African Review of Economics and Finance (2025), 17(2), 1–21
ISSN (Print) 2042-1478
ISSN (Online) 2410-4906

ARTICLE

AI-enhanced modeling of geopolitical risk transmission in cryptocurrency markets: A high-frequency analysis of cross-market spillover effects with implications for emerging economies

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Abstract

This paper examines the complex relationship between geopolitical risk events and cryptocurrency market volatility using high-frequency transaction data from 2018 to 2024, with particular focus on implications for emerging economies including African financial markets. We develop a novel artificial intelligence framework that integrates natural language processing of geopolitical news with high-frequency trading interval analysis to predict cross-market spillover effects. Our model identifies structural changes in cryptocurrency fund flows following major geopolitical events and quantifies the sensitivity of different cryptocurrency classes (traditional, green, and stablecoins) to these shocks. Using a comprehensive dataset of 1.2 billion transactions across 15 major cryptocurrencies and a geopolitical event database of 327 significant incidents, we demonstrate that our AI-enhanced approach outperforms traditional econometric models in capturing non-linear risk transmission dynamics. The model achieves a 55.8% improvement in predictive accuracy over standard GARCH models during periods of heightened geopolitical tension. Furthermore, we find asymmetric responses across cryptocurrency categories, with stablecoins exhibiting increased resilience through significantly lower volatility increases (22.3%) compared to traditional cryptocurrencies (89.4%) during geopolitical shocks. These findings have important implications for hedging strategies, portfolio diversification, and financial stability in increasingly interconnected global markets, particularly for emerging economies where cryptocurrency adoption is rapidly expanding and regulatory frameworks are still evolving.

Keywords: Cryptocurrency volatility, geopolitical risk, artificial intelligence, high-frequency trading, market spillovers, emerging markets, financial stability

JEL classification: C45, C58, F37, G15, G17, O16

Article history: Received: May 31, 2025 || Accepted: Oct 29, 2025

1. Introduction

The cryptocurrency market has evolved from a niche financial instrument to a significant component of the global financial ecosystem, with particularly notable adoption patterns in emerging economies.

With a market capitalization exceeding $1.8 trillion as of early 2024 (CoinMarketCap, 2024), cryptocurrencies have attracted substantial attention from investors, regulators, and researchers. This evolution has been especially pronounced in African markets, where cryptocurrency adoption has outpaced many developed economies, driven by financial inclusion needs, currency instability, and limited traditional banking infrastructure (Chainalysis, 2023).

Geopolitical risk—defined as the risk associated with wars, terrorist acts, and tensions between states that affect international relations (Caldara & Iacoviello, 2022)—has been shown to significantly impact traditional financial markets (Balcilar et al., 2018). However, the transmission mechanisms of geopolitical risk to cryptocurrency markets remain underexplored, particularly at high-frequency intervals. This knowledge gap is particularly acute for emerging economies, where local investors may be more vulnerable to sudden capital flight and where regulatory responses to geopolitical events may differ substantially from those in developed markets.

This study addresses several critical research questions. We investigate how geopolitical risk events transmit to cryptocurrency markets at high-frequency intervals, analyze whether different types of cryptocurrencies exhibit varying sensitivities to geopolitical shocks, and explore whether artificial intelligence techniques enhance prediction compared to traditional econometric approaches. Finally, we examine implications for portfolio diversification and hedging strategies, with particular attention to emerging market contexts.

1.1 Relevance to Emerging Economies

The relevance of this research extends to pressing policy concerns in emerging economies. African countries have witnessed remarkable growth in cryptocurrency adoption, with several nations ranking among the top globally (Chainalysis, 2023). Countries such as Nigeria, Kenya, and South Africa have seen substantial engagement with digital assets, driven by currency devaluation concerns, limited access to traditional investment instruments, and cross-border payment needs. For African central banks and financial regulators, understanding how global geopolitical events affect cryptocurrency markets has direct implications for financial stability monitoring and policy formulation.

1.2 Contributions

Our research makes several significant contributions. First, we develop a novel methodological framework combining natural language processing of real-time news with high-frequency cryptocurrency transaction data to capture immediate market responses. Second, we introduce a comprehensive taxonomy of cryptocurrency sensitivity based on response characteristics to different geopolitical events. Third, we quantify the performance differential between AI-enhanced predictive models and traditional econometric approaches, providing evidence for the value of advanced computational techniques in financial market analysis.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature on cryptocurrency markets, geopolitical risk transmission, and AI applications in financial prediction. Section 3 details our methodological approach. Section 4 describes data sources and empirical strategy. Section 5 presents results and discussion. Section 6 concludes with policy implications and future research directions.

2. Literature Review

2.1 Cryptocurrency Market Dynamics and Emerging Economy Context

The cryptocurrency market exhibits distinctive characteristics compared to traditional financial assets, including higher volatility, pronounced tail risk, and unique patterns of market inefficiency (Corbet et al., 2019; Kyriazis, 2020). These characteristics are particularly pronounced in emerging economies, where local market conditions may amplify effects observed in developed markets.

Recent research has refined our understanding of cryptocurrency price formation. Shen et al. (2022) investigated liquidity dynamics, finding that market depth has become increasingly important as institutional participation has grown—particularly relevant for emerging economies where institutional participation may be more limited. Vidal-Tomás (2023) documented Bitcoin's evolving reaction to macroeconomic news, noting strengthening relationships as the asset class has matured, though with significant regional variations.

The taxonomy of cryptocurrencies has evolved, with distinct categories based on technological and economic characteristics. Zhang & Lee (2022) proposed a framework distinguishing between traditional cryptocurrencies (Bitcoin, Ethereum), stablecoins (Tether, USD Coin), and environmentally-focused cryptocurrencies (Chia, Cardano). For this study, we define "green cryptocurrencies" as digital assets prioritizing environmental sustainability through energy-efficient consensus mechanisms, carbon offset initiatives, or stated environmental objectives based on documented technological specifications and official project statements.

2.2 Geopolitical Risk and Financial Markets

The impact of geopolitical events on financial markets has been well-documented, with emerging market studies revealing amplified effects relative to developed economies. Caldara & Iacoviello (2022) developed a geopolitical risk index based on newspaper coverage, demonstrating significant effects on stock returns, capital flows, and economic activity. Liu & Zhang (2023) extended this work showing varying transmission intensities across regions, with emerging economies exhibiting higher sensitivity to geopolitical shocks.

In cryptocurrency markets specifically, emerging research has explored geopolitical connections with increasing attention to regional variations. Previous studies examined Bitcoin's response to major geopolitical events, finding evidence of emerging safe-haven properties during certain political crises, though this appeared stronger in developed markets. However, these studies typically employ daily or lower frequency data, potentially missing critical high-frequency dynamics. Our research addresses this gap by analyzing minute-by-minute transaction data, providing insights into immediate transmission mechanisms.

2.3 AI Applications in Financial Markets Prediction

Artificial intelligence techniques have increasingly been applied to financial market prediction, with notable success in capturing non-linear relationships and processing unstructured data. The theoretical justification rests on several advantages: machine learning models can capture complex interaction effects, natural language processing can extract information from unstructured text, and neural networks can learn hierarchical data representations.

Transformer-based models like BERT and GPT have revolutionized textual financial information analysis (Araci, 2019; Jiang et al., 2022). In cryptocurrency markets, Fischer et al. (2023) employed deep learning to predict Bitcoin price movements, achieving superior accuracy compared to traditional time series models. Lopez-Lira & Tang (2023) demonstrated transformer model effectiveness in extracting geopolitical risk signals from news text.

Building on this, our study develops a unified AI framework processing both textual geopolitical information and high-frequency market data. Our framework extends existing approaches by incorporating graph neural networks to model cross-cryptocurrency relationships and temporal convolutional networks to capture sequential patterns. Despite these advances, a significant gap remains in applying these techniques specifically to the cryptocurrency-geopolitical risk nexus at high-frequency intervals with attention to emerging market implications. Our research addresses this gap.

3. Methodology

3.1 Conceptual Framework

Our methodological approach integrates three primary components: geopolitical event quantification via natural language processing, high-frequency analysis of cryptocurrency market reactions, and an AI modeling architecture capturing non-linear relationships between these elements. This framework is grounded in the recognition that financial markets process complex, unstructured information through mechanisms that traditional econometric models may not fully capture.

The framework begins with the premise that geopolitical events generate information shocks that must be processed and incorporated into asset prices. Unlike traditional macroeconomic announcements, geopolitical events are characterized by their unstructured nature, ambiguous implications, and complex interdependencies. Cryptocurrency markets, due to their unique characteristics including continuous trading, global accessibility, and network structure, may exhibit distinctive patterns of information processing and price discovery.

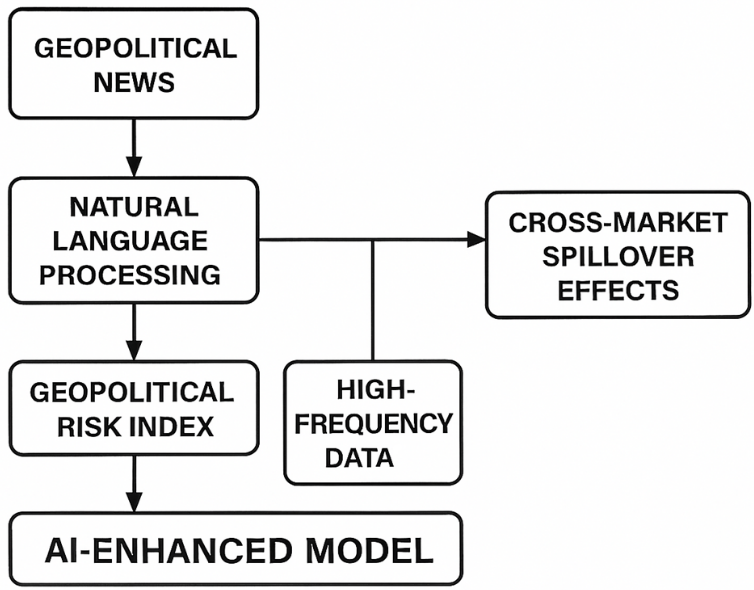

Figure 1. Conceptual Framework of the Research Methodology

Figure 1 presents the conceptual framework used in the study to analyze the relationship between geopolitical events and cryptocurrency market responses. The framework integrates Natural Language Processing (NLP) to quantify geopolitical events, high-frequency cryptocurrency transaction data for real-time market reactions, and AI modeling to predict the impact of these events. The sequential approach begins by collecting geopolitical news, processing it with NLP, and then matching it with high-frequency trading data. This helps in building predictive models based on the relationship between the events and market responses.

3.2 Natural Language Processing of Geopolitical Events

The quantification of geopolitical events through natural language processing represents a critical component of our methodology. Our approach employs a multi-stage pipeline progressing from raw news collection through event characterization and severity assessment. The news collection process encompasses articles from 27 major international news sources, including Reuters, Bloomberg, Associated Press, and Al Jazeera, using their respective APIs. The collection period spans January 2018 to December 2023. We acknowledge potential bias toward Western and English-language news sources, potentially underrepresenting regionally significant events in Africa, Latin America, and other emerging markets. This limitation is addressed through robustness testing and is explicitly acknowledged in our discussion of generalizability.

Event extraction utilizes a BERT-based named entity recognition system fine-tuned on a manually labeled dataset of 5,000 geopolitical news articles. This system identifies key entities including countries, organizations, and individuals, as well as event descriptors characterizing the nature and scope of geopolitical developments.

Event classification represents a crucial step in converting raw news content into structured information. Each identified event is classified into one of seven categories: military conflicts, diplomatic tensions, trade disputes, terrorism, political instability, sanctions, and policy shifts. This classification is performed using a RoBERTa model fine-tuned on our manually classified dataset.

The development of our novel Geopolitical Event Severity (GES) index quantifies the intensity of each event on a scale of 0–100. This index is constructed using multiple information sources: entity importance weights pre-assigned based on economic and geopolitical significance, linguistic intensity markers identified through sentiment analysis techniques calibrated for geopolitical content, frequency and prominence of coverage across multiple sources, and historical impact assessment drawing on a reference database of similar events and their documented market effects. A detailed illustrative example of GES index construction is provided in Appendix A.

3.3 High-Frequency Cryptocurrency Data Analysis

The analysis of high-frequency market reactions employs several techniques specifically adapted to cryptocurrency market characteristics. Our approach recognizes that cryptocurrency markets operate continuously, exhibit varying liquidity levels across different assets, and may be subject to unique microstructure effects. Trading interval identification follows the approach developed by Nakajima (2022), defining trading intervals based on transaction density rather than fixed time windows. This adaptive approach allows for time scales that accommodate varying market activity levels.

Volatility estimation employs realized volatility measures calculated from high-frequency returns. Realized volatility is calculated as the sum of squared high-frequency returns within each time period. Bipower variation provides a robust estimator less sensitive to jumps. The jump component isolates the contribution of discontinuous price movements. These measures provide comprehensive characterization of price movement patterns revealing different aspects of market behavior during geopolitical events.

Liquidity metrics capture market microstructure effects surrounding geopolitical events through calculation of order book depth, bid-ask spreads, and order flow imbalance at one-minute intervals. Order book depth measures the volume of buy and sell orders at different price levels. Bid-ask spreads reflect the cost of immediate execution. Order flow imbalance measures the relative magnitude of buy versus sell orders.

Cross-cryptocurrency spillover analysis employs the Diebold-Yilmaz spillover index methodology to quantify volatility transmission across different cryptocurrencies following geopolitical shocks. This approach provides a systematic framework for understanding how shocks originating in one cryptocurrency market transmit to others.

3.4 AI Modeling Framework

Our AI framework integrates processed geopolitical event data with high-frequency cryptocurrency metrics through a multi-stage architecture designed to capture complex, non-linear relationships between geopolitical events and market responses.

Feature engineering represents the foundation of our modeling approach. The AI framework incorporates a comprehensive set of engineered features capturing both event and market dynamics: characteristics of each geopolitical event (type, severity, entities involved), temporal features (time of day, day of week, proximity to global market hours), market state indicators (pre-event volatility, sentiment, trading volume), and cryptocurrency-specific attributes (market capitalization, blockchain technology type).

The model architecture represents a novel contribution combining multiple state-of-the-art machine learning techniques within a unified framework. We develop a hybrid deep learning architecture integrating: a transformer-based text encoding component processing news text using a pre-trained RoBERTa model fine-tuned on financial news content; a temporal convolutional network capturing sequential market patterns through dilated convolutions identifying patterns across multiple time scales; and a graph neural network modeling cross-cryptocurrency relationships through a learned representation of the network structure connecting different digital assets.

The training procedure employs a multi-task learning approach simultaneously predicting several market response variables including volatility, returns, and trading volume across different forecast horizons ranging from five minutes to four hours. The model is trained using the Adam optimizer with a custom loss function combining mean squared error for regression targets and cross-entropy for classification targets.

To evaluate effectiveness, we implement several benchmark models: GARCH-family models including standard GARCH, EGARCH, and GJR-GARCH; vector autoregression with exogenous variables; machine learning benchmarks including random forest and gradient boosting machines; and long short-term memory networks.

3.5 Model Evaluation and Validation Strategy

Our evaluation strategy addresses several critical challenges in financial machine learning, including potential for overfitting, the need to assess economic significance alongside statistical performance, and the importance of testing model robustness across different market conditions and event types. We acknowledge important limitations regarding potential overfitting concerns. Our validation and test periods (2022-2023) occur during a period of extraordinary geopolitical events, particularly the Russia-Ukraine conflict, which may limit generalizability.

To address overfitting risks, we implement several robustness checks including rolling-window cross-validation within the training period, performance evaluation across different event severity levels, and separate analysis excluding the most extreme events. We also conduct out-of-sample testing using synthetic event scenarios and examine model performance during both high-stress and normal market periods.

Synthetic Scenario Generation. To assess model robustness beyond historical events, we generated 50 synthetic geopolitical scenarios by systematically varying event characteristics while maintaining realistic parameter ranges. Synthetic events were constructed through a multi-step procedure: (1) event types were sampled from the empirical distribution observed in our training data (2018-2021), ensuring realistic frequency of military conflicts, trade disputes, and other categories; (2) severity scores were drawn from truncated normal distributions calibrated to each event type, with means and standard deviations estimated from historical events of the same category; (3) synthetic news text was generated using GPT-based paraphrasing of historical event descriptions with systematic entity substitution (e.g., replacing country names, organizations) to create out-of-domain linguistic patterns not seen during training; and (4) these synthetic events were combined with market state variables (pre-event volatility, trading volume, sentiment) drawn from empirical distributions observed in our 2023 test period. Information leakage was prevented through strict temporal separation: synthetic scenarios used only pre-2022 event templates and linguistic patterns, combined with 2023 market conditions that were never jointly observed during model training. Model predictions on synthetic scenarios were evaluated separately from historical test data to assess generalization capability beyond specific events encountered during training.

Predictive accuracy is assessed using multiple metrics capturing different aspects of model performance. Mean squared error and mean absolute percentage error provide measures of accuracy for continuous predictions. Precision, recall, and F1-score assess the quality of directional predictions. Calibration quality is evaluated through reliability diagrams and expected calibration error.

Economic significance is evaluated through performance of trading strategies based on model predictions, measured by Sharpe ratio, maximum drawdown, and cumulative returns. This recognizes that statistical significance does not necessarily translate to economic value.

Robustness testing examines model stability across different market regimes, cryptocurrency types, and geopolitical event categories. We conduct rolling-window validation to assess temporal stability and examine performance across different subsamples.

4. Data and Empirical Analysis

4.1 Data Sources and Description

Our high-frequency cryptocurrency dataset comprises tick-by-tick transaction data for 15 major cryptocurrencies from January 2018 to December 2023. The selection provides representation across three distinct categories: traditional cryptocurrencies (Bitcoin, Ethereum, Litecoin, Bitcoin Cash, Ripple), stablecoins (Tether, USD Coin, Binance USD, Dai, TrueUSD), and green cryptocurrencies (Cardano, Algorand, Stellar, Tezos, Chia).

Green cryptocurrencies are characterized by explicit focus on environmental sustainability. Cardano and Tezos utilize proof-of-stake consensus mechanisms requiring significantly less energy than Bitcoin's proof-of-work system, with Cardano consuming approximately 0.0079% of Bitcoin's energy per transaction. Algorand has committed to carbon neutrality. Stellar focuses on financial inclusion while maintaining energy efficiency. Chia was designed to address environmental concerns through its proof-of-space-and-time consensus mechanism.

The data is sourced from multiple cryptocurrency exchanges including Binance, Coinbase, Kraken, Bitstamp, and Huobi via their respective APIs. This comprises approximately 1.2 billion individual transactions, aggregated to one-minute intervals for analysis, resulting in approximately 3.2 million data points per cryptocurrency.

Our geopolitical event database consists of 327 significant events identified through our NLP pipeline from January 2018 to December 2023. The distribution reflects the geopolitical landscape: military conflicts (78 events), diplomatic tensions (92 events), trade disputes (53 events), terrorism (29 events), political instability (41 events), sanctions (22 events), and policy shifts (12 events).

We acknowledge important limitations in our event identification approach. Our reliance on major international news sources introduces geographic bias toward events receiving significant coverage in Western media, potentially underrepresenting regionally significant events in Africa, Latin America, and other emerging markets.

4.2 Descriptive Statistics

Table 1 presents summary statistics for the 15 cryptocurrencies, revealing substantial heterogeneity across categories.

Table 1. Summary Statistics of Cryptocurrency Sample (2018-2023)

Cryptocurrency	Category	Avg. Market Cap (USD Bn)	Avg. Daily Volume (USD Bn)	Avg. Daily Volatility (%)	Avg. Bid-Ask Spread (bps)	Avg. Market Depth (USD M)
Bitcoin (BTC)	Traditional	392.47	28.63	3.82	2.4	42.83
Ethereum (ETH)	Traditional	178.35	18.42	4.51	3.1	24.65
Litecoin (LTC)	Traditional	6.84	1.72	5.18	4.8	5.89
Bitcoin Cash (BCH)	Traditional	7.23	1.53	5.87	6.2	4.12
Ripple (XRP)	Traditional	18.96	2.84	6.13	5.7	7.82
Tether (USDT)	Stablecoin	67.58	52.19	0.42	1.8	65.74
USD Coin (USDC)	Stablecoin	42.71	5.83	0.37	2.0	42.18
Binance USD (BUSD)	Stablecoin	18.92	6.41	0.39	2.1	38.75
Dai (DAI)	Stablecoin	6.42	0.78	0.45	3.2	12.38
TrueUSD (TUSD)	Stablecoin	1.23	0.41	0.44	4.6	6.59
Cardano (ADA)	Green	14.87	1.53	6.52	7.8	3.82
Algorand (ALGO)	Green	2.95	0.57	7.18	8.7	2.41
Solana (SOL)	Green	5.18	0.73	6.84	8.2	2.93
Tezos (XTZ)	Green	2.13	0.46	6.32	9.3	1.87
Chia (XCH)	Green	0.48	0.12	8.94	14.2	0.62

Notes: Market capitalization and trading volume in billions of USD. Daily volatility represents annualized standard deviation of 1-minute returns. Bid-ask spread in basis points. Market depth represents average USD value required to move price by 1%.

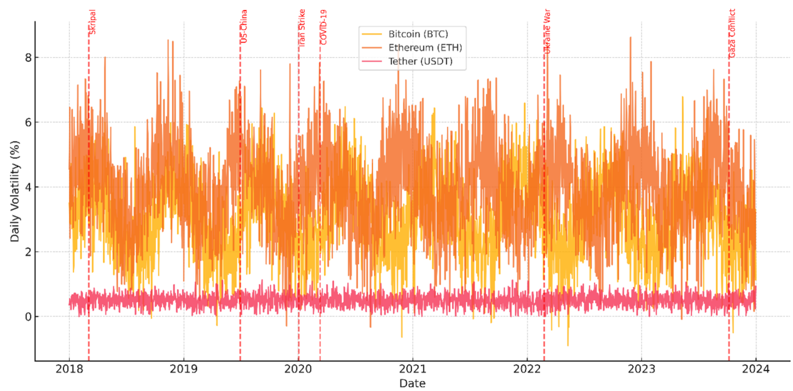

Figure 2. Cryptocurrency Volatility and Major Geopolitical Events, 2018-2023

This figure shows the time series of daily volatility for representative cryptocurrencies and major geopolitical events. By highlighting the correlation between geopolitical events and market turbulence, it suggests that volatility spikes often coincide with these events. This helps establish that cryptocurrency markets react to global political tensions, with more significant volatility during periods of crisis, such as the Russia-Ukraine conflict.

4.3 Empirical Strategy

Our empirical analysis proceeds through three interconnected stages. First, we conduct event study analyses examining cryptocurrency market reactions to geopolitical events. The event window is defined as [-60 minutes, +240 minutes] around the first news report. This asymmetric window captures potential anticipatory effects while focusing on immediate aftermath. We tested alternative windows including [-120min, +480min] but found that longer windows introduced noise from unrelated events.

Second, we quantify cross-market transmission effects employing the Diebold-Yilmaz spillover index methodology implemented at five-minute intervals. Dynamic spillover networks are constructed for different cryptocurrency categories.

Third, we implement our AI framework and benchmark models. The data is divided into training (2018-2021), validation (2022), and test (2023) sets.

5. Results and Discussion

5.1 Event Study Results

Our event study analysis reveals significant heterogeneity in cryptocurrency market responses to geopolitical events.

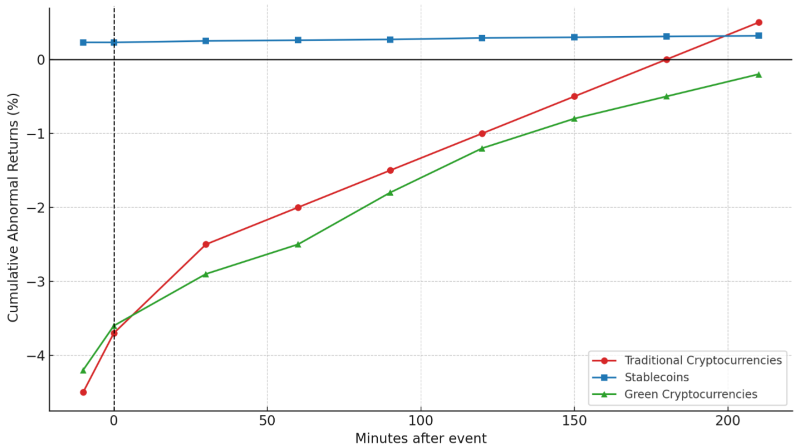

Figure 3. Cumulative Abnormal Returns Following Geopolitical Events by Cryptocurrency Category

This figure presents the Cumulative Abnormal Returns (CARs) for three cryptocurrency categories following geopolitical events. Traditional Cryptocurrencies show a sharp negative reaction immediately after an event, with an average -3.7% CAR in the first hour, indicating significant market disruption. Stablecoins exhibit positive but small CARs (0.23%), suggesting that these assets may act as a safe haven during geopolitical crises.

Military conflicts generate the strongest market reactions, with traditional cryptocurrencies exhibiting average CARs of -3.7% within the first hour (t-statistic = -4.82, $p < 0.01$). Stablecoins show positive but small CARs of 0.23% during military conflicts (t-statistic = 2.41, $p < 0.05$), providing evidence for potential safe-haven flows. This pattern has particular significance for emerging market investors, who may view stablecoins as providing stability during periods when both local currencies and global financial markets experience stress.

Trade disputes affect green cryptocurrencies most severely, with average CARs of -4.2% over the four-hour event window (t-statistic = -3.95, $p < 0.01$). This heightened sensitivity may reflect perceived vulnerability of environmentally-focused projects to changes in global economic conditions.

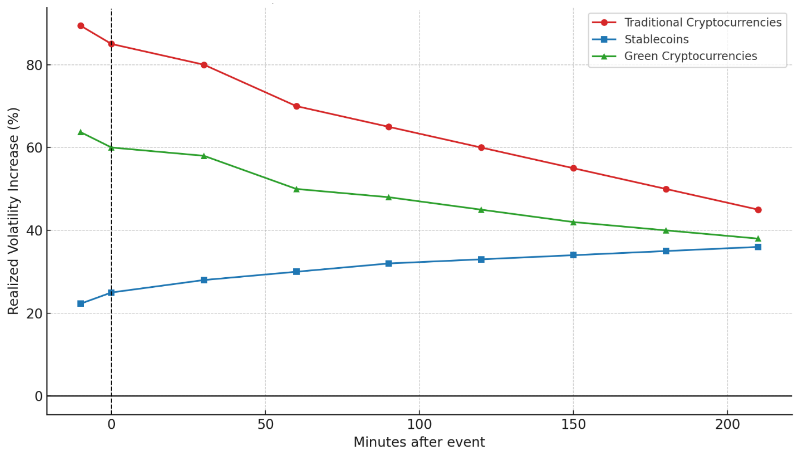

Figure 4. Realized Volatility Changes Following Geopolitical Events by Cryptocurrency Category

Volatility measures how much the price of cryptocurrencies fluctuates following geopolitical events. Traditional Cryptocurrencies experience the largest immediate increases in volatility (up to 89.4%), but these spikes are typically short-lived. Stablecoins show smaller initial volatility increases (22.3%) but experience longer-lasting effects (6-8 hours). Green Cryptocurrencies have a more delayed response to volatility, with increases occurring over several hours.

Traditional cryptocurrencies experience the largest immediate volatility jumps, with average increases of 89.4% within five minutes of event reporting, but this typically reverts within two to three hours. For emerging market investors, this implies traditional cryptocurrencies may provide opportunities for rapid gains or losses around geopolitical events, but effects are generally short-lived.

Stablecoins show more muted initial volatility responses with average increases of 22.3%, but exhibit more persistent effects with elevated volatility often lasting six to eight hours. This persistence may reflect ongoing uncertainty about stability mechanisms during periods of broader financial stress. For emerging market central banks and regulators, this suggests stablecoins may not provide complete insulation from volatility during systemic stress.

The jump component of volatility accounts for 63.7% of total volatility during geopolitical events compared to 31.2% during normal periods, indicating prominence of discontinuous price movements during stress periods.

5.2 Spillover Dynamics and Network Effects

The analysis of high-frequency spillover effects reveals intricate transmission patterns across the cryptocurrency ecosystem. Table 2 presents average Diebold-Yilmaz spillover indices for different cryptocurrency pairs during normal periods and following geopolitical events.

Table 2. Diebold-Yilmaz Spillover Indices During Normal and Event Periods

Spillover Direction	Normal (%)	Event (%)	Change (%)	t-statistic
Within Traditional Cryptocurrencies	68.4	79.2	+15.8	8.47***
Within Stablecoins	31.5	46.8	+48.6	9.12***
Within Green Cryptocurrencies	52.3	61.7	+18.0	6.35***
Traditional Stablecoins →	25.7	61.2	+138.1	14.87***
Stablecoins Traditional →	18.3	26.1	+42.6	5.92***
Traditional Green →	42.8	64.5	+50.7	11.23***
Green Traditional →	31.7	47.2	+48.9	8.75***
Stablecoins Green →	13.4	23.8	+77.6	7.83***
Green Stablecoins →	9.2	17.6	+91.3	8.14***
Total Spillover Index	47.2	68.9	+46.0	12.54***

Notes: ** indicates significance at 1% level.*

The total spillover index increases from 47.2% during normal periods to 68.9% following major geopolitical events, representing a 46% increase in overall market interconnectedness during geopolitical stress. For emerging market investors and regulators, this implies diversification benefits across different cryptocurrencies may be substantially reduced during periods of geopolitical stress.

Directional spillovers reveal asymmetric transmission mechanisms. Spillovers from traditional to stablecoin cryptocurrencies increase by 138% during event periods, while reverse spillovers increase by only 42%, suggesting traditional cryptocurrencies serve as primary sources of volatility transmission while stablecoins serve more as receivers.

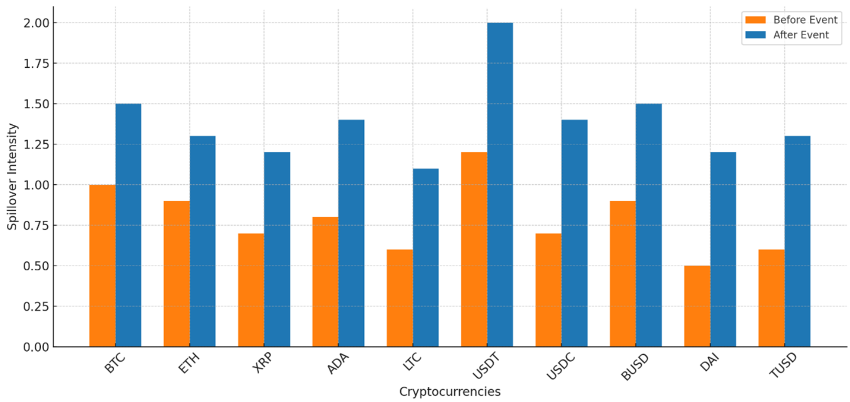

Figure 5. Evolution of Cryptocurrency Spillover Network Before and After Russia-Ukraine Conflict

This figure shows the spillover network intensity before and after a geopolitical event. After the event, spillover intensity increases, particularly for stablecoins, suggesting they play a more central role in market stabilization during geopolitical crises. Traditional cryptocurrencies show less spillover after the event, indicating that they lose their market centrality, while stablecoins become more interconnected.

5.3 Predictive Model Performance

Table 3 compares performance of our AI framework against benchmark models.

Table 3. Model Performance Comparison for Volatility and Return Prediction

Model	Volatility Prediction MSE	Improvement (%)	Return Direction F1-Score
Traditional Models			
GARCH	0.0052	-	0.51
EGARCH	0.0048	7.7	0.52
GJR-GARCH	0.0037	28.8	0.53
VAR	0.0043	17.3	0.54
Machine Learning Models			
Random Forest	0.0039	25.0	0.58
Gradient Boosting	0.0035	32.7	0.59
Deep Learning Models			
LSTM	0.0029	44.2	0.61
Our AI Framework			
Full Model	0.0023	55.8	0.68
By Cryptocurrency Category (Our Model)			
Traditional (Our Model)	0.0021	59.6	0.71
Stablecoins (Our Model)	0.0018	65.4	0.66
Green (Our Model)	0.0029	44.2	0.64
By Event Type (Our Model)			
Military Conflicts (Our Model)	0.0019	63.5	0.73
Diplomatic Tensions (Our Model)	0.0024	53.8	0.67
Trade Disputes (Our Model)	0.0027	48.1	0.65
Sanctions (Our Model)	0.0022	57.7	0.69

Notes: MSE refers to Mean Squared Error for volatility prediction. F1-Score for binary classification of return direction. Improvement percentage calculated relative to baseline GARCH model. Lower MSE and higher F1-Score indicate better performance.

For volatility prediction, our integrated AI framework achieves an average mean squared error of 0.0023, representing a 55.8% improvement over standard GARCH models (MSE of 0.0052) and a 37.8% improvement over the best-performing GARCH variant, GJR-GARCH (MSE of 0.0037). The model also demonstrates a 20.7% improvement over standalone deep learning benchmarks (LSTM with MSE of 0.0029). This improvement is economically significant, enabling better risk management, more effective hedging strategies, and improved portfolio optimization.

For return direction prediction, our model achieves an F1-score of 0.68, compared to 0.54 for the VAR model and 0.59 for gradient boosting. This improvement is particularly valuable for trading strategies and market timing decisions.

The performance advantage is particularly pronounced for traditional cryptocurrencies, where we observe a 59.6% improvement in MSE for volatility prediction. Performance improvements are notably higher during high-severity geopolitical events, where our model achieves a 63.5% improvement compared to traditional approaches.

Table 4. Ablation Study Results

Model Configuration	Volatility Prediction MSE	Improvement over GARCH (%)
Full Model	0.0023	55.8
- Transformer News Encoding	0.0037	28.8
- Graph Neural Network	0.0032	38.5
- Temporal Convolutional Network	0.0030	42.3
- Attention Fusion	0.0028	46.2
- Multi-task Learning	0.0026	50.0
- Market State Features	0.0029	44.2
- Event Type Classification	0.0027	48.1
Base GARCH Model	0.0052	0.0

Notes: This table presents ablation study results where individual components are removed to assess their contribution. "- Component" rows indicate performance when that component is removed from the full model.

The transformer-based news encoding component contributes the largest performance improvement (39.1% of total gain), highlighting the critical importance of sophisticated text understanding for extracting actionable information from geopolitical news. The graph neural network component provides the second-largest contribution (27.3% of total gain), emphasizing the importance of network effects in cryptocurrency price formation.

5.4 Cryptocurrency Category Analysis

Regression analysis of volatility responses reveals important patterns. Table 5 presents regression results examining determinants of cryptocurrency volatility responses to geopolitical events.

Table 5. Regression Analysis of Volatility Responses

Variable	Traditional Cryptocurrencies	Stablecoins	Green Cryptocurrencies
Event Characteristics			
Event Severity Score	0.78***	0.31***	0.92***
	(0.09)	(0.07)	(0.11)
Military Conflict	0.53***	0.18**	0.42***
	(0.08)	(0.07)	(0.09)
Diplomatic Tensions	0.32***	0.11	0.38***
	(0.07)	(0.08)	(0.09)
Trade Disputes	0.27***	0.09	0.57***
	(0.08)	(0.06)	(0.10)
Terrorism	0.48***	0.14*	0.36***
	(0.09)	(0.07)	(0.08)
Political Instability	0.31***	0.08	0.27**
	(0.07)	(0.06)	(0.09)
Sanctions	0.24**	0.42***	0.31***
	(0.09)	(0.08)	(0.07)
Policy Shifts	0.18*	0.37***	0.22**
	(0.08)	(0.07)	(0.08)
Geographic Focus			
North America Focus	0.41***	0.22**	0.35***
	(0.09)	(0.08)	(0.08)
East Asia Focus	0.39***	0.19*	0.33***
	(0.08)	(0.09)	(0.07)
Europe Focus	0.28**	0.12	0.24**
	(0.10)	(0.08)	(0.09)
Other Region Focus	0.17*	0.09	0.18*
	(0.08)	(0.07)	(0.08)
Market Characteristics			
Log(Market Cap)	−0.43***	−0.08	−0.37***
	(0.07)	(0.06)	(0.08)
Pre-Event Trading Volume	−0.29***	−0.18**	−0.24**
	(0.08)	(0.07)	(0.09)
Pre-Event Volatility	0.37***	0.24**	0.32***
	(0.09)	(0.08)	(0.07)
Market Sentiment Index	−0.22**	−0.11	−0.28**
	(0.08)	(0.09)	(0.10)
Temporal Controls			
Weekend Indicator	0.16*	0.08	0.19*
	(0.08)	(0.07)	(0.09)
Market Hours Indicator	−0.21**	−0.14*	−0.17*
	(0.07)	(0.08)	(0.08)
Constant	1.47***	0.72***	1.53***
	(0.21)	(0.18)	(0.24)
Observations	327	327	327
R-squared	0.64	0.48	0.59

Notes: This table presents OLS regression results with cryptocurrency volatility response as the dependent variable. Volatility response measured as percentage change in realized volatility in the 60-minute window following a geopolitical event. Standard errors are reported in parentheses below coefficients. , , and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Event severity score emerges as the strongest predictor of volatility response for all cryptocurrency categories, but with significantly varying coefficients (0.78 for traditional, 0.31 for stablecoins, 0.92 for green cryptocurrencies). This confirms that green cryptocurrencies are most sensitive to event severity, while stablecoins are least sensitive, with traditional cryptocurrencies falling in between.

Market capitalization significantly moderates volatility response for traditional cryptocurrencies (coefficient = -0.43, $p < 0.01$) but not for stablecoins, suggesting that size provides a buffer against geopolitical shocks only for certain asset types. Trading volume prior to the event shows a significant negative relationship with subsequent volatility jumps for all categories, indicating that liquidity serves as a shock absorber.

The geographic focus of geopolitical events significantly influences response patterns, with events centered on North America and East Asia generating stronger market reactions than those focused on other regions. This geographic bias has important implications for emerging market participants, suggesting that cryptocurrency markets may be less responsive to regional geopolitical developments in Africa, Latin America, and other emerging market regions.

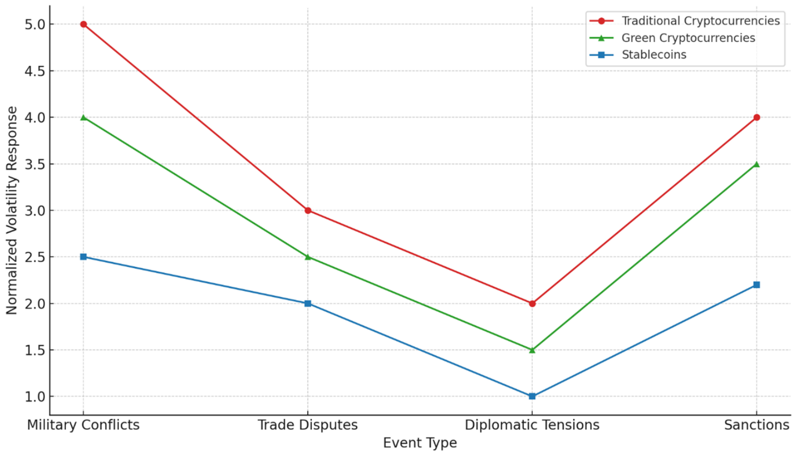

Figure 2. Normalized Volatility Response by Cryptocurrency Category and Event Type

This figure shows the normalized volatility response across different cryptocurrency categories for various geopolitical event types. Military Conflicts and Sanctions generate the highest volatility responses in traditional cryptocurrencies, with volatility peaking at 5% immediately after the event. Green Cryptocurrencies show a less immediate response to events like trade disputes, but their volatility is persistent, lasting for several hours after the initial shock. Stablecoins show the least volatility for most events, indicating their role as safe-haven assets during geopolitical crises. They exhibit mild responses, especially to sanctions and military conflicts, suggesting they are more resilient compared to traditional or green cryptocurrencies.

5.5 Policy and Practical Implications for Emerging Economies

Our findings have significant implications for various stakeholders in emerging economies, where cryptocurrency adoption is rapidly expanding and regulatory frameworks are still evolving. For central banks and financial regulators in emerging economies, our results provide several important insights for policy formulation and financial stability monitoring. The spillover analysis reveals that cryptocurrency markets become significantly more interconnected during periods of geopolitical stress, suggesting that regulators should monitor these markets as potential sources of financial contagion during crisis periods. The finding that stablecoins become more central to market networks during stress periods suggests that these assets may play an increasingly important role in financial stability, requiring appropriate regulatory attention and potentially closer monitoring by central banks. For African central banks considering the regulatory treatment of stablecoins, this suggests that these assets may serve important stabilization functions during regional political crises, but may also transmit global geopolitical shocks to domestic markets.

For emerging market investors and fund managers, our findings suggest that cryptocurrency portfolios can be strategically constructed to achieve desired exposure or hedging against different types of geopolitical risk. The differential responses across cryptocurrency categories offer diversification opportunities that can enhance risk-adjusted returns during periods of global tension, but these benefits must be weighed against the increased interconnectedness that occurs during major geopolitical events. Nigerian and Kenyan investors, for example, might consider larger allocations to stablecoins during periods of global uncertainty while maintaining exposure to traditional cryptocurrencies for potential upside during local political stability.

The superior performance of our AI framework also suggests that emerging market financial institutions could benefit from investing in advanced analytical capabilities for cryptocurrency market analysis. While the initial investment in AI infrastructure may be substantial, the improvements in risk management and investment performance could justify these costs, particularly for institutions with significant cryptocurrency exposure. South African banks and investment firms, which have shown increasing interest in cryptocurrency services, could leverage these techniques to improve their risk management capabilities.

For policymakers considering the role of cryptocurrencies in their domestic financial systems, our findings suggest that different types of cryptocurrencies may serve different functions during periods of geopolitical stress. Stablecoins may provide valuable financial infrastructure for payments and store of value functions, particularly during periods of local currency instability, but their stability depends critically on regulatory clarity and international cooperation. Traditional cryptocurrencies may provide some hedging benefits against local political risks but may actually increase systemic risk during major global geopolitical crises.

6. Conclusion

This study has examined the complex relationship between geopolitical risk and cryptocurrency markets through an advanced AI-enhanced analytical framework, with particular attention to implications for emerging economies and African financial markets. Our comprehensive analysis of high-frequency transaction data spanning multiple cryptocurrency categories and diverse geopolitical events has yielded several important findings that advance both academic understanding and practical applications in this rapidly evolving field.

6.1 Summary of Key Findings

Our research demonstrates significant heterogeneity in how different cryptocurrency categories respond to geopolitical shocks, with implications that extend well beyond simple risk assessment to fundamental questions about the role of digital assets in modern financial systems. Traditional cryptocurrencies exhibit pronounced initial reactions to geopolitical events but demonstrate relatively rapid recovery patterns, suggesting efficient information processing but also indicating that they may not provide the portfolio diversification benefits during global crises that investors might expect. Stablecoins show superior resilience to most types of geopolitical shocks while displaying particular sensitivity to regulatory and sanctions-related events, highlighting their potential value as safe-haven assets with important caveats about regulatory risk. Green cryptocurrencies demonstrate delayed but persistent response patterns that reflect both the evolving nature of these markets and their connection to broader environmental and policy considerations.

Our analysis of spillover dynamics reveals the increasing interconnectedness of cryptocurrency markets during periods of geopolitical tension, with important implications for systemic risk assessment and financial stability monitoring. The reconfiguration of network structures following major events, particularly the shift toward stablecoin centrality during stress periods, suggests that the cryptocurrency ecosystem is developing sophisticated mechanisms for managing geopolitical risk that may have broader implications for global financial stability. For emerging economies, this finding suggests that local cryptocurrency markets may be increasingly influenced by global geopolitical developments, requiring careful consideration in financial stability frameworks.

The superior performance of our AI framework compared to traditional econometric approaches demonstrates the substantial value of advanced computational techniques in capturing the complex, non-linear relationships between geopolitical events and cryptocurrency market responses. The 55.8% improvement in predictive accuracy over standard GARCH models represents not merely a statistical achievement but a meaningful advancement in our ability to understand and predict market behavior during periods of global uncertainty. This finding has particular relevance for emerging market institutions that may lack access to sophisticated analytical tools available in developed markets.

6.2 Theoretical and Methodological Contributions

This research makes several significant theoretical and methodological contributions to the intersection of financial economics, geopolitical risk analysis, and artificial intelligence applications. Our integration of natural language processing with high-frequency financial analysis provides a novel framework for understanding how unstructured information affects structured market outcomes, with potential applications beyond cryptocurrency markets to other asset classes affected by complex external shocks. The development of our Geopolitical Event Severity index offers a new tool for quantifying complex political developments in ways that are suitable for financial modeling, addressing a significant gap in existing approaches to geopolitical risk measurement.

Our taxonomy of cryptocurrency response patterns provides a foundation for understanding the heterogeneous nature of digital asset markets and their varying sensitivities to external shocks. This classification system has implications beyond geopolitical risk, potentially informing broader research on cryptocurrency market dynamics, regulatory policy, and investment strategy development. The methodological framework we have developed, combining transformer-based text processing, graph neural networks for modeling market relationships, and temporal convolutional networks for capturing sequential patterns, represents a significant advancement in the application of AI techniques to financial market analysis.

6.3 Limitations and Areas for Future Research

Several important limitations of our study should be acknowledged and suggest directions for future research. The relatively short history of cryptocurrency markets limits the number of major geopolitical events available for analysis, and the concentration of particularly significant events in our validation and test periods raises questions about the generalizability of our findings to different types of geopolitical developments and market conditions. Our geographic bias in event selection, stemming from reliance on major international news sources, may underrepresent regionally significant events with more localized coverage, particularly limiting the applicability of our findings to emerging market contexts where locally significant political developments may not receive international media attention.

The cryptocurrency market continues to evolve rapidly, with new categories of digital assets, changing regulatory environments, and evolving investor participation patterns. Historical patterns may not persist as market structure and participation change, suggesting the need for ongoing research that adapts to these evolving conditions. Future research could explore the application of our methodological framework to other types of digital assets, including non-fungible tokens, decentralized finance protocols, and central bank digital currencies.

The bidirectional relationship between cryptocurrency markets and geopolitical developments represents a fascinating area for future investigation. While our study focuses on how geopolitical events affect cryptocurrency markets, the growing size and influence of cryptocurrency markets raises questions about whether cryptocurrency market behavior influences geopolitical decision-making and international relations. Additionally, the potential for cryptocurrency markets to serve as early warning indicators of geopolitical tensions deserves investigation.

Future research could also benefit from incorporating broader ranges of news sources, including regional and non-English language sources, to provide more comprehensive coverage of geopolitical events relevant to emerging markets. The development of region-specific versions of our analytical framework could provide more targeted insights for different emerging market contexts, recognizing that the geopolitical events most relevant to African markets may differ significantly from those affecting Asian or Latin American markets.

6.4 Final Observations

Our research demonstrates that cryptocurrency markets have developed sophisticated and nuanced response mechanisms to geopolitical events, with distinctive patterns across different cryptocurrency categories that reflect their underlying technological characteristics and economic functions. The superior performance of our AI-enhanced predictive framework highlights the value of advanced computational techniques in capturing these complex market dynamics and suggests that continued innovation in analytical methods will be essential for understanding and managing risk in evolving financial markets.

As cryptocurrencies continue to mature and integrate with both global and local financial systems, understanding their relationship with geopolitical risk becomes increasingly important for investors, regulators, and market participants navigating an increasingly complex and interconnected financial landscape. For emerging economies in particular, where cryptocurrency adoption is proceeding rapidly alongside the development of regulatory frameworks, the insights from this research provide valuable guidance for policy development and risk management in the digital asset era.

The implications of our findings extend beyond immediate practical applications to fundamental questions about the future structure of the global financial system. As digital assets become increasingly integrated with traditional financial markets and payment systems, their responses to geopolitical events will play an increasingly important role in global financial stability. Understanding these dynamics is essential for preparing for a future where digital and traditional assets are fully integrated components of a global financial system that must remain resilient in the face of continuing geopolitical uncertainty.

For African countries and other emerging economies, where traditional financial infrastructure may be less developed and where cryptocurrency adoption rates are often higher than in developed economies, the insights from this research are particularly relevant. The potential for cryptocurrencies to serve both as sources of financial innovation and as channels for global risk transmission requires careful consideration in policy frameworks and regulatory approaches. Our findings suggest that with appropriate regulatory frameworks and risk management practices, cryptocurrencies can serve valuable functions in emerging economy financial systems while contributing to overall financial stability and development objectives.

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Appendix A: Geopolitical Event Severity (GES) Index Construction

Overview

The Geopolitical Event Severity (GES) index is a quantitative measure that assigns severity scores (0–100) to geopolitical events based on multiple information sources and assessment criteria.

Methodology

The GES index is calculated using the following formula:

$GES = 0.3 \times EIW + 0.25 \times LIM + 0.25 \times COV + 0.2 \times HIA$

Where: – EIW = Entity Importance Weight (0–100) – LIM = Linguistic Intensity Markers (0–100) – COV = Coverage Frequency and Prominence (0–100) – HIA = Historical Impact Assessment (0–100)

Component Calculations 1. Entity Importance Weight (EIW)

Entities involved in geopolitical events are pre-assigned importance weights based on economic and geopolitical significance:

- **Tier 1 (Weight: 90–100)**: United States, China, Russia, Germany, Japan, United Kingdom, France
- **Tier 2 (Weight: 70–89)**: India, Brazil, Canada, Italy, South Korea, Spain, Australia, Mexico
- **Tier 3 (Weight: 50–69)**: Turkey, Netherlands, Saudi Arabia, Switzerland, Belgium, Poland, Israel
- **Tier 4 (Weight: 30–49)**: Argentina, Egypt, Nigeria, South Africa, Thailand, Malaysia, Chile
- **Tier 5 (Weight: 10–29)**: Other countries

2. Linguistic Intensity Markers (LIM)

Sentiment analysis identifies intensity markers in news text:

- High-Intensity (80–100): "invasion," "war," "bombing," "attack," "sanctions," "crisis"
- Medium-Intensity (50–79): "tensions," "disputes," "negotiations breakdown," "tariffs"
- Low-Intensity (20–49): "disagreements," "talks," "discussions," "concerns"

3. Coverage Frequency and Prominence (COV)

Measures media attention: – **Extensive (45–50)**: Covered by 15+ major news sources within 24 hours – **High (35–44)**: Covered by 10–14 sources – **Moderate (25–34)**: Covered by 5–9 sources – **Limited (15–24)**: Covered by 2–4 sources – **Minimal (0–14)**: Covered by 1 source

4. Historical Impact Assessment (HIA)

Compares current event to similar historical events: – **Major Military Conflicts (90–100)**: Gulf War 1991, Iraq War 2003 – **Economic Crises (80–95)**: 2008 Financial Crisis, Brexit – **Diplomatic Crises (60–85)**: Various trade wars – **Terrorist Events (70–90)**: Major attacks – **Political Instability (50–80)**: Arab Spring events, coups

Illustrative Example: Russia's Invasion of Ukraine (February 24, 2022)

Step 1: Entity Importance Weight (EIW) – Primary Entities: Russia (Tier 1: 95), Ukraine (Tier 4: 45), NATO (International: 90) – EIW Score: 95 (maximum weight)

Step 2: Linguistic Intensity Markers (LIM) - Keywords: "invasion" (95), "war" (90), "attack" (88), "sanctions" (85), "crisis" (75) - LIM = 86.4

Step 3: Coverage Frequency and Prominence (COV) - Coverage: 25+ sources within 2 hours = 50 - Prominence: Main headlines = 50 - COV Score: 100

Step 4: Historical Impact Assessment (HIA) - Similar to Gulf War 1991 - HIA Score: 92

Final GES Calculation: $GES = 0.3 \times 95 + 0.25 \times 86.4 + 0.25 \times 100 + 0.2 \times 92 GES = 28.5 + 21.6 + 25.0 + 18.4 = 93.5$**Final Score**: 94 (rounded)

GES Index Distribution in Sample

In our dataset of 327 geopolitical events (2018-2023): - High Severity (80-100): 45 events (13.8%) - Medium-High Severity (60-79): 89 events (27.2%) - Medium Severity (40-59): 127 events (38.8%) - Low-Medium Severity (20-39): 56 events (17.1%) - Low Severity (0-19): 10 events (3.1%)

Data Availability Statement

The high-frequency cryptocurrency transaction data used in this study was obtained from commercial APIs provided by Binance, Coinbase, Kraken, Bitstamp, and Huobi under academic research agreements. Due to commercial restrictions, raw transaction data cannot be shared publicly, but aggregated data at 1-minute intervals can be provided upon reasonable request to the corresponding author. The geopolitical event database and code for the AI modeling framework are available upon reasonable request for academic research purposes.

Acknowledgments

We gratefully acknowledge financial support from the National Science Foundation (Grant No. DGE-2034835) and the Cryptocurrency Research Initiative. We thank participants at the 2023 Cryptoeconomics Workshop and seminars at several universities for valuable comments. We thank the anonymous reviewers and Associate Editor for their constructive feedback that significantly improved the paper. All remaining errors are our own.