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Research paper

Cryptocurrency Price Volatility and Safe-Haven Properties During Geopolitical Shocks

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Abstract

This study investigates the impact and spillover effects on major cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH) and Tether (USDT) amid geopolitical shocks, employing a Vector Autoregressive, Granger Causality, Variance Decomposition and to test the spillover impact, the approach Time-Varying Parameter Vector Autoregression (TVP-VAR) model is implemented. Drawing on daily data from November 25th, 2019, to September 19th, 2025, we incorporate traditional safe-haven proxies (GC.F) and risky assets (CL.F); global equity (URTH) and benchmarks like the (VIX) volatility index, Economic Policy Uncertainty (EPU) index. Our findings reveal that BTC and ETH exhibit time-varying hedge properties during low-to-moderate volatile episodes but fail as safe havens during extreme shocks. USDT demonstrates superior stability as a digital safe-haven. Policy implications underscore the maturation of crypto markets for portfolio diversification, contingent on shock intensity.

Keywords: *Cryptocurrency; Volatility; Safe-Haven Assets; Geopolitical Shocks; TVP-VAR.*

1. Introduction

Cryptocurrencies, especially Bitcoin (BTC), Ethereum (ETH), and Tether (USDT), have revolutionized global financial markets over the past decade, emerging not merely as speculative investments but as alternative stores of value during moments of acute economic distress. Their behavior and value dynamics during geopolitical shocks have become a major focal point for academic and policy research, especially as traditional safe-haven assets like gold and government bonds face new challenges in a fast-evolving risk landscape (Mo, 2025). The multifaceted role of digital assets in investors' portfolios, ranging from hedge instruments to potential safe-havens, demands a deeper empirical investigation, particularly given the unprecedented volatility triggered by recent global events, wars, and regulatory interventions (Yae, 2024). The last few years have witnessed seismic changes in global risk indicators, reflected through spikes in indices such as the VIX (Volatility Index) and EPU (Economic Policy Uncertainty Index), as well as dramatic corrections in equity and commodity markets. Against this backdrop, cryptocurrencies have displayed unique volatility profiles; while their price movements are often magnified compared to traditional assets, periods of uncertainty see remarkable increases in trading volumes and investor demand for digital assets, as observed during pandemic-induced market stress and geopolitical flashpoints (Zhang, 2024; Long, 2022). In many countries, especially developing economies, Bitcoin has acted as a buffer during currency devaluations, high inflation, and external shocks, signaling its evolving role as a shelter from systemic risk and as a vehicle for value preservation in turbulent times (Petti & Sergio, 2024).

A central question explored in this research is the extent to which cryptocurrencies genuinely serve as safe havens during geopolitical disruptions, particularly in relation to critical variables like the VIX, global equity indices (URTH), gold (GC.F), crude oil (CL.F), and policy uncertainty (EPU). Prior research suggests that Bitcoin's volatility far exceeds that of the S&P 500 and other traditional assets, challenging its long-term suitability as a safe-haven and raising concerns about its effectiveness as a hedge (Yae, 2024; Kumar et al., 2022). Nevertheless, findings also reveal short-term resilience: Bitcoin often outperforms equities or maintains value when shocks first occur, leading investors to seek rapid exposure to crypto markets in response to intensified risk (Investing.com, 2025). This duality, high volatility but short-term stability, anchors the contemporary debate about cryptocurrency's safe-haven potential. The importance of studying these dynamics cannot be overstated, as escalating geopolitical risks have forced asset managers, government agencies, and retail investors to rethink diversification strategies for the digital age. The Russia-Ukraine war, ongoing US-China tensions, Middle East crises, and global financial disruptions have fundamentally changed the way participants view risk, information transmission, and market correlations. Recent work finds that not all cryptocurrencies are affected equally by geopolitical shocks; coins with lower geopolitical beta tend to outperform during periods of high risk, while others suffer substantial drawdowns (Long, 2022; Mo, 2025). Such findings suggest nuanced relationships and highlight the demand for empirical models capable of capturing time-varying causality, dynamic correlations, and nonlinear market reactions.

This paper addresses critical gaps in the literature by rigorously evaluating the causal impacts of major risk indicators on the volatility and safe-haven properties of leading cryptocurrencies, employing robust methodologies including VAR, Granger causality, nonlinear Granger causality, impulse response functions, and TVP-VAR models. By integrating these approaches, the research enables precise identification of information flows, volatility transmission, and asymmetric effects, offering actionable insight for both academics and market practitioners. Notably, while many earlier studies focus exclusively on Bitcoin's price or sentiment transmission, this work leverages multiple market and macroeconomic indicators to construct a comprehensive framework for testing relationships and hedging effectiveness across diverse asset classes (Zhang, 2024). The role of policy uncertainty and media attention has become pivotal in shaping crypto market reactions. Studies now show that shocks in EPU or direct changes in geopolitical risk indices can trigger both long-lasting and immediate shifts in trading patterns, liquidity, and bid-ask spreads (Zhang et al., 2023; Yae, 2024). Increased investor attention, whether due to speculation or a flight to safety, has transformed cryptocurrency markets from niche financial ecosystems into globally relevant barometers of risk sentiment. This transition emphasizes the need for advanced econometric techniques, including TVP-VAR and nonlinear Granger causality, to adequately capture evolving interasset linkages and identify periods when cryptocurrencies transition from risk-on assets to safe havens (Doblas, 2023).

Moreover, as institutional investors and hedge funds allocate more assets to cryptocurrencies, the underlying market dynamics are shifting from speculative, retail-driven cycles to a landscape dominated by cross-asset arbitrage, regulatory considerations, and sophisticated risk management practices (Yae, 2024). Time-varying correlations integral for assessing diversification and portfolio optimization now determine the hedging demands for crypto assets, impacting equilibrium prices, investor behavior, and policy responses (Gao & Nardari, 2018). Analyzing these shifts is essential for understanding the consequences of regulatory interventions, like quantitative easing, which have direct implications for cryptocurrency valuations (JFRC, 2024). In investigating these phenomena, this paper models not only first-moment dynamics (mean returns) but also volatility structures, extreme events, and structural breaks tied to major geopolitical shocks, a methodological advance over traditional single-equation models. The focus on conditional and time-varying causality facilitates a sharper understanding of how shocks are transmitted, how market participants respond under stress, and when crypto assets actually fulfill their presumed safe-haven role (Doblas, 2023; Zhang, 2024). The multi-layered framework spanning linear and nonlinear causality tests, impulse responses, and TVP-VAR analytics enables researchers to diagnose both transient and persistent effects, uncover asymmetric spillovers, and predict future risk scenarios in crypto markets.

2. Literature Review

Cryptocurrency volatility and its potential to act as a safe-haven asset during global shocks have gained significant attention in financial studies. Researchers have mainly focused on Bitcoin (BTC), Ethereum (ETH), and stablecoins like Tether (USDT), especially during times of market stress and geopolitical events. Other key financial variables, such as the VIX (volatility index), global equity indices, gold, crude oil, and economic policy uncertainty (EPU), have also been studied for their impacts on cryptocurrency markets. Early work by Baur & McDermott (2010) introduced the concept of safe-havens, which are assets that remain stable or appreciate during crises. Bouri et al. (2017, 2018) investigated Bitcoin's behavior using wavelet regression and found unique hedging features, especially during financial instability. Ustaoglu (2022) and Melki (2022) used portfolio analysis and found that Bitcoin and Ethereum could act as hedges and weak safe-havens for emerging stock markets under stress. Chemkha et al. (2021) focused on dynamic conditional correlations and confirmed that Bitcoin and gold serve as diversifiers, hedges, and sometimes weak safe-havens during the COVID-19 crisis.

Urquhart (2019) looked at safe-haven behavior at the currency level and found that Bitcoin acts as a hedge or safe-haven for major currencies, especially during extreme downturns. Gold was frequently compared, and studies showed that the two share some safe-haven features, especially during periods of high uncertainty. Research has shown that cryptocurrencies behave differently in the face of global disruptions. Attarzadeh et al. (2022) used the TVP-VAR model to study volatility spillovers and dynamic connections among crypto assets, gold, and the VIX during global crises. Their results show time-varying and asymmetric volatility transmission, especially during periods like COVID-19. Similarly, Cao et al. (2022) used TVP-VAR to track evolving connectedness among markets, finding that shocks such as pandemic-related news or wars increase spillovers to and from crypto markets.

Many studies utilized the VAR and ARDL models. Ferchichi et al. (2025) studied the Saudi market, using VAR and impulse response analysis, finding differing volatility and causal dynamics before and after major global shocks like the pandemic and the Russo-Ukrainian conflict. Hong et al. (2025) introduced extreme time-varying Granger causality tests, showing that shocks to oil markets and other assets could rapidly shift causal dynamics with cryptocurrencies.

Standard Granger causality models have established dynamic and sometimes bidirectional causal relationships between cryptocurrencies and other financial variables. Sarker et al. (2022) studied co-movements and Granger causality between Bitcoin, M2 money supply, inflation, and EPU in the UK and Japan. Their findings showed strong causality and dynamic spillovers, which intensified during crisis periods. Banerjee et al. (2022) used nonlinear Granger causality techniques and transfer entropy, finding that information flow between news sentiment, VIX, and cryptocurrency returns is mostly nonlinear and asymmetric. Nonlinear models were shown to offer a better picture of crypto market behavior in volatile times. Moni et al. (2025) compared linear and nonlinear models and confirmed that nonlinear causality and asymmetric spillovers are prevalent in cryptocurrency and commodity interactions, particularly during market shocks.

Quantile Granger causality tests have emerged as another robust method to capture complex interactions during times of stress, as shown by recent studies exploring causality between trade policy uncertainty and cryptocurrency returns. Impulse response functions (IRFs) are commonly used with VAR and TVP-VAR models to illustrate the effect of shocks in one market (like VIX or oil) on cryptocurrency prices. Studies by Yousaf et al. (2025) and Bibi et al. (2025) highlight how crypto price volatility responds to shocks in global risk, governance, and ESG indices. The flexibility of the TVP-VAR methodology allows these IRFs to track evolving market responses in real-time. Attarzadeh et al. (2022), Cao et al. (2022), and GSVI-based analyses (Panagiotidis et al., 2018) showed that time-varying models are superior in capturing shifts in relationships between cryptocurrencies, traditional assets, policy uncertainty, and investor sentiment. The Bayesian TVP-VAR approach also demonstrated how crypto returns are influenced more by internal crypto-market variables and sentiment than by traditional assets like oil or gold in some periods.

Other studies have examined the transmission of shocks from traditional markets, VIX, gold, oil, S&P 500, ESG indices and policy uncertainty (EPU) to cryptocurrency prices. These works consistently report that the influence is highly time-varying, crisis-dependent, and that cryptocurrencies may switch from being diversifiers to safe-havens as crises unfold and investor behavior adapts. The literature affirms that cryptocurrency price volatility and safe-haven properties are highly dependent on geopolitical shocks, market stress, and dynamic causal relationships with other financial variables. While VAR, Granger causality, nonlinear Granger causality models, impulse response functions, and TVP-VAR models play central roles in recent research, findings are consistent: crypto assets sometimes provide unique hedging and safe-haven benefits, but their status is not fixed and evolves with global events and information flows.

3. Data and Methodology

Since our study considers only return series, we collected data from Yahoo Finance. For returns, we calculated them using the formula: "Pt is the daily closing exchange rate at time t, and

rt = 100*Lg(Pt/Pt-1)

This formula was used to determine the foreign exchange returns. The data is collected from Yahoo Finance from November 25th, 2019, to September 19th, 2025, and then subjected to a variety of tests (using ADF, PP) to check for stationarity. Every return series is stationary at a level.

VAR Model: Unlike traditional models, VAR treats all factors as interconnected. Originally developed by Holtz-Eakin et al. (1988), VAR is now widely used in economics and finance.

$$y_t = \sum_{k=1}^{P} a_t y_{t-k} + u_t \tag{1}$$

Where Yt is a vector containing K endogenous variables, t=1 … T time periods, while Yt is specified as

$Y_t = BTC_t, ETH_t, USDT_t, URTH_t, VIX_t, GC_t, CL_t, EPU_t$

$Yt{-}k$ stands for the lagged estimates of the endogenous variables, and Ut is a $K{\times}I$ vector of random errors, and it is specified as

$$Ut=[U1t,U2t,\ldots\ldots UNt]\backslash{\sim}iid(0,\delta) \tag{1.1}$$

αt is allowed to be dependent cross-sectional. In cases where there exist exogenous variables,

$$Yt=\sum pk=1\alpha tYt-k+DijRt+Ut \tag{1.2}$$

Where Dij are $K{\times}M$ matrices for each lag j=1,…..p, and Rt is an $M{\times}1$ vector of exogenous covariates similar to all countries i Similarly, VAR can be expressed in a reduced form as follows:

$$Yt=\sum pk=1\alpha tYt-k+\tau 2Rt+\lambda i+\gamma t+et \tag{1.3}$$

If exogenous variables (Rit) are included, it departs from the specification of Love and Zicchino (2006). In this framework, $Yt{-}k$ denotes a three-variable vector [BTC_t, ETH_t, $USDT_t$, $URTH_t$, VIX_t, GC_t, CL_t, EPU_t], while Rt represents the exogenous variables, if present. The term λi captures country-specific fixed effects, reflecting unobserved time-invariant characteristics, whereas γt denotes time dummies that account for global economic shocks. Finally, et represents the disturbance term. Here, the concepts of hedge, diversifier, and safe-haven have been clearly defined following established literature (Baur and McDermott, 2010), where a hedge is an asset uncorrelated or negatively correlated on average, a diversifier is positively but imperfectly correlated, and a safe-haven is uncorrelated or negatively correlated specifically during periods of market stress; these definitions have been consistently applied throughout the revised manuscript.

Granger Causality: The Granger causality test will be conducted using a VAR (vector autoregression) model. This model is commonly used in econometrics to analyse interdependencies and progress between multiple time series. The VAR model treats all variables in the system symmetrically by including an equation for each variable to explain its evolution based on its lags and the lags of the other variables in the model. The VAR model used in this study will describe a set of variables measured over a time period as a linear function of solely their past changes. The VAR model will be estimated using symmetrical lags, meaning the same lag length will be applied to all variables in the model. To test for causal relationships between spot prices and futures prices, a system of equations will be applied, using two lags based on the AIC (Akaike information criterion) criterion.

TVP-VAR Approach: Researchers have studied how assets like stocks or cryptocurrencies connect over time using Diebold and Yılmaz's method, but its results depend on the window size, reducing accuracy. Antonakakis et al. (2020) improved this with a TVP-VAR model using a Kalman filter, offering more reliable, consistent, and accurate results even with small datasets.

$$z_t = B_t z_{t-1} + u_t u_t \sim N(0, S_t) \tag{6}$$

$$vec(B_t) = vec(B_{t-1}) + v_t v_t \sim N(0, R_t) \tag{7}$$

Where z_t, z_{t-1} and u_t are $k \times 1$ dimensional vectors and B_t and S_t are $k \times k$ dimensional matrices. vec(B_t) and v_t are $k^2{\times}1$ dimensional vectors, whereas R_t is a $k2 \times k2$ dimensional matrix.

The study uses a method called Generalized Forecast Error Variance Decomposition (GFEVD) to see how different factors, like Bitcoin or gold prices, affect each other over time. This method comes from the ideas of Koop et al. (1996) and Pesaran and Shin (1998). Unlike another approach by Diebold and Yilmaz (2009), GFEVD does not depend on the order of the factors, making it fairer. It is based on a math idea called the Wold representation theorem, which helps turn the time-varying model (TVP-VAR) into a different form (TVP-VMA) to study how shocks spread.

$$z_t = \Sigma_{i=1}^{P} B_{it} z_{t-1} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j} \tag{8}$$

The scaled Forecast Error Variance Decomposition (GFEVD) standardizes the unscaled GFEVD, denoted as ϕ_(ij,t)^g (H), to ensure that each row adds up to one. Therefore, ϕ̃_(+ij,t·)^g (H) represents the impact of variable j on variable i in relation to its share of forecast error variance. This signifies the directional influence from variable j to variable i. The indicator is expressed in the following manner:

$$\phi_{ij,t}^{g}(H) = \frac{S_{ii,t}^{-1}\sum_{t=1}^{H-1}\left(l_i' A_t s_t l_j\right)^2}{\sum_{j=1}^{k}\sum_{t=1}^{H-1}(l_i A_t s_t A_t' l_i)} \tag{9}$$

$$\tilde{\phi}_{+ij,t\cdot}^{g}(H) = \frac{\Phi_{ij,t}^{g}(H)}{\sum_{j=1}^{k}\phi_{ij,t}^{g}(H)} \tag{10}$$

With $\sum_{j=1}^{k}\tilde{\phi}_{ij,t}^{g}(H) = 1, \quad \sum_{i,j=1}^{k}\tilde{\phi}_{ij,t}^{g}(H) = k$ and (l_i)corresponds to a selection vector with unity on the ith position and zero otherwise.

Following the GFEVD framework, various measures of connectedness are developed, including total, directional, and pairwise measures (Diebold and Yilmaz, 2012, 2014).

$$TO_{jt} = \sum_{i=1, i\neq j}^{k}\tilde{\phi}_{ij,t}^{g}(H) \tag{11}$$

$$FROM_{jt} = \sum_{i=1, i\neq j}^{k}\tilde{\phi}_{ji,t}^{g}(H) \tag{12}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{13}$$

$$TCI_t = k^{-1}\sum_{j=1}^{k} T\,O_{jt} \equiv k^{-1}\sum_{j=1}^{k} FRO\,M_{jt} \tag{14}$$

$$NPDC_{ij,t} = \tilde{\phi}_{ijt}(H) - \tilde{\phi}_{ji,t}(H) \tag{15}$$

The formula $\tilde{\phi}\ g\ ij,t(H)$ helps explain how a change in one variable, such as Bitcoin prices, influences another variable like gold prices. Equation (11) measures how one factor affects all others in the system, such as oil, stocks, or market fear. This is called the total directional connectedness to others, showing how much influence one factor spreads to the rest. Conversely, Equation (12) measures the total directional connectedness from others, which shows how much one factor is influenced by the rest of the system. Equation (13) examines the balance between these two directions. By subtracting the influence a factor gives from the influence it receives, we get the net total directional connectedness. If a factor, such as Bitcoin, has a stronger impact on others than it receives, it is called a net transmitter (NET_jt > 0). If it receives more influence than it gives, it is a net receiver (NET_jt < 0). Equation (14) introduces the Total Connectedness Index (TCI_t), which shows the overall degree of linkage among all variables. A high TCI_t means that all markets are highly connected, so shocks in one market can quickly affect others, increasing financial risk. A low TCI_t means weaker connections, making the system more stable. Finally, the Net Pairwise Directional Connectedness (NPDC_ij,t) helps identify which of two variables has a stronger influence. A positive value means variable j affects i more, while a negative value means i influences j more.

4. Results and Discussion

Prior to delving into the econometric modeling, an examination of the descriptive statistics for the log returns of the selected variables provides foundational insights into their distributional properties, volatility patterns, and potential implications for safe-haven dynamics during geopolitical shocks. The variables under consideration include cryptocurrency returns (BTC_USD_CLOSE for Bitcoin, ETH_USD_CLOSE for Ethereum, and USDT_USD_CLOSE for Tether), a global equity proxy (URTH_CLOSE for the iShares MSCI World ETF), traditional commodity safe-haven and risk assets (GC_F_CLOSE for gold futures and CL_F_CLOSE for WTI crude oil futures), a market volatility gauge (VIX_CLOSE for the CBOE Volatility Index), and an uncertainty measure (EPU_CLOSE for the Economic Policy Uncertainty Index). These statistics are computed over the sample period from November 25th, 2019, to September 19th, 2025 (N ≈ 1,462 observations, assuming daily frequency with holidays excluded), and encompass measures of central tendency, dispersion, asymmetry, tail heaviness, and normality.

The mean returns reveal differing performances across assets, with cryptocurrencies showing the highest gains. Bitcoin (BTC) averages 0.00189 (0.189%) daily, and Ethereum (ETH) is slightly higher at 0.002321 (0.232%), reflecting bullish phases like the 2021 rally and recoveries after the 2022 downturn amid geopolitical tensions. Tether (USDT), pegged to the USD, has a near-zero mean (-1.71E-06), confirming its stability role. Traditional assets record modest returns, gold (GC) at 0.000629 (0.063%) and oil (CL) at 0.000468 (0.047%), affected by inflation, OPEC actions, and regional conflicts. The global equity index (URTH) shows 0.000434 (0.043%), indicating steady but lower growth, while volatility and uncertainty indices VIX (0.000154) and EPU (0.000514) capture mild positive drifts and policy shocks. Medians mostly follow means. BTC (0.001212) and ETH (0.001640) have lower medians, showing upward-skewed distributions due to large positive returns. USDT's median remains near zero, while URTH's (0.000870) exceeds its mean, reflecting occasional equity downturns. GC and CL medians surpass means, showing resilience during shocks. Negative medians for VIX and EPU highlight right-tailed distributions with rare but intense spikes during crises. Volatility levels confirm risk profiles: ETH (0.052855) and BTC (0.039630) are the most volatile, reacting to speculation, regulation, and war-related shocks. USDT's minimal 0.002741 confirms low variance. CL (0.032203) and GC (0.010412) show moderate volatility, while URTH (0.012753) reflects partial contagion from crises. VIX (0.079266) and EPU (0.529519) show extreme fluctuations, emphasizing their sensitivity to global stress.

Distribution metrics reveal non-normality. Cryptos and commodities exhibit fat tails (high kurtosis) and negative skewness, suggesting crash risks. USDT shows extreme kurtosis from rare deviations. All variables reject normality in Jarque-Bera tests. Finally, ADF and PP unit root tests confirm data stationarity, supporting further Granger causality analysis on volatility spillovers across crypto, traditional assets, and uncertainty indicators under geopolitical shocks.

Table 1: Descriptive Statistics

	BTC_USD_CLOSE	ETH_USD_CLOSE	USDT_USD_CLOSE	URTH_CLOSE	GC_F_CLOSE	CL_F_CLOSE	VIX_CLOSE	EPU_CLOSE
Mean	0.001890	0.002321	-1.71E-06	0.000434	0.000629	0.000468	0.000154	0.000514
Median	0.001212	0.001640	-8.46E-06	0.000870	0.000864	0.001970	-0.007942	-0.014836
Maximum	0.191527	0.343523	0.053393	0.087061	0.057775	0.319634	0.554110	2.583465
Minimum	-0.46473	-0.550732	-0.05257	-0.120786	-0.051069	-0.282206	-0.442449	-2.635148
Std. Dev.	0.039630	0.052855	0.002741	0.012753	0.010412	0.032203	0.079266	0.529519
Skewness	-1.226311	-0.873006	0.706263	-0.909637	-0.303304	0.024291	1.204650	0.124575
Kurtosis	19.18727	15.63945	208.6996	19.01833	6.170944	27.78000	10.01996	4.916737
Jarque-Bera	16328.29	9917.487	2577648.	15832.04	634.9260	37354.75	3355.568	227.5821
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	2.763499	3.392927	-0.002494	0.634682	0.920043	0.683249	0.224763	0.751848
Sum Sq. Dev.	2.294609	4.081581	0.010980	0.237600	0.158396	1.513013	9.179546	409.6500

Table 2: Stationarity Test

	Criteria= SIC						Criteria = Newey West using Bartlett Kernel					
	Augmented Dickey Fuller Test (ADF) Level						Phillips Perron Test (P-P) Level					
	None		Intercept		Trend & Intercept		None		Intercept		Trend & Intercept	
	Probability	Lag	Probability	Lag	Probability	Lag	Probability	Bandwidth	Probability	Bandwidth	Probability	Bandwidth
BTC	0.00	0	0.00	0	0.00	0	0.00	9	0.00	9	0.00	9
ETH	0.00	0	0.00	0	0.00	0	0.00	9	0.00	9	0.00	9
USDT	0.00	0	0.00	0	0.00	0	0.00	30	0.00	30	0.00	30
URTH	0.00	0	0.00	0	0.00	0	0.00	9	0.00	9	0.00	9
GC	0.00	0	0.00	0	0.00	0	0.00	21	0.00	21	0.00	21
CL	0.00	0	0.00	0	0.00	0	0.00	6	0.00	6	0.00	6
VIX	0.00	0	0.00	0	0.00	0	0.00	18	0.00	18	0.00	18
EPU	0.00	0	0.00	0	0.00	0	0.00	148	0.00	148	0.00	148

Stationarity is essential for reliable VAR analysis, as non-stationary data can produce misleading results. ADF and PP tests (under none, intercept, and trend specifications) confirm all variables are stationary at level (I(0)), with p-values of 0.00. ADF used SIC-based lag selection, while PP applied Newey–West bandwidth. Bandwidth variation reflects differences in volatility and persistence, especially high for EPU due to episodic shocks. Overall, results are consistent with financial return series, which become stationary after log-differencing and exhibit mean-reverting behavior. The VAR analysis shows that cryptocurrencies (BTC, ETH, USDT) are primarily driven by their own past values and stablecoin dynamics, with minimal influence from traditional assets like VIX, global stocks, gold, and oil. Stablecoin (USDT) plays a key supporting and transmitting role, while policy uncertainty (EPU) has a mild positive effect, especially on BTC. Strong interlinkages exist among variables like ETH and BTC, which act as key predictors, and USDT transmits volatility across markets. Overall, relationships are mostly linear with no significant nonlinear effects. Forecast Error Variance Decomposition (FEVD) over 1–10 periods confirms internal dominance. BTC's variance is 93.9% own at horizon 10, with ETH (1.16%) and USDT (1.3%) key, and VIX and CL.F growing slightly. ETH relies heavily on BTC (63.8%), with its own shocks at 31.3%. USDT, though stable, sees 10.2% from URTH and 4.9% from CL.F, revealing vulnerability. Overall, cryptocurrencies depend more on internal and stable coin dynamics than external markets, though VIX, equities, and oil gain influence during prolonged shocks like geopolitical crises.

Table 3: Average Dynamic Connectedness Table

	BTC.USD.Close	ETH.USD.Close	USDT.USD.Close	VIX.Close	URTH.Close	GC.F.Close	CL.F.Close	EPU.Close	FROM
BTC.USD.Close	47.52	33.37	2.90	5.19	7.40	1.65	1.58	0.38	52.48
ETH.USD.Close	33.66	48.10	1.89	5.57	7.91	1.30	1.25	0.33	51.90
USDT.USD.Close	5.32	3.31	84.20	1.33	2.17	0.76	1.45	1.47	15.80
VIX.Close	5.86	6.26	1.29	52.20	29.99	1.03	2.80	0.57	47.80
URTH.Close	7.77	8.21	2.30	27.12	48.79	2.08	3.34	0.40	51.21
GC.F.Close	3.15	2.78	0.95	1.92	4.63	81.77	3.71	1.09	18.23
CL.F.Close	2.15	2.02	1.10	3.72	5.52	2.88	82.03	0.59	17.97
EPU.Close	1.17	1.30	1.83	1.26	1.20	1.30	0.87	91.07	8.93
TO	59.08	57.25	12.27	46.10	58.83	10.99	14.99	4.83	264.33
INC.OWN	106.60	105.35	96.47	98.30	107.62	92.76	97.02	95.89	cTCI/TCI
NET	6.60	5.35	-3.53	-1.70	7.62	-7.24	-2.98	-4.11	37.76/33.04
NPT	7.00	6.00	3.00	4.00	4.00	1.00	3.00	0.00	

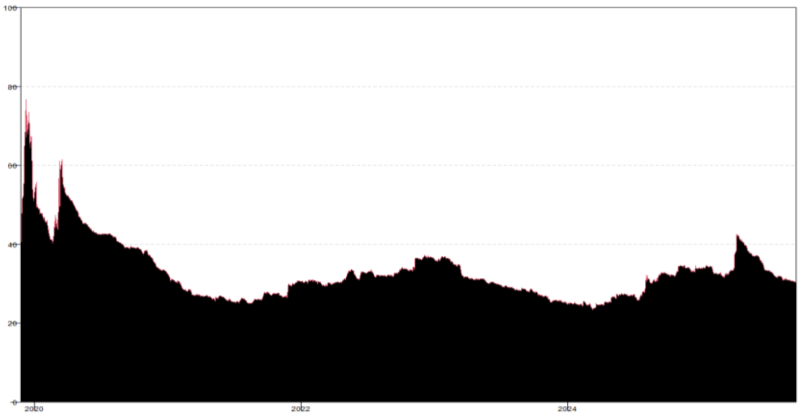

Fig.1: TVP-VAR- TCI.

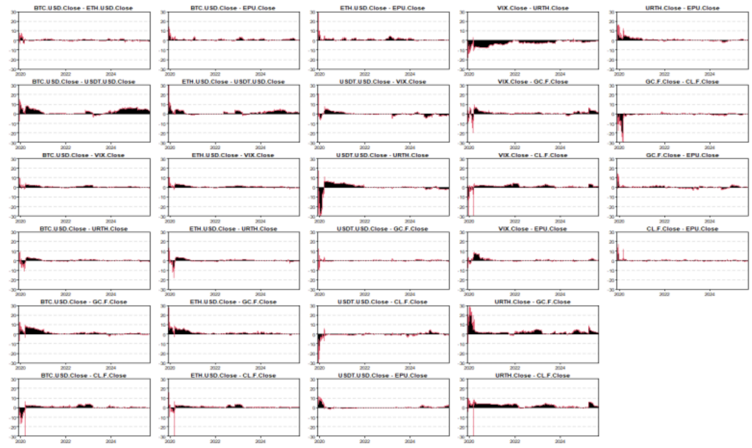

Fig. 2: NET.

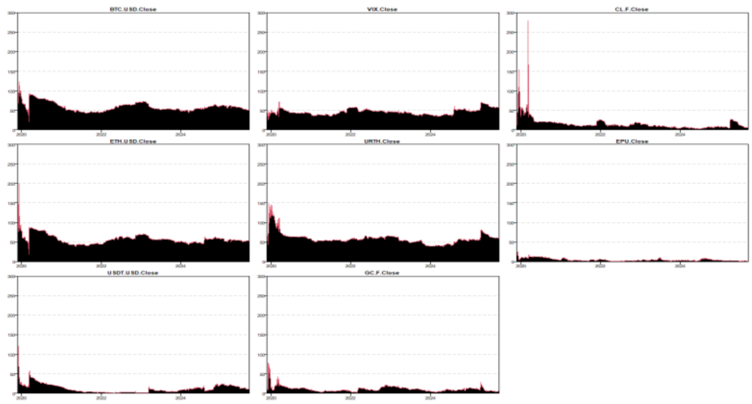

Fig. 3: From.

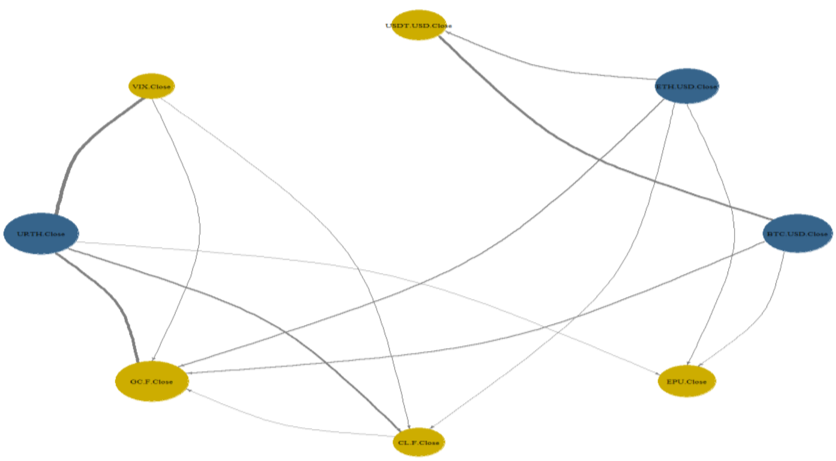

Fig. 4: Network Graph.

FEVD reveals that VIX variance is largely self-explained (83.4%), but BTC (9.96%) and ETH (2.27%) contribute significantly, indicating crypto volatility amplifies market fear. Similarly, URTH variance drops from 38.7% to 34.1% own-contribution, with VIX (37.3%) and BTC (14.3%) as key drivers, highlighting strong equity-volatility-crypto feedback. Gold remains highly independent (89.3%), influenced mainly by oil and equities, while oil shows diversified spillovers. EPU is almost entirely self-absorbed (96.5%), emitting minimal shocks. Over longer horizons, FEVD shows cryptocurrencies increasingly vulnerable to VIX (up to 10%) and URTH (1–10%), but less to gold, oil (0.3–5%), or EPU (0.3–0.7%), confirming contagion from equity and volatility shocks rather than commodities or policy.

TVP-VAR connectedness table reports moderate system integration (33.04%). BTC and ETH act as net transmitters (+6.60% and +5.35%), sending spillovers especially to each other (33.66%), VIX, and URTH, but receive heavily during stress. URTH is the strongest transmitter (+7.62%), while VIX is near neutral. USDT, gold, oil, and EPU are net receivers, with USDT absorbing shocks (–3.53%) yet bridging volatility. Net pairwise transmitters rank BTC highest (7), followed by ETH (6), underscoring crypto leadership in spillovers. No nonlinear effects were found, supporting linear policy responses. During 2022–2025 geopolitical events (Ukraine, Middle East, tariffs), VIX and URTH heightened crypto turbulence, eroding safe-haven claims. Gold offers weak hedging; oil affects BTC linearly via risk aversion. EPU plays a passive role, receiving but not driving crypto movements. Investors should monitor VIX above 30 and diversify with gold/oil. Policymakers must regulate stablecoins to limit spillovers. Cryptos remain conditional hedges, maturing but not fully safe amid uncertainty.

5. Findings, Conclusion and Suggestions

The empirical study explores the complex volatility of cryptocurrency prices and their safe-haven roles during geopolitical crises, focusing on Bitcoin (BTC), Ethereum (ETH), and Tether (USDT). Using a Vector Autoregression (VAR) model with up to 10 lags, it examines interactions with key factors: VIX (market fear), URTH (global stocks), GC.F (gold), CL.F (oil), and EPU (policy uncertainty). Internal crypto dynamics are dominant. BTC shows persistence in returns with a positive own lag 3 effect (0.116, p=0.014), while ETH's lag 5 negatively affects BTC (-0.125, p=0.0004), indicating short-term volatility drag. USDT acts as a stabilizer, positively influencing BTC (lag 1: 1.210, p=0.021) and ETH (lag 2: 2.075, p=0.003) due to its stablecoin peg, providing liquidity in turbulent times. EPU has mild positive lagged effects on BTC and ETH (e.g., lag 6: 0.011 for both), suggesting investors turn to cryptocurrencies amid policy uncertainty, supporting Sarker et al.. However, VIX, URTH, gold, and oil mostly show insignificant direct impacts on BTC and ETH, except for rare cases like gold's negative effect on ETH at lag 4 (-0.280, p=0.047).

Granger causality reveals asymmetries: BTC predicts USDT, URTH, oil, and EPU, while ETH influences BTC and others, reflecting its DeFi leadership. USDT strongly drives most variables, serving as a transmission channel. VIX and URTH affect cryptos, but EPU reacts rather than leads. Nonlinear tests find no tail asymmetries, favoring linear models. Forecast Error Variance Decomposition (FEVD) over 10 periods shows own shocks declining (BTC: 100% to 93.9%; ETH: to 63.8%), with VIX and URTH contributing modestly to variance (up to 1.1% for ETH). Time-Varying VAR indicates 33% system connectedness, with BTC and ETH as net transmitters (+6.60%, +5.35%).

In conclusion, this study reveals that cryptocurrency prices become more volatile during geopolitical shocks. Bitcoin (BTC) and Ethereum (ETH) can act as temporary hedges during mild uncertainties but fail as safe-haven assets in extreme crises. In contrast, the stablecoin USDT consistently maintains stability, serving as a reliable digital anchor. The research employs multiple models to analyse market behaviour from 2018 to 2025, covering major events like COVID-19, the Ukraine war, and Middle East conflicts. Key findings include: VAR models show internal persistence in crypto prices with mild influence from Economic Policy Uncertainty (EPU); linear Granger causality identifies USDT, VIX (volatility index), and URTH (global equities) as main transmitters, while nonlinear effects are absent; Forecast Error Variance Decomposition (FEVD) indicates growing contagion from equities and volatility, with VIX explaining up to 37% of variance in URTH, which then affects cryptos; Time-Varying Parameter VAR (TVP-VAR) reports 33% overall connectedness, with cryptos acting as net transmitters.

BTC and ETH display risk-on characteristics, with ETH's variance largely self-driven (63.8%) but also influenced by BTC (33.4%). Their safe-haven role weakens during high Geopolitical Risk (GPR) periods, supporting prior studies. E fil EPU has minimal impact (0.3–0.7% in FEVD), acting more as a reflector than a driver, unlike some earlier research. Traditional assets like gold and oil show weak links to cryptos, limiting their hedging value. Practically, the $2+ trillion crypto market demands adaptive risk management due to high volatility (BTC standard deviation 3.96%, ETH 5.29%). Investors may allocate a small portion to USDT-BTC mixes for geo-hedging, as USDT absorbs shocks effectively (-3.53% net). Rebalance to gold when VIX exceeds 30 or GPR surpasses 200. Policymakers need stronger stablecoin regulation to prevent contagion, harmonise global rules, and integrate EPU monitoring into financial stability frameworks.

Future research should use machine learning to detect nonlinear patterns, include real-time GPR data, apply DCC-MGARCH for volatility clustering, and expand to emerging markets or altcoins. Scenario simulations can improve predictive hedging. Investors may adopt threshold strategies and diversify into gold-oil hybrids, while regulators enforce reserve requirements and develop EPU-linked oversight. Central banks could explore stable digital currencies to reduce risks in developing economies. Overall, cryptos are not absolute safe-havens but evolve conditionally, requiring dynamic strategies and policies in a geopolitically uncertain world. Crypto scholars can consider conducting systematic reviews in order to curate and collate scattered in-depth insights in the domain (Khan and Azam 2023; Khan et al. 2025, 2026).

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