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The Impact of Geopolitical Risk on Stock Market Volatility and Returns: Evidence from Southeast Asia

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ABSTRACT. This study investigates the impact of geopolitical risk (GPR) on stock market volatility and returns across six Southeast Asian countries. The motivation stems from the increasing frequency and severity of geopolitical events in recent years, particularly as emerging economies remain highly vulnerable to external shocks. Employing a panel vector autoregression model with exogenous variables (P-VARX), the analysis reveals that market volatility exhibits strong persistence, consistent with the well-documented phenomenon of volatility clustering in the financial literature. Contrary to much of the existing evidence from developed markets, the findings suggest that past geopolitical shocks tend to dampen current market volatility, reflecting a swift adjustment mechanism among investors in Southeast Asia. Furthermore, GPR exerts a positive influence on future stock returns. Impulse response functions and forecast error variance decompositions further elucidate the dynamic and asymmetric relationship between volatility and returns over time. These results offer novel empirical insights, indicating that while Southeast Asian markets are susceptible to geopolitical disturbances, they also demonstrate a remarkable capacity to absorb shocks and recover promptly. The study provides valuable implications for investors and policymakers in formulating effective risk management and investment strategies amidst rising global uncertainties.

1. Introduction

Geopolitical risk typically arises when political or military tensions escalate in a specific region, with the potential to disrupt local economic activity and trigger broader repercussions for the global economy [1]. From an academic perspective, Caldara & Iacoviello (2022) [2] define GPR as "the risks associated with wars, terrorist acts, and tensions among states that affect the normal and peaceful course of international relations." In today's international landscape, geopolitical

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events are occurring with greater frequency, heightened uncertainty, and far-reaching consequences for global financial markets. Small, trade-dependent economies such as those in Southeast Asia are particularly vulnerable to shocks stemming from geopolitical instability. As such, examining the impact of GPR on stock market volatility and returns in this region is both academically relevant and practically important.

Global shocks such as international financial crises, public health emergencies, and armed conflicts have significantly heightened uncertainty – ranging from economic policy to market sentiment – with geopolitical risk emerging as a central driver. In recent years, escalating conflicts in Ukraine, tensions on the Korean Peninsula, territorial disputes in the South China Sea, and the looming threat of war in the Middle East have further intensified global instability. These events not only exert immediate pressure on investor sentiment and business activity but also propagate risk across borders through channels such as capital flows, exchange rate volatility, and shifts in macroeconomic policy. GPR not only amplifies commodity price fluctuations but also accelerates the transmission of risk across global financial markets [3-5]. Particularly when GPR coincides with other systemic shocks – such as financial crises or pandemics – the resulting compounding effects exacerbate uncertainty in global financial systems.

The economic implications of geopolitical risk have been acknowledged and emphasized by major international institutions such as the European Central Bank (ECB) and the International Monetary Fund (IMF) [6]. Recent studies further underscore the growing role of GPR in shaping economic and financial interactions at both national and global levels [7, 8]. As geopolitical tensions escalate, economic activity tends to slow, equity returns decline, and capital is reallocated from emerging markets to advanced economies as a defensive response [2].

A growing body of empirical research has established a strong link between geopolitical risk and stock market volatility. Zhang et al. (2023) [9] identify GPR as a key determinant of investor behavior, documenting a clear positive correlation between rising geopolitical tensions and market volatility [10]. As GPR intensifies, the investment environment becomes increasingly uncertain, prompting investors to rebalance portfolios and revise their strategies. According to Bloom's (2009) [11] uncertainty theory, heightened risk leads to delayed or suspended investment decisions, thereby slowing economic activity and triggering short-term turbulence in financial markets. These effects are particularly pronounced in emerging economies such as those in Southeast Asia, where financial systems tend to be fragile and highly sensitive to cross-border capital flows. Zhang et al. (2023) [9] further show that emerging markets, oil-exporting countries, and nations experiencing periods of peace tend to exhibit greater volatility in response to rising GPR. The region's heavy reliance on trade and foreign investment renders its markets especially vulnerable during episodes of geopolitical instability.

Beyond its influence on volatility, geopolitical risk also affects stock market returns. Elevated levels of GPR increase investment risk, leading to greater fluctuations in equity returns. This is largely driven by investors' tendency to retreat from riskier assets in favor of safe havens such as gold, government bonds, or more liquid instruments. Ma et al. (2022) [12] demonstrate that the GPR index possesses predictive power for future stock returns, enabling investors to make more informed decisions. Supporting this view, several studies argue that GPR not only has a direct impact on returns but also enhances return predictability in empirical models [9, 10, 13, 14]. However, other research finds no significant relationship between geopolitical risk and stock returns[15-17], or suggests that the nature of the relationship may be contingent on macroeconomic fundamentals and the level of market development [18]. Thus, a consensus on the impact of geopolitical risk on equity returns has yet to emerge. Moreover, much of the existing literature remains focused on major economies, while empirical evidence from Southeast Asia is still notably limited.

Southeast Asia comprises relatively small, open economies with high exposure to international trade and a strong reliance on foreign investment, rendering the region particularly vulnerable to global shocks [19-22]. Despite this vulnerability, empirical research examining the impact of geopolitical risk on the region's financial markets remains limited. In particular, few studies have explored how GPR interacts with both volatility and stock market returns in Southeast Asian markets. This gap in the literature is especially noteworthy given the region's heightened sensitivity to external disruptions.

This study seeks to fill a gap in the literature by providing empirical evidence on the impact of geopolitical risk on stock market volatility and returns across six Southeast Asian countries. The findings reveal that, contrary to much of the existing literature, GPR does not amplify short-term market volatility; instead, it appears to play a stabilizing role, reflecting the region's capacity for rapid shock absorption. Moreover, lagged GPR exerts a positive influence on subsequent stock returns, suggesting a potential for repricing and post-crisis recovery. These results not only contribute to a deeper academic understanding of GPR in the context of emerging markets but also carry important practical implications, offering valuable insights for investors and policymakers in designing effective strategies to navigate future global shocks.

The remainder of the paper is structured as follows. Section 2 provides a review of the relevant literature. Section 3 describes the data and research methodology. Section 4 presents the empirical results and discussion. Section 5 offers concluding remarks.

2. Measuring an Inefficient Market

2.1. The impact of geopolitical risk on stock market volatility

Theoretically, the relationship between geopolitical risk and stock market volatility can be traced back to foundational studies by Eugene & French (1992) [23], Fama (1970) [24], Frey &

Kucher (2001) [25], Sharpe (1964) [26] and is grounded in the notion that asset prices incorporate historical events [27]. From a behavioral finance perspective, Caldara & Iacoviello (2022) [2], He (2023) [28] find that geopolitical risk exerts a clear and powerful influence on investor sentiment. Guo & Shi (2024) [29] further argue that geopolitical tensions may trigger exaggerated psychological responses among investors. In the face of geopolitical events such as armed conflict, terrorism, or regional political instability, investors tend to become more cautious as their aversion to risk intensifies. This heightened risk perception leads to downward revisions in return expectations, diminished confidence in market outlooks, and a reallocation of capital toward safe-haven assets such as gold or government bonds. This "flight to safety" behavior places selling pressure on equity markets – particularly in emerging economies – thereby amplifying market volatility. In many instances, this effect is further intensified by media coverage, which can exacerbate panic and contribute to volatility spillovers across markets.

An alternative perspective offered by Bloom (2009) [11] suggests that when uncertainty in the economy rises – such as during periods of heightened geopolitical risk – both investors and firms tend to delay or suspend investment and consumption decisions. This hesitation triggers sharp short-term market reactions, often reflected in greater fluctuations in asset prices. Elevated volatility emerges as a consequence of imbalances between supply and demand during periods of defensive market sentiment. Geopolitical risk is regarded as a key driver of such uncertainty and, as a result, can have a direct and significant impact on instability in financial markets.

A growing body of empirical research highlights the significant role of geopolitical risk in amplifying stock market volatility, particularly in emerging and developing economies. Using a Panel GARCH framework, Bouras et al. (2019) [15] show that global GPR has a pronounced impact on market volatility, whereas the influence of country-specific GPR is relatively weaker. Similarly, Salisu et al. (2022) [10] employing a GARCH-MIDAS model, find that markets in emerging economies exhibit stronger reactions to GPR – especially when risk manifests as concrete actions rather than mere threats. Expanding on this approach, Segnon et al. (2024) [27] introduce a GARCH-MIDAS model integrated with a Markov-switching mechanism to disentangle the short- and long-term effects of GPR, concluding that geopolitical risk significantly enhances volatility forecasting accuracy. In a different methodological direction, Niu et al. (2023) [30] apply machine learning models and reveal that GPR associated with war escalation and military conflict exerts the greatest impact on U.S. stock market volatility. At the sectoral level, Guo and Shi (2024) [29] utilize quantile regression and find that GPR originating from China and the United States exerts heterogeneous and asymmetric effects across industries and market conditions, particularly at the lower and upper quantiles. Collectively, these findings suggest that GPR not only heightens volatility but also improves risk forecasting, with its impact varying by risk type, country context, and institutional characteristics of financial markets.

2.2. The impact of geopolitical risk on stock market returns

Several foundational theories help explain the relationship between geopolitical risk and stock market returns. Sharpe's (1964) [26] Capital Asset Pricing Model (CAPM) establishes the link between expected returns and systematic risk. According to this framework, when systemic risk – such as GPR – increases, investors demand higher risk premiums, which leads to a decline in asset prices and, consequently, affects returns. At the same time, Fama's (1970) [24] Efficient Market Hypothesis posits that asset prices fully reflect all available information, including news related to geopolitical shocks. This implies that GPR can quickly influence market valuations and equity returns.

In addition, Bloom's (2009) [11] uncertainty theory has been widely used to explain the effect of geopolitical risk on stock returns. According to this framework, heightened uncertainty in the economic environment – such as that caused by war or political conflict – tends to delay investment and consumption decisions, resulting in slower growth and a negative impact on firms' expected earnings. From a behavioral perspective, research in behavioral finance suggests that GPR can trigger adverse emotional responses among investors, including loss aversion, herd behavior, and negativity bias. These reactions often lead to irrational pricing and abnormal return fluctuations during periods of geopolitical instability.

In terms of transmission channels, geopolitical risk can influence stock market returns by altering the flow of international capital. As geopolitical tensions rise, global investors tend to withdraw from high-risk markets – such as emerging economies – and shift their capital toward safe-haven assets in developed countries [31]. This reallocation often triggers large-scale capital outflows from vulnerable stock markets, leading to falling equity prices and corresponding declines in returns [32, 33]. The impact is particularly pronounced in economies with high financial openness and strong dependence on foreign capital, such as those in Southeast Asia, where the effects of GPR-induced capital flight are more immediate and substantial [34].

Empirical studies examining the impact of geopolitical risk on stock market returns consistently show that GPR triggers strong negative reactions in financial markets. Umar et al. (2022) [35] and Ahmed et al. (2023) [36], analyzing the Russia – Ukraine conflict, report significant declines in stock returns across both European and Russian markets, with varying negative responses across sectors and countries. They also highlight a notable increase in global financial market interconnectedness during the crisis. Research by Balcilar et al. (2018) [37] on BRICS economies, along with studies by Brounen & Derwall (2010) [38], Chen & Siems (2007) [39], Chesney et al. (2011) [40] on the effects of terrorist attacks, also document adverse impacts of GPR, marked by sharp increases in stock market volatility – particularly in the lower quantiles associated with downside risk. Overall, the literature suggests that stock markets tend to respond swiftly and negatively to geopolitical events, but often demonstrate a relatively quick recovery in the short term – except in the case of exceptionally severe incidents, such as the September 11 attacks.

2.3. The relationship between stock market volatility and returns

The relationship between stock market returns and volatility has long been a central topic in financial economics. Classical asset pricing models, such as the Capital Asset Pricing Model by Sharpe (1964) [26] and the Intertemporal CAPM (ICAPM) by Merton (1973) [41], posit a positive relationship between expected returns and risk, with volatility commonly serving as a proxy for risk. However, empirical evidence on this relationship has been mixed and inconclusive.

Baillie & DeGennaro (1990) [42] employed the GARCH-in-Mean model to examine this relationship and found that, although a positive link between expected returns and volatility is theoretically plausible, the empirical evidence is weak and statistically insignificant when using daily and monthly data. Extending the analytical framework, Li et al. (2005) [43] applied a semiparametric approach and discovered that in several major global markets, the relationship between expected returns and volatility is negative and statistically significant. This finding suggests that rising volatility may substantially erode equity returns.

Theoretically, two primary channels are often cited to explain the negative relationship between returns and volatility. The first is the leverage effect, introduced by Black (1976) [44], which posits that negative returns increase a firm's financial leverage, thereby leading to higher volatility. The second is the volatility feedback hypothesis [45, 46], which suggests that when investors anticipate higher future volatility, they demand higher expected returns, resulting in a decline in current stock prices. These hypotheses have received strong empirical support, particularly in the U.S. market [47, 48], and have also been validated in international markets, as demonstrated by Li et al. (2005) [43], especially when using volatility models with flexible specifications.

The relationship between returns and volatility in stock markets remains a subject of ongoing interest in recent research. In India’s fintech market, despite high levels of risk, investors are still able to achieve attractive returns that correspond to the level of risk undertaken [49]. In contrast, broader studies on the Indian stock market suggest that expected returns do not increase significantly with rising market volatility, indicating a lower risk premium than commonly anticipated by investors [50]. Within BRICS economies, the link between returns and volatility has also been shown to be heterogeneous. In most cases, no clear relationship is observed, with the notable exception of the South African market, where a more pronounced connection has been confirmed [51].

These findings suggest that empirical studies have yet to reach a consensus, reinforcing the view that the relationship between returns and volatility is inherently unstable. It appears to be highly dependent on the specific characteristics of individual markets, varies over time, and is sensitive to the choice of econometric model employed.

3. Methodology

3.1. *Data*

This study investigates the impact of geopolitical risk on stock markets in Southeast Asia, focusing on Indonesia, Singapore, Thailand, Malaysia, the Philippines, and Vietnam. Specifically, the analysis examines whether GPR influences stock market returns and volatility across these countries. In addition, the study explores the relationship between stock returns and market volatility within the region.

The dataset includes a monthly geopolitical risk index, as well as daily stock market indices for each country, from which monthly return and volatility measures are derived. Monthly yields on one-year government bonds are used as the risk-free rate to compute excess returns (RET).

All data are collected over the period from November 1, 2011, to January 31, 2025. The geopolitical risk index is obtained from the website: policyuncertainty.com, while stock market indices and one-year government bond yields for each country are sourced from Investing.com. The variables are described in the table below:

Table 1. Variable description

Variable	Description	Formula	Reference
vola	Monthly realized volatility, measured as the standard deviation of daily returns within each month for a given market index, measuring market volatility and reflecting market risk.	$= \sqrt{\frac{1}{N}\sum_{t=1}^{N}(R_t - \overline{R})^2}$	[52-54]
RET	Monthly excess market return, calculated as the difference between the stock index return and the risk-free rate, reflecting the risk premium demanded by the market.	= returnt – rft	[55]
dGPR	Monthly change in the geopolitical risk index, capturing the degree of variation in geopolitical risk from month to month.	= GPRt - GPRt-1	[2]

Source(s): Authors' calculation based on collected data

3.2. P-VARX model

To examine the impact of geopolitical risk on stock market returns and volatility across Southeast Asian countries, this study employs a Panel Vector Autoregressive model with exogenous variables, grounded in the methodological framework of Holtz-Eakin et al. (1998) [56]. The choice of this model is motivated by the nature of the dataset, which combines both temporal and cross-sectional dimensions (panel data from six Southeast Asian stock markets). The endogenous variables – market volatility (vola) and excess returns (RET) – are likely to exhibit dynamic interdependence and mutual endogeneity [57]. By incorporating shocks from geopolitical risk (dGPR) as an exogenous variable into the VAR framework, the model allows for a more precise identification of the one-directional impact of geopolitical risk, while preserving the ability to capture feedback effects between the endogenous variables [58]. Compared to single-equation regression models, the P-VARX approach enables the use of impulse response functions (IRFs) and forecast error variance decomposition (FEVD), thereby providing deeper insights into the transmission mechanisms and absorption capacity of Southeast Asian stock markets in response to geopolitical shocks.

The regression equation employed in the analysis is specified as follows:

$$\mathbf{Y}_{i,t} = \mathbf{A}_0 + \mathbf{A}_1\mathbf{Y}_{i,\,t-1} + \mathbf{A}_2\mathbf{Y}_{i,\,t-2} + \ldots + \mathbf{A}_p\mathbf{Y}_{i,\,t-p} + \mathbf{B}\mathbf{X}_{t-1} + \boldsymbol{\alpha}_i + \boldsymbol{\varepsilon}_{i,t}$$

Where: $\mathbf{Y}_{i,t}$ is the vector of endogenous variables, including vola and RET; $\mathbf{A}_t$ is the matrix of coefficients; $\mathbf{X}_{t-1}$ is the vector of exogenous variables at time t-1, including dGPR; **B** is the coefficient matrix for the exogenous variables; **p** is the lag order of the model; $\boldsymbol{\alpha}_i$ captures country-specific fixed effects; and $\boldsymbol{\varepsilon}_t$ is the vector of idiosyncratic error terms.

The optimal lag length p in the P-VARX model is determined based on a set of information criteria, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan–Quinn Criterion (HQIC), and Forecast Prediction Error (FPE). These criteria strike a balance between model fit and parsimony by penalizing excessive parameterization.

To ensure the stability of the P-VARX model, all variables included in the system must be stationary. The Augmented Dickey – Fuller (ADF) test is applied to each time series to verify stationarity. Once the optimal lag length is identified and stationarity is confirmed, the P-VARX model is estimated to quantify the dynamic relationships among the variables.

To explore the interaction between stock market returns and volatility, this study employs impulse response functions (IRFs) and forecast error variance decomposition (FEVD). This approach provides insights into the transmission mechanisms and the temporal dynamics of spillovers between returns and risk across Southeast Asian stock markets.

4. Results

4.1. Descriptive Statistics and Preliminary Analysis

Table 2. Descriptive Statistics

		vola	RET	dGPR
Indonesia	Mean	0.956	-0.0925	0.0672
	Median	0.605	0.359	-1.01
	Standard Deviation	1.50	3.70	25.4
	Kurtosis	75.5	6.60	9.38
	Skewness	7.58	-1.22	0.245
	Minimum	0.141	-18.8	-128
	Maximum	16.5	8.69	103
Singapore	Mean	0.653	0.145	0.0672
	Median	0.436	0.536	-1.01
	Standard Deviation	1.15	3.79	25.4
	Kurtosis	99.2	6.80	9.38
	Skewness	9.11	-0.991	0.245
	Minimum	0.0866	-19.4	-128
	Maximum	13.5	9.36	103
Thailand	Mean	0.874	0.0426	0.0672
	Median	0.514	0.402	-1.01
	Standard Deviation	1.79	4.21	25.4
	Kurtosis	105	5.95	9.38
	Skewness	9.38	-0.157	0.245
	Minimum	0.0513	-17.5	-128.
	Maximum	21.1	16.4	103
Malaysia	Mean	0.424	-0.219	0.0672
	Median	0.258	0.0802	-1.01
	Standard Deviation	0.634	2.89	25.4
	Kurtosis	81.1	3.69	9.38
	Skewness	7.83	-0.330	0.245
	Minimum	0.0438	-9.53	-128
	Maximum	7.15	6.75	103
Philippines	Mean	1.37	-0.0778	0.0672
	Median	0.948	0.471	-1.01
	Standard Deviation	2.30	4.78	25.4
	Kurtosis	88.4	6.60	9.38
	Skewness	8.53	-1.17	0.245
	Minimum	0.218	-24.6	-128
	Maximum	26.1	9.26	103
Vietnam	Mean	1.32	0.368	0.0672
	Median	0.856	0.865	-1.01
	Standard Deviation	1.34	5.91	25.4
	Kurtosis	9.55	5.98	9.38
	Skewness	2.32	-0.764	0.245
	Minimum	0.118	-28.9	-128
	Maximum	8.48	14.8	103

Source(s): Authors' calculation based on collected data

Based on the descriptive statistics of Southeast Asian stock markets during the study period, as presented in Table 2, which summarizes key variables across countries, notable differences are observed in volatility, returns, and sensitivity to geopolitical risk – largely driven by substantial fluctuations in the underlying indicators.

There are significant cross-country differences in market characteristics among the six Southeast Asian economies, particularly in terms of return volatility, excess returns, and variations in geopolitical risk. With regard to stock market volatility (vola), the Philippines and Vietnam exhibit the highest average volatility levels, at 1.37 and 1.32 respectively, indicating pronounced monthly return fluctuations. In contrast, Malaysia and Singapore report lower average volatility, reflecting relatively greater short-term market stability. However, despite these differences in means, all markets display clear evidence of fat-tailed distributions, with kurtosis values well above the standard benchmark of 3 for a normal distribution—suggesting a much higher frequency of extreme shocks than would be expected under normality. Skewness values are positive and substantial across the board, particularly in Thailand (9.38) and Singapore (9.11), pointing to right-skewed distributions and a higher likelihood of sudden upward price movements.

The average excess return (RET) across markets hovers around zero, with Vietnam standing out as the only country registering a significantly positive mean (0.368), while most others show slightly negative averages. Importantly, the distribution of RET exhibits marked asymmetry. All skewness coefficients are negative, indicating that, during large shocks, downside movements tend to be more severe than upside gains – implying that losses dominate in magnitude. Moreover, kurtosis values for RET are consistently above the normal threshold, suggesting fat-tailed distributions and a relatively high probability of extreme returns. This is a common trait in emerging markets, where investor sentiment is highly sensitive to adverse news and market conditions are often less stable.

As for the geopolitical risk variable (dGPR), the statistics show a slightly positive mean but a negative median, alongside a very high standard deviation. This indicates that geopolitical factors tend to fluctuate substantially and are more often associated with periods of instability (as reflected in the negative median), although there are also episodes of marked improvement in geopolitical conditions (when dGPR drops sharply). The wide range – from -128 to 103 – underscores the intensity of geopolitical swings, further suggesting that Southeast Asian stock markets may be highly susceptible to major geopolitical events..

In summary, the descriptive statistics reveal that the financial variables under study are characterized by asymmetric and fat-tailed distributions. These features not only underscore the high-risk nature of regional markets but also point to the potential presence of feedback mechanisms between volatility and returns – a relationship consistent with the volatility feedback hypothesis, which has been supported by a wide body of empirical research

4.2. Stationarity tes

To ensure the validity, stability, and predictive capacity of the P-VARX model, the study conducts a stationarity test – a crucial step in time series analysis. Specifically, the Augmented Dickey-Fuller (ADF) test is employed to assess the stationarity of the variables. The test results confirm that all variables included in the model are stationary time series.

Table 3. Stationarity test

		vola	RET	dGPR
Indonesia	**Dickey-Fuller**	-5.27	-4.84	-6.05
	P-value	0.01	0.01	0.01
	Time series	Stationary	Stationary	Stationary
Singapore	**Dickey-Fuller**	-5.10	-4.22	-6.09
	P-value	0.01	0.01	0.01
	Time series	Stationary	Stationary	Stationary
Thailand	**Dickey-Fuller**	-5.07	-4.89	-5.34
	P-value	0.01	0.01	0.01
	Time series	Stationary	Stationary	Stationary
Malaysia	**Dickey-Fuller**	-5.03	-3.83	-4.92
	P-value	0.01	0.0193	0.01
	Time series	Stationary	Stationary	Stationary
Philippines	**Dickey-Fuller**	-4.98	-4.71	-5.83
	P-value	0.01	0.01	0.01
	Time series	Stationary	Stationary	Stationary
Vietnam	**Dickey-Fuller**	-5.68	-5.18	-5.49
	P-value	0.01	0.01	0.01
	Time series	Stationary	Stationary	Stationary

Source(s): Authors' calculation based on collected data

The stationarity test results for the three key variables – return volatility (vola), excess returns (RET), and geopolitical risk (dGPR) – across six Southeast Asian stock markets indicate that all time series are stationary at the 1% significance level. Specifically, the Dickey-Fuller test statistics for all three variables in each country are lower than their respective critical values, with p-values below 0.01. These findings lead to a rejection of the null hypothesis of a unit root, confirming that the series do not exhibit non-stationary behavior and instead fluctuate around a constant mean throughout the study period.

Establishing stationarity at level form is a critical prerequisite for the reliability of subsequent regression and econometric analyses – particularly in dynamic frameworks such as the P-VARX model and related forecasting techniques. Furthermore, the stationarity of the dGPR variable – measured as the first difference of the geopolitical risk index – supports its treatment as an exogenous regressor within the extended VAR framework. This specification helps mitigate the risk of spurious correlations and ensures the statistical validity of inference. Overall, the test results reinforce the robustness and credibility of the dynamic models employed in the study.

4.3. Determining the optimal lag length

By exploring various lag specifications and applying multiple information criteria – including the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Hannan-Quinn Criterion (HQIC), and the Forecast Prediction Error (FPE) – the optimal lag length for the VAR model is determined, based on the AIC, to be one (see Table 4).

Table 4. VAR Order Selection (* Highlights the minimums)

	AIC	BIC	HQIC	FPE
1	3.450086*	3.542723*	3.485396*	31.50324*
2	3.477494	3.617871	3.531035	32.37902
3	3.477271	3.666377	3.549442	32.37257
4	3.507473	3.746332	3.598690	33.36658
5	3.542372	3.832045	3.653065	34.55385
6	3.572070	3.913655	3.702684	35.59886
7	3.583735	3.978369	3.734733	36.02144
8	3.581571	4.030432	3.753431	35.95020
9	3.615382	4.119693	3.808603	37.19559
10	3.649010	4.210038	3.864107	38.47985

Source(s): Authors' calculation based on collected data

4.4. Estimating the P-VARX Model

Table 5. Summary of Regression Results

		Coefficients	*Standard Error*	*t Stat*	*P-value*
vola	**Lag1.vola**	0.2285***	0.0332	6.8732	0.0000
	Lag1.RET	-0.0442***	0.0119	-3.7038	0.0002
	Lag1.dGPR	-0.0105***	0.0019	-5.5269	0.0000
RET	**Lag1.vola**	0.4146***	0.0968	4.2857	0.0000
	Lag1.RET	0.0682*	0.0348	1.9621	0.0497
	Lag1.dGPR	0.0217***	0.0055	3.9215	0.0000

Source(s): Authors' calculation based on collected data

The estimation results from the P-VARX model reveal the dynamic and complex interplay between market volatility, excess returns, and geopolitical risk in Southeast Asian stock markets.

To begin with, lagged market volatility (Lag1.vola) exerts a strong and statistically significant positive effect on current volatility (coefficient = 0.2285, p-value < 0.001). This finding reflects the well-documented phenomenon of volatility clustering, commonly observed in financial markets: once a market experiences high volatility, it tends to remain volatile for some time. Conversely, lagged excess returns (Lag1.RET) have a negative and significant impact on current volatility (coefficient = -0.0442, p-value < 0.001), suggesting that periods of high excess returns are often followed by market stabilization and reduced volatility. This dynamic points to a natural adjustment mechanism in investor behavior after periods of strong performance.

Regarding the influence of geopolitical risk, the lagged value of dGPR (Lag1.dGPR) shows a clear and strongly significant negative effect on market volatility (coefficient = -0.0105, p-value < 0.001). This counterintuitive result may reflect the rapid and effective adaptation of investors in Southeast Asian markets. When confronted with geopolitical shocks, investors tend to swiftly revise expectations and rebalance portfolios, often reallocating capital toward safer assets. Such prompt adjustments help mitigate uncertainty in subsequent periods, enabling markets to stabilize and dampening large fluctuations. This underscores the role of defensive investor behavior and rapid information absorption in moderating market reactions during geopolitical turmoil.

With respect to excess returns, several noteworthy patterns also emerge. First, lagged volatility (Lag1.vola) has a strong positive effect on current excess returns (coefficient = 0.4146, p-value < 0.001), which aligns well with classical financial theory on risk compensation – higher past volatility leads investors to demand greater returns to offset perceived risk. Additionally, lagged excess returns (Lag1.RET) continue to exert a positive, albeit weaker, effect on current returns (coefficient = 0.0682, p-value < 0.05), indicating a degree of return persistence across Southeast Asian markets.

Most strikingly, lagged geopolitical risk (Lag1.dGPR) exhibits a significant and robust positive impact on current excess returns (coefficient = 0.0217, p-value < 0.001). This result suggests that Southeast Asian equity markets not only absorb geopolitical shocks quickly but also provide conditions that enable investors to earn higher excess returns in the immediate aftermath. Such a mechanism may stem from more proactive portfolio repositioning once markets have internalized the shock, allowing investors to capitalize on profitable opportunities during the recovery phase.

Overall, the model results highlight the multidimensional and asymmetric nature of Southeast Asian markets' responses to geopolitical risk. While geopolitical tensions typically heighten short-term uncertainty, this effect tends to be swiftly absorbed and, in many cases, converted into opportunities for return enhancement in the following period. These insights hold valuable implications for investors, risk managers, and policymakers in designing investment strategies and policy responses to geopolitical shocks.

4.5. Impulse Response Function (IRF) Analysis

To shed light on the immediate response and dynamic adjustment between stock returns and market volatility, the study employs impulse response function (IRF) analysis. This method traces the trajectory of one variable's reaction over time following a one-unit shock to another variable. Estimating the IRF, along with bootstrap confidence intervals, allows for the identification of the magnitude, direction, and duration of the response across all Southeast Asian stock markets. The analysis provides quantitative evidence on how risk propagates to returns and vice versa. The IRF results are presented in Figure 1.

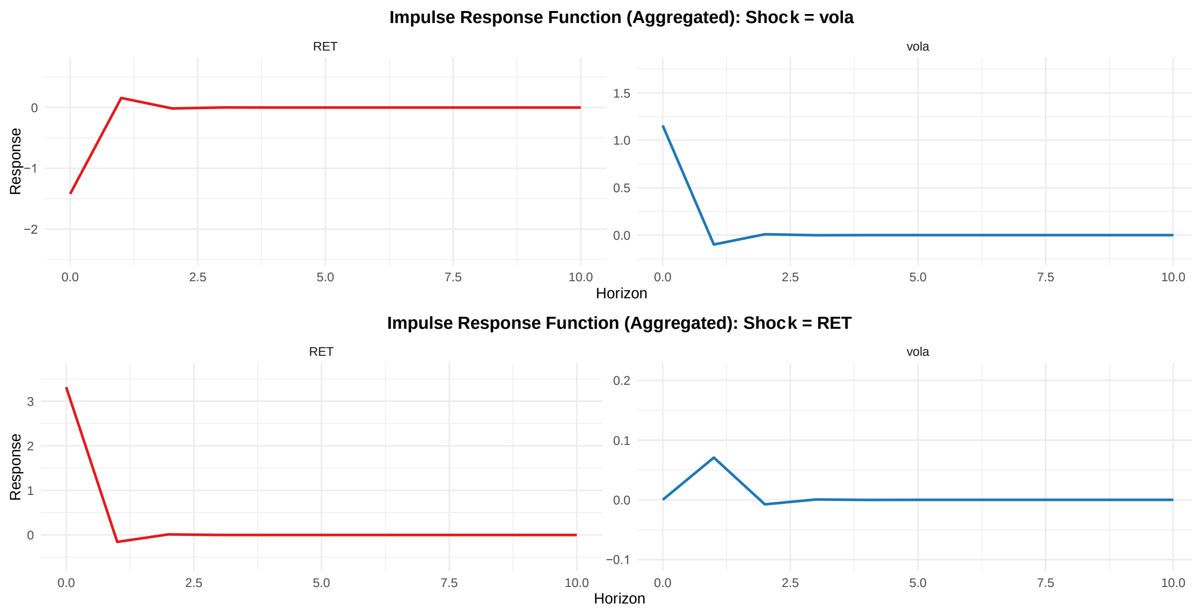

Figure 1. Impulse responses (orthogonalized)

Source(s): Authors' calculation based on collected data

The aggregated impulse response function (IRF) clearly illustrates the transmission dynamics of shocks between two key variables: excess returns (RET) and return volatility (vola). When Southeast Asian stock markets experience a volatility shock, an immediate spike in market volatility is observed. However, this elevated volatility gradually diminishes over time, returning to equilibrium. This pattern is consistent with established financial theory and empirical evidence, reflecting the well-documented phenomenon of volatility clustering – the tendency for periods of high volatility to occur in short-lived bursts, followed by a gradual decline [45, 59-61]. In contrast, volatility shocks have a pronounced negative impact on excess returns, underscoring a cautious, risk-averse response from investors [48, 61, 62]. When market volatility increases sharply, investors lower their short-term return expectations, leading to a decline in excess returns. However, this decline is most pronounced in the immediate aftermath of the shock and gradually subsides, suggesting that the adverse effect is temporary in nature.

Conversely, when a positive shock to excess returns occurs, markets respond with an immediate uptick in returns. Yet this initial gain is quickly followed by a reversion toward a more stable level, reflecting the market's natural adjustment after short-term exuberance [63, 64]. Simultaneously, market volatility rises in response to the unexpected surge in returns [62]. This behavior captures the inherent risk–return trade-off: while a positive return shock fuels investor optimism and higher expectations, it also introduces greater uncertainty, prompting increased volatility in the periods that follow before eventually stabilizing.

Overall, the IRF analysis sheds light on the dynamic and bidirectional nature of the relationship between returns and volatility. On one hand, volatility shocks tend to suppress returns as investors adopt a more defensive stance. On the other, positive return shocks heighten short-term volatility, reflecting increased risk-taking and uncertainty. These findings support theoretical arguments regarding the complex interplay between risk and return, while offering practical insights for investors, risk managers, and policymakers in formulating strategies to mitigate downside risk and capitalize on emerging market opportunities.

4.6. Forecast Error Variance Decomposition (FEVD)

To quantify the relative contribution of each shock to the system's forecast errors, the study further employs the Forecast Error Variance Decomposition (FEVD) technique. FEVD disaggregates the proportion of each variable's forecast error variance that is attributable to its own innovations versus those originating from other variables, across different forecast horizons. This approach complements the impulse response analysis by providing a clearer assessment of the extent and direction of spillovers between returns and market volatility over time. In doing so, it helps identify the dominant sources of risk driving stock price fluctuations in Southeast Asian markets. The FEVD results are presented in Figure 2.

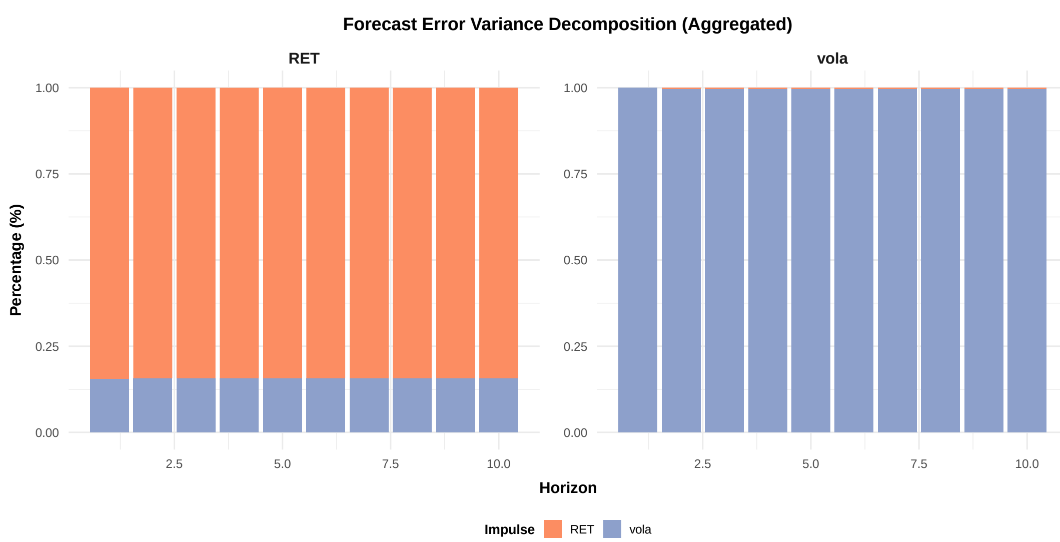

Figure 2. Forecast error variance decomposition (FEVD)

Source(s): Authors' calculation based on collected data

The aggregated Forecast Error Variance Decomposition (FEVD) results offer valuable insights into how each variable contributes to the explanation of its own future fluctuations as well as those of the other. Specifically, excess returns (RET) are found to be explained almost exclusively by their own shocks across all forecast horizons, whether short-, medium-, or long-term [65]. This indicates that excess returns in Southeast Asian stock markets are predominantly driven by internal factors and remain largely insulated from the influence of market volatility.

As for return volatility (vola), it also appears primarily self-explanatory throughout the various forecast horizons [65]. Although the explanatory contribution of excess returns to volatility exhibits a modest increase over longer horizons, the magnitude of this effect remains notably limited. In other words, returns have minimal influence on volatility – even when considering extended forecast periods.

Overall, the FEVD analysis underscores a relatively weak interdependence between returns and volatility within the region. These two variables appear largely autonomous, each driven by its own underlying factors rather than mutual interaction. Such findings align closely with earlier impulse response function (IRF) results, collectively suggesting that investors and risk managers should approach these variables as distinct considerations when formulating investment strategies and managing risk exposure in Southeast Asian financial markets.

5. Conclusion

This study provides new empirical evidence concerning the impact of geopolitical risk on stock market volatility and returns across six Southeast Asian countries. Descriptive statistical results indicate that these regional markets are characterized by pronounced volatility, fat-tailed distributions with notable right-skewness in volatility, and left-skewed distributions for returns. Such characteristics underscore the substantial uncertainty and heightened sensitivity of the region to external shocks.

Employing a panel VARX (P-VARX) approach, the analysis reveals significant persistence in market volatility, consistent with the well-established phenomenon of volatility clustering documented extensively in foundational theories [26, 41]. However, in contrast to findings from earlier studies such as [15] and [10], this research finds that geopolitical risk does not lead to an increase in short-term market volatility. On the contrary, lagged geopolitical risk exhibits a significantly negative impact on current volatility, suggesting that Southeast Asian markets rapidly absorb geopolitical shocks. This dynamic likely reflects adaptive market mechanisms and the swift defensive responses of regional investors, providing a fresh perspective relative to prior international evidence, which predominantly emphasizes immediate negative impacts of GPR on market volatility.

Additionally, lagged geopolitical risk positively influences subsequent excess returns, highlighting the rapid recovery and opportunistic behavior of markets following periods of uncertainty. From a behavioral finance viewpoint, this could be attributed to investors initially overreacting to negative events, triggering significant market adjustments. Subsequently, as new information is gradually assimilated, markets undergo repricing processes, creating conditions conducive to returns recovery. This insight enriches existing knowledge about the relationship between GPR and stock returns and offers a contrast to prior studies – such as [35] and [36] – that have typically emphasized prolonged negative market reactions within developed economies.

Further analyses employing impulse response functions (IRF) and forecast error variance decompositions (FEVD) clarify the dynamic interplay between returns and volatility in the stock markets examined. Specifically, volatility shocks tend to depress returns in the short run, indicating heightened investor risk aversion. Conversely, positive return shocks provoke increased volatility, demonstrating that higher return expectations in emerging markets frequently coincide with greater risk. These findings reinforce the volatility feedback hypothesis proposed by [46] and [45], according to which heightened risk expectations tend to depress stock prices. Additionally, the analysis reveals an asymmetric interaction between returns and volatility, underscoring a complex, conditional relationship evolving over time in Southeast Asian markets.

In summary, this research contributes significantly to the literature on geopolitical risk and financial markets by providing novel empirical evidence from the Southeast Asian context, where GPR not only heightens uncertainty but also activates mechanisms of rapid market adjustment and recovery. These findings hold critical implications for policymakers and investors alike, highlighting the importance of adopting flexible risk management and investment strategies in a global environment increasingly characterized by intricate and intensifying geopolitical risks.

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