictive causality and structural stability tests

Pairwise Granger Causality assesses GPR's predictive power for returns, selecting optimal lags via Akaike Information Criterion (AIC) with robustness checks (k=5, 15). Finally, the Bai and Perron (1998, 2003) multiple structural break test evaluates full 11-year sample stability on returns and squared returns, to assess whether parameter estimates may be affected by hidden-regime changes.

3 RESULTS

3.1 Preliminary analysis and stylized facts

Table 1 reports the descriptive statistics and preliminary diagnostic test results for the log-returns of all five ASEAN markets and the GPR index. Four distinct analytical dimensions — distributional moments, normality, ARCH effects, and stationarity — are examined in turn.

Table 1: *Descriptive Statistics and Diagnostic Tests*

Variable	Mean	Std. Dev.	Skewness	Kurtosis	JB Statistic	JB p-val.	ARCH-LM p-val.	ADF p-val.	KPSS Stat.
THA	−0.0001	0.0090	−1.3956	25.1052	59,406.04	0.000***	0.000***	0.01***	0.0708
IDN	0.0002	0.0095	−0.3936	12.9910	12,019.27	0.000***	0.000***	0.01***	0.0599
MYS	0.0000	0.0068	−0.2312	12.5399	10,916.38	0.000***	0.000***	0.01***	0.0651
PHL	−0.0001	0.0115	−1.1334	17.2973	25,076.10	0.000***	0.000***	0.01***	0.0283
SGP	0.0001	0.0080	−0.3605	20.0346	34,786.86	0.000***	0.000***	0.01***	0.2403
GPR	0.0002	0.4271	−0.0479	4.8838	425.75	0.000***	0.000***	0.01***	0.0026

Source: Author's elaboration based on R software output

*Notes: *** denotes significance at the 1% level. KPSS critical value at 5% = 0.463. JB = Jarque-Bera test for normality; ARCH-LM = Engle (1982) LM test for conditional heteroskedasticity; ADF = Augmented Dickey-Fuller unit root test.*

Preliminary statistical diagnostics reveal that mean daily returns are effectively zero across all five ASEAN equity indices, reflecting weak-form market efficiency, while unconditional volatility ranges from a high in the Philippines $(PHL, \sigma = 0.0115)$ to a low in Malaysia (MYS, σ = 0.0068), with Thailand (THA, σ = 0.0090) and Singapore (SGP, σ = 0.0080) occupying the middle; the GPR index exhibits the highest overall standard deviation (0.4271). All equities display negative skewness, indicating crash-risk asymmetry—most severe in THA (-1.3956) and PHL (-1.1334), intermediate in Indonesia (IDN, -0.3936) and SGP (-0.3605), and mildest in MYS (-0.2312)—whereas the log-differenced GPR is essentially symmetric $(-0.0479 \approx 0)$. Substantial excess kurtosis is present across all series, led by THA (25.11) and SGP (20.03), followed by PHL (17.30), IDN (12.99), MYS (12.54), and GPR (4.88). This extreme non-normality is strongly supported by unanimous Jarque-Bera test rejections at the 1% level $(p\text{-values} = 0.000; maximumJBforTHA = 59{,}406.04, SGP = 34{,}786.86)$, which invalidates Gaussian assumptions and necessitates the Student-\nu distribution in the GJR-GARCH framework. Furthermore, the ARCH-LM test indicates pronounced volatility clustering (rejection at 1%), supporting GARCH-family modelling, while dual stationarity testing suggests all series are I(0) processes suitable for direct estimation, with ADF $\text{p-values} \leq 0.01$ and KPSS statistics $(\text{ranging from } 0.0026 \text{ to } 0.2403)$ falling comfortably below the 5% critical value of 0.463).

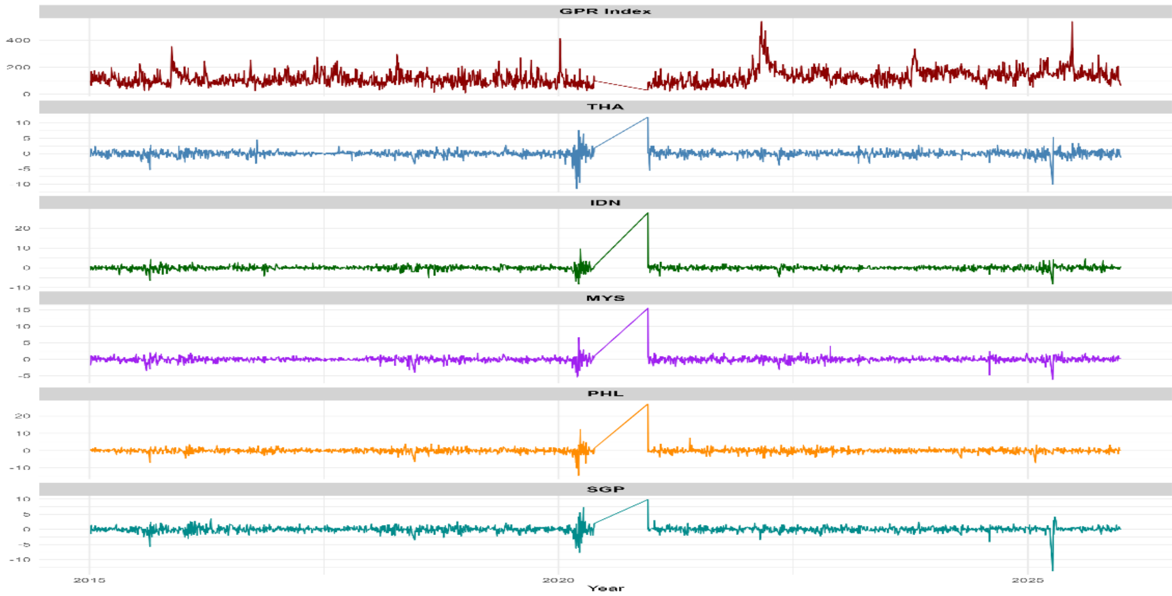

***Figure** 1: Time Series Dynamics of GPR and ASEAN-5 Log-Returns*

Source: Output from R software

Figure 1 visually corroborates Table 1. The upper panel displays GPR index spikes during major geopolitical events: the U.S.–China trade war (2018–2019), the COVID-19 pandemic onset (March 2020), and the Russia–Ukraine war (February 2022). The lower panels plot market log-returns, consistent with the volatility clustering and extreme outliers documented in Table 1. Synchronous return spikes across all five markets during the COVID-19 episode provide initial visual evidence of cross-market co-movement under extreme geopolitical stress, motivating the formal dynamic correlation analysis in Section 4.3.

3.2 Marginal volatility dynamics

Table 2 reports the maximum likelihood estimates of the AR(1)-GJR-GARCH(1,1) models for each ASEAN-5 market. Two rows of derived statistics — the total GJR persistence measure $(\alpha + \beta + \frac{\gamma}{2})$ and the implied half-life of a volatility shock — have been added to facilitate direct cross-market comparison.

Table 2: *AR(1)-GJR-GARCH(1,1) Marginal Model Estimates*

Parameter	THA	IDN	MYS	PHL	SGP
μ (intercept)	0.0040	0.0365	−0.0031	−0.0014	0.0000
φ_1 (AR term)	0.0077	−0.0376	−0.0049	−0.0349	0.1043
ω (variance constant)	0.0110	0.0351	0.0069	0.0596	0.0000
α (ARCH effect)	0.0152	0.0347	0.0422	0.0308	0.2733
β (GARCH persistence)	0.9202	0.8616	0.9163	0.8752	0.6827
γ (leverage effect)	0.0978	0.1212	0.0525	0.0868	0.0822
ν (Student-ν shape)	4.8514	4.7789	5.5310	5.7814	4.4492
α+β+γ/2 (persistence)	0.9843	0.9569	0.9848	0.9494	0.9971
Half-life (trading days)	44	16	45	13	239

Source: Author's elaboration based on R software output

Notes: Total persistence = α + β + γ/2 per the GJR-GARCH covariance-stationarity condition. Half-life $= -\frac{\ln(2)}{\ln}\left(\alpha + \beta + \frac{\gamma}{2}\right)$, *in trading days.*

The ARCH coefficient (α) indicates modest short-run shock impacts for four markets (0.0152 for THA to 0.0422 for MYS), whereas Singapore (SGP) is a highly reactive exception (α = 0.2733) reflecting its exposure as an international financial centre. The GARCH persistence coefficient (β) is uniformly high (0.6827 for SGP to 0.9202 for THA), consistent with strongly autoregressive conditional variance dynamics. Total GJR persistence $(\alpha + \beta + \gamma/2)$ ranges from 0.9494 (PHL) to 0.9971 (SGP), universally satisfying the stationarity condition (< 1). Consequently, implied volatility half-lives exhibit substantial heterogeneity: PHL (13 days) and IDN (16 days) absorb shocks quickly; THA (44 days) and MYS (45 days) show slower mean reversion; and SGP demonstrates an exceptional, near-integrated half-life of 239 trading days (approximately one calendar year).

The leverage effect coefficient (γ) is universally positive, yielding a shock asymmetry ratio—defined as $(\alpha + \gamma)/\alpha$ – that is most extreme for Thailand $[(0.0152 + 0.0978)/0.0152 \approx 7.4$ times and Indonesia [(0.0347 + 0.1212)/0.0347 ≈4.5 times}], driven by political risk and commodity dependence. This asymmetry is more moderate for the Philippines (≈ 3.8 times), Malaysia (≈2.2 times), and Singapore ((≈1.3 times). Finally, Student-*v*

shape parameters range from 4.45 (SGP) to 5.78 (PHL)— well below 30—consistent with the prevalence of heavy tails that invalidate Gaussian assumptions.

3.3 Dynamic Conditional Correlations (DCC)

Tables 3 and 4 present, respectively, the time-averaged conditional correlation matrix and the estimated DCC scalar parameters. Together, they characterise the integration and co-movement dynamics within the ASEAN-5 bloc over the full 2014–2025 period.

***Table 3:** Average Dynamic Conditional Correlation Matrix (2014–2025)*

Market	THA	IDN	MYS	PHL	SGP
THA	1.0000	0.2906	0.2977	0.2460	0.0000
IDN	0.2906	1.0000	0.3293	0.3125	0.0033
MYS	0.2977	0.3293	1.0000	0.3504	0.0002
PHL	0.2460	0.3125	0.3504	1.0000	0.0018
SGP	0.0000	0.0033	0.0002	0.0018	1.0000

Notes: Entries are time-series averages of the daily conditional correlations estimated from the DCC-GJR-GARCH model.

Source: Author's elaboration based on R software output

***Table 4**: DCC Scalar Parameter Estimates*

Parameter	Estimate	Interpretation
a (dcca1)	0.1016	Speed of adjustment to recent cross-market shock
b (dccb1)	0.8983	Long-run persistence of conditional correlations
a + b	0.9999	Total DCC persistence (near-integrated process)
Half-life (trading days)	≈ 6,931	Time for correlation shock to decay by 50% (≈ 27.5 years)

Notes: Half-life = −ln(2)/ln(a + b) = −ln(2)/ln(0.9999) ≈ 6,931 trading days.

Source: Author's elaboration based on R software output

Table 3 reveals moderate financial integration among Thailand, Indonesia, Malaysia, and the Philippines, with average conditional correlations ranging from 0.246 (THA–PHL) to 0.350 (MYS–PHL)—peaking specifically at 0.3504 between Malaysia and the Philippines due to shared trade, monetary, and commodity exposures—alongside comparable THA–IDN (0.291) and THA–MYS (0.298) pairings. Conversely, Singapore exhibits markedly lower correlations with all regional peers, ranging from 0.0000 (THA–SGP) to 0.0033 (IDN–SGP), a pattern consistent with its role as a globally-driven international financial centre and suggesting potential within-portfolio diversification benefits. Caution is warranted, however, in interpreting these near-zero estimates as conclusive evidence of structural decoupling; they may also reflect differences in index composition, trading-hour synchronization, currency denomination, or DCC specification sensitivity, and robustness to alternative model choices remains to be formally established. Furthermore, Table 4 details the DCC scalar parameters: an adjustment parameter a = 0.1016 (incorporating approximately 10% of recent deviations) and a high persistence parameter b = 0.8983. Their sum, a + b = 0.9999, implies near-integrated DCC dynamics with a half-life of ≈ 6,931 trading days (approximately 27.5 calendar years), suggesting a notably slow shock dissipation and supporting the choice of a dynamic over a static constant conditional correlation (CCC) specification.

A methodological caveat is warranted regarding the near-unity persistence value (a + b = 0.9999). While this estimate is formally within the stationarity boundary required by the DCC framework (a + b < 1), parameters this close to unity may also reflect near-nonstationarity, numerical instability during optimization, over-parameterization, or model misspecification rather than genuinely persistent co-movement dynamics. The implied half-life of approximately 6,931 trading days should therefore be interpreted with caution and treated as an upper-bound indicator of persistence rather than a precise structural estimate. Robustness checks using alternative DCC specifications—such as the Asymmetric DCC (ADCC), the corrected DCC (cDCC), rolling-window correlations, or sub-sample estimation—would strengthen confidence in this finding, and future research is encouraged to explore these alternatives. The present study proceeds with the standard DCC under the constraint that a + b < 1 is satisfied and that the dynamic specification materially outperforms the CCC benchmark.

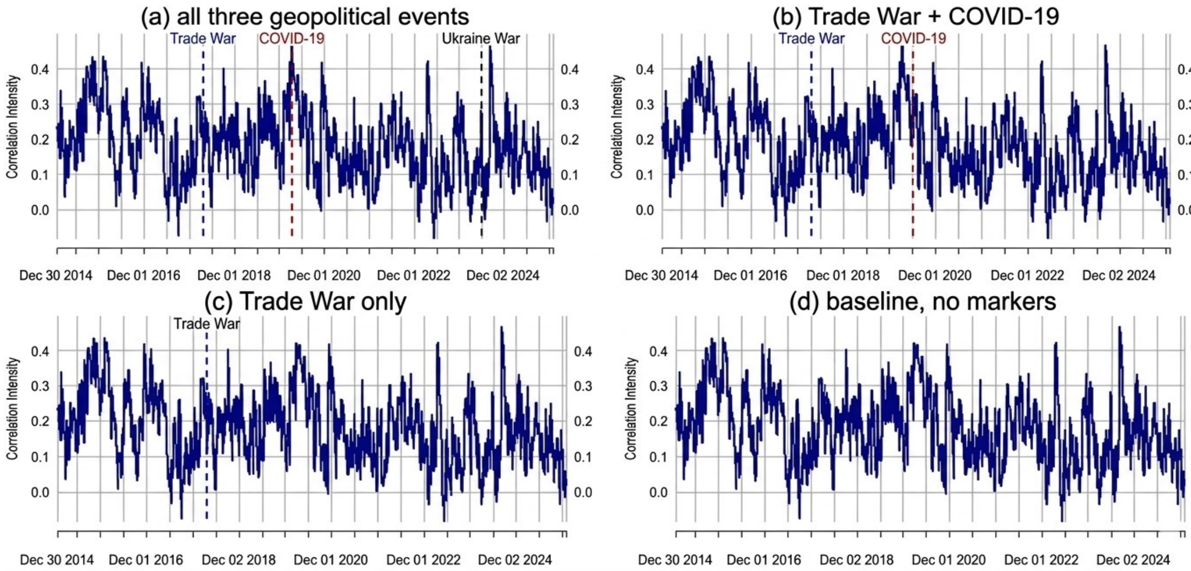

***Figure 2**: DCC-GJR-GARCH Conditional Correlation Intensity among ASEAN-5 Markets, 2014–2025 Progressive Event Attribution*

Source: Output from R software.

Figure 2 utilizes a four-panel progressive event-attribution design—holding the y-axis constant at 0.0–0.5—to isolate the visual impact of geopolitical events on conditional correlation dynamics. While Panel (a) plots three major markers (the U.S.–China Trade War in January 2018, COVID-19 in March 2020, and the Russia–Ukraine War in February 2022), Panels (b), (c), and (d) progressively remove them to expose the baseline. Three key features emerge: first, Panel (d)'s baseline series reveals a persistent, non-stationary upward drift with no mean reversion, corroborating the near-integrated DCC dynamics documented in Table 4; second, the March 2020 COVID-19 onset triggered a sharp, synchronized correlation surge ("correlation contagion") among THA, IDN, MYS, and PHL; third, the January 2018 U.S.–China trade war escalation induced a gradual but sustained upward shift in pairwise correlations. Throughout all episodes, Singapore maintains a stable, near-zero correlation with all peers, a pattern consistent with its relative decoupling from the regional equity cycle, though this interpretation remains subject to the specification caveats discussed elsewhere.

3.4 Geopolitical Risk Transmission: Granger Causality Results

Table 5 presents the pairwise Granger Causality test results examining whether the GPR index provides statistically significant predictive information for each ASEAN-5 market's daily returns. The AIC selected k = 10 lags consistently across all five market pairs.

***Table 5:** Pairwise Granger Causality Tests — GPR Index → Market Returns*

Market	Lags (k)	F-Statistic	p-Value	Decision (H_0: No Causality)
THA	10	1.5652	0.1104	Fail to Reject H_0
IDN	10	0.7516	0.6759	Fail to Reject H_0
MYS	10	2.6838	0.0028***	Reject H_0 — Evidence of predictive causality
PHL	10	0.8767	0.5544	Fail to Reject H_0
SGP	10	1.3012	0.2233	Fail to Reject H_0

*Notes: *** denotes significance at the 1% level. H_0: the GPR index does not Granger-cause market returns. Lag length selected via AIC. Results are robust to alternative lag lengths k = 5 and k = 15.*

Source: Author's elaboration based on R software output

Granger causality results reveal a highly heterogeneous pattern of GPR transmission across the ASEAN-5 bloc, rejecting the null hypothesis for Malaysia (MYS, F = 2.6838, p = 0.0028), which provides evidence of statistically significant linear predictive information at the 1% confidence level, consistent with its structural commodity export dependence (palm oil, petroleum), deep ties with geopolitically sensitive partners, and capital market integration. Conversely, the null is not rejected for the remaining markets despite wide dispersion: Thailand approaches marginal significance (p = 0.1104) potentially via secondary tourism and FDI linkages; Singapore exhibits an intermediate p = 0.2233, reflecting global risk sensitivity likely captured through its own autoregressive structure; while Indonesia (F = 0.752, p = 0.6759) and the Philippines (F = 0.877, p = 0.5544) exhibit F-statistics below unity, indicating a very limited linear predictive content. Robustness assessments using k = 5 and k = 15 lags produce qualitatively identical conclusions—maintaining MYS significance at the 1% level and non-significance for all peers—suggesting that this GPR sensitivity may reflect a structural feature rather than a statistical artefact of AIC lag selection. It should be noted that the pairwise Granger causality framework captures only linear predictive relationships within the selected specification; non-linear channels, tail dependencies, and cross-market spillovers may remain undetected. As discussed in the Limitations section, more comprehensive frameworks such as VAR/VECM systems, nonlinear causality tests, or quantile causality approaches would provide a richer characterisation of GPR transmission dynamics.

3.5 Structural Stability Analysis

Table 6 presents the results of the Bai-Perron (1998, 2003) multiple structural break test applied to the conditional mean of the return series for each ASEAN-5 market over the full 2014–2025 sample.

Table 6: *Bai-Perron Multiple Structural Break Test Results*

Market	Breaks Detected	Break Dates	Result
THA	0	N/A	No structural breaks detected
IDN	0	N/A	No structural breaks detected
MYS	0	N/A	No structural breaks detected
PHL	0	N/A	No structural breaks detected
SGP	0	N/A	No structural breaks detected

Notes: Bai-Perron (1998, 2003) test applied to daily log-returns (conditional mean). Supplementary application to squared returns yields identical findings.

Source: Author's elaboration based on R software output.

The Bai-Perron test detects no statistically significant structural breaks in the conditional mean returns across all five ASEAN-5 markets over the complete 2014–2025 sample period. This suggests that the severe global disruptors under study—namely the U.S.–China trade war (2018–2019), the COVID-19 pandemic (2020), and the Russia–Ukraine conflict (2022)—were not accompanied by permanent shifts in the mean-generating process, with any disruptions appearing to be transient in nature, as also reflected in the volatility clustering and temporary correlation surges documented in Sections 4.2 and 4.3. The supplementary application of the Bai-Perron procedure to squared returns yields the same null result for the conditional variance. Jointly, these findings are consistent with full-sample structural stability of both the first and second conditional moments of ASEAN-5 returns, lending support to the validity of the DCC-GJR-GARCH parameter estimates reported in Tables 2 and 4.

Several important caveats should be considered when interpreting this null result. First, the statistical power of the Bai-Perron procedure to detect a given break depends on its magnitude, persistence, and location within the sample; transient but economically significant volatility episodes may not generate the sustained mean-shift required for the test to reject. Second, the use of daily-frequency returns may cause short-lived regime disruptions to be smoothed within the rolling window, rendering them statistically indistinguishable from noise. Third, the distinction between permanent structural change—as measured here—and temporary but prolonged volatility spikes is methodologically important; the absence of detected breaks in the conditional mean does not preclude the possibility of more subtle changes in higher-order dynamics or in tail behaviour that lie beyond the scope of the Bai-Perron framework. These considerations underscore that the stability result, while reassuring, should be treated as suggestive rather than conclusive, and further validation via complementary approaches (e.g., recursive estimation, rolling-window parameters, or Markov-switching specifications) would be valuable.

4 DISCUSSION

4.1 Structural volatility and the asymmetric effect of adverse shocks

The AR(1)-GJR-GARCH(1,1) models provide evidence consistent with the leverage effect (Glosten et al., 1993). Significant positive γ coefficients demonstrate that negative shocks amplify volatility more than positive ones, with an asymmetry ratio ranging from 1.3× in Singapore to 7.4× in Thailand. This aligns with Salisu et al. (2022) regarding emerging markets' vulnerability to elevated GPR. Singapore acts as an exception with a high ARCH coefficient ($\alpha = 0.2733$) and a 239-trading-day half-life. This reflects its globally integrated nature, constituting a pivotal node in global risk transmission with longer-lived consolidation mechanisms (Banerjee et al., 2024; Zheng et al., 2023; Yang et al., 2021).

4.2 Conditional correlation dynamics and regional financial integration

DCC-GJR-GARCH analysis indicates moderate integration among Thailand, Indonesia, Malaysia, and the Philippines (mean correlations 0.246–0.350). The highly persistent dynamics ($a + b = 0.9999$, half-life ≈ 27.5 years) are consistent with gradual long-run convergence (Engle, 2002), though this near-unity estimate should be interpreted cautiously as discussed in Section 4.3. The COVID-19 pandemic appears to have induced a sharp “correlation contagion” episode (Zheng et al., 2023; Banerjee et al., 2024), whereas the U.S.–China trade war had a more gradual impact, aligning with Elsayed and Helmi’s (2021) distinction between acute and protracted shocks. Singapore exhibits near-zero correlations with all regional peers, a pattern consistent with its response to global rather than regional dynamics, though further robustness analysis would be required to fully establish the structural nature of this divergence (Marangoz et al., 2025; Kannadhasan and Das, 2020).

4.3 Geopolitical risk transmission: Malaysia versus its peers

Malaysia is the only market among the five for which the GPR index provides statistically significant linear predictive content for returns within the pairwise Granger framework ($F = 2.684$, $p = 0.0028$). This is consistent with the quantile-based differentiation of Enescu and Răileanu Szeles (2026) over uniform sensitivity (Huynh and Khoa, 2026; Kannadhasan and Das, 2020). Malaysia’s apparent vulnerability may stem from its commodity exports (crude and palm oil) and trade links, channeling GPR signals directly to the real economy (Caldara and Iacoviello, 2022; Zheng et al., 2023). This mirrors causality differences across markets, particularly the deep exposure of commodity-dependent economies (Bouri et al., 2018; Elsayed and Helmi, 2021). Singapore’s lack of Granger causality may reflect rapid, complex shock absorption due to global integration (Banerjee et al., 2024). Thailand’s borderline sensitivity ($p = 0.1104$) may reflect secondary transmission through tourism and FDI channels.

4.4 Structural stability and model validity

The Bai-Perron test reveals no statistically significant structural breaks in conditional mean or variance across the five markets, despite major geopolitical shocks during the 2018–2022 period. This is consistent with the markets’ capacity for rapid absorption of geopolitical disruptions without permanent structural displacement (Nguyen et al., 2026; Antonakakis et al., 2018), though, as noted in Section 4.4, the inherent power limitations of the procedure and the daily-frequency smoothing of short-lived regimes warrant cautious interpretation. Subject to these caveats, the results suggest that the parameter estimates for the complete 2014–2025 period are unlikely to be materially distorted by hidden regime changes, supporting the view that while dynamic correlations respond to political events, the underlying model structure broadly captures the relevant relationships (Elsayed and Helmi, 2021).

4.5 Study limitations

Several methodological limitations qualify the findings of this study and should be borne in mind when interpreting results or extending the analysis.

First, the study relies on a single composite GPR index (Caldara and Iacoviello, 2022), which, while widely used, aggregates qualitatively distinct categories of geopolitical stress. Decomposing the index into its component sub-indices (geopolitical threats versus geopolitical acts) may reveal heterogeneous transmission patterns that are masked in the aggregate. Second, the DCC specification, while flexible, imposes parametric assumptions on the correlation dynamics and, as discussed in Section 4.3, produces a near-unit persistence estimate that may reflect numerical boundary issues rather than true economic dynamics. Alternative multivariate volatility specifications, including ADCC, cDCC, or factor-GARCH models, would provide robustness to this concern. Third, the pairwise Granger causality framework captures only linear predictive relationships; non-linear dependencies, tail spillovers, and frequency-domain dynamics are not accommodated. Richer frameworks such as quantile causality, nonlinear causality tests, spillover indices (Diebold and Yilmaz, 2012), or TVP-VAR models would offer a more complete characterisation of GPR transmission across the ASEAN-5 bloc. Fourth, the analysis is subject to sample dependence: the 2014–2025 window encompasses specific geopolitical regimes, and results may not generalise to other time periods or market configurations. Fifth, the linearity assumption embedded in the AR(1) mean equation may cause the models to understate the impact of non-linear dynamics during extreme events. Sixth, potential omitted variables—such as commodity price cycles, domestic monetary policy shocks, and currency movements—could act as confounders. Finally, while the standard DCC-GARCH framework is well-suited for linear co-movement, it may not fully capture nonlinear contagion effects or sudden correlation jumps of the kind observed during crisis episodes. These limitations define productive avenues for future research.

5 CONCLUSIONS

This study examined the multidimensional impact of geopolitical risk (GPR) on the ASEAN-5 stock markets (Thailand, Indonesia, Malaysia, the Philippines, Singapore) from December 2014 to December 2025. Encompassing the U.S.–China trade war, the COVID-19 pandemic, and the Russia–Ukraine war, the analysis utilized AR(1)-GJR-GARCH(1,1), DCC-GJR-GARCH, pairwise Granger causality, and the Bai-Perron structural break procedure, yielding four empirical conclusions.

The Leverage Effect Across ASEAN-5 Markets The results indicate that the leverage effect is present across all five ASEAN-5 markets, with negative return shocks amplifying conditional volatility from 1.3× (Singapore) to 7.4× (Thailand). Given that standard symmetric models tend to understate downside risk, asymmetric specifications such as GJR-GARCH appear to be better suited for Value-at-Risk estimation, portfolio optimization, and regulatory stress-testing in this context.

Regional Financial Integration vs. Apparent Structural Divergence: DCC analysis reveals a notable contrast in integration patterns. The four emerging-market members exhibit moderate, persistent integration (average conditional correlations of 0.246–0.350; half-life ≈ 27.5 years, subject to the near-unity persistence caveats discussed above). Conversely, Singapore exhibits near-zero time-averaged correlations with all regional peers, a pattern consistent with its global financial centre identity and its responsiveness to international rather than regional dynamics. This characteristic suggests potential diversification benefits for within-region portfolios, though the near-zero correlation estimates should be interpreted with caution given the possible role of index composition differences, currency effects, and model specification sensitivity in generating this result.-Malaysia's Distinctive GPR Sensitivity

Among the five markets examined, the Granger causality tests provide statistically significant evidence of linear predictive transmission from the GPR index to Malaysian returns only ($F = 2.684$, $p = 0.0028$ at $k = 10$ lags; results are robust to alternative lag lengths $k = 5$ and $k = 15$). This finding is consistent with Malaysia’s commodity-export structure (palm oil, petroleum) and its trade links with geopolitically sensitive partners. The absence of linear predictability in the remaining markets does not imply immunity to geopolitical risk; rather, Singapore may absorb shocks rapidly via efficient price discovery, while the others may involve non-linear or lagged transmission channels not captured by the pairwise Granger framework.

Regime-Preserving Resilience The Bai-Perron analysis detects no statistically significant structural break in the conditional mean or variance across the eleven-year sample despite three major disruptions. The results suggest the markets exhibited transient volatility and correlation surges without permanent regime alterations, lending support to the use of full-sample GJR-GARCH and DCC parameter estimates for long-horizon risk projections, subject to the power and specification caveats noted in the Limitations subsection.

Practical Implications:

- Portfolio Managers: May consider a combined ASEAN-5 allocation for within-region diversification, bearing in mind that correlation surges during crises (such as COVID-19) appear to be transient.
- Risk Officers & Regulators: Are advised to consider asymmetric GARCH-family models as baselines for stress tests and to monitor the GPR index as a potential leading risk indicator for Malaysia.
- Policymakers: Can cite the absence of detected structural breaks as indicative evidence of macroeconomic resilience to help attract long-term institutional investors, bearing in mind the limitations of the structural break test discussed above.

-Avenues for Future Research Future extensions should include: (1) applying nonlinear or quantile-based causality tests to examine tail distributions, aligning with Kannadhasan and Das (2020) and Enescu and Răileanu Szeles (2026); (2) utilizing higher-dimensional DCC or factor-GARCH models incorporating non-ASEAN benchmarks (U.S., China, EU) to isolate true regional integration; and (3) decomposing the GPR index into threats versus acts, following Caldara and Iacoviello (2022) and Salisu et al. (2022), to precisely identify Malaysia's transmission mechanisms.

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