Safe havens in the digital age: Cryptocurrencies and geopolitical risks

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ABSTRACT

This study examines the impact of geopolitical risks (GPR) on cryptocurrency volatility, with a focus on green and non-green cryptocurrencies. Geopolitical risks - stemming from conflicts, terrorism, and political tensions - have significant implications for financial markets and investment decisions, as highlighted by recent events such as the Russia-Ukraine war, Israel-Hamas conflict, tensions in the Korean Peninsula, China-Taiwan disputes, and US-UK actions against Houthi forces in the Red Sea. Using a dataset of 10 cryptocurrencies from 2014 to 2023, the analysis employs the GARCH-M-GJR-LEV econometric model to investigate volatility dynamics. The results show a negative correlation between geopolitical risks and cryptocurrency volatility, indicating that as geopolitical tensions increase, cryptocurrency markets tend to stabilize, suggesting their potential as safe havens. Moreover, the findings reveal that green cryptocurrencies are more resilient to geopolitical shocks than non-green ones, highlighting the rising importance of sustainability in financial markets. This research contributes to the literature by offering insights into the differential responses of green and non-green cryptocurrencies to geopolitical events. The findings have practical implications for investors looking for hedging tools during periods of heightened geopolitical uncertainty, as well as for policymakers aiming to understand the broader impacts of geopolitical dynamics on emerging financial markets like cryptocurrencies.

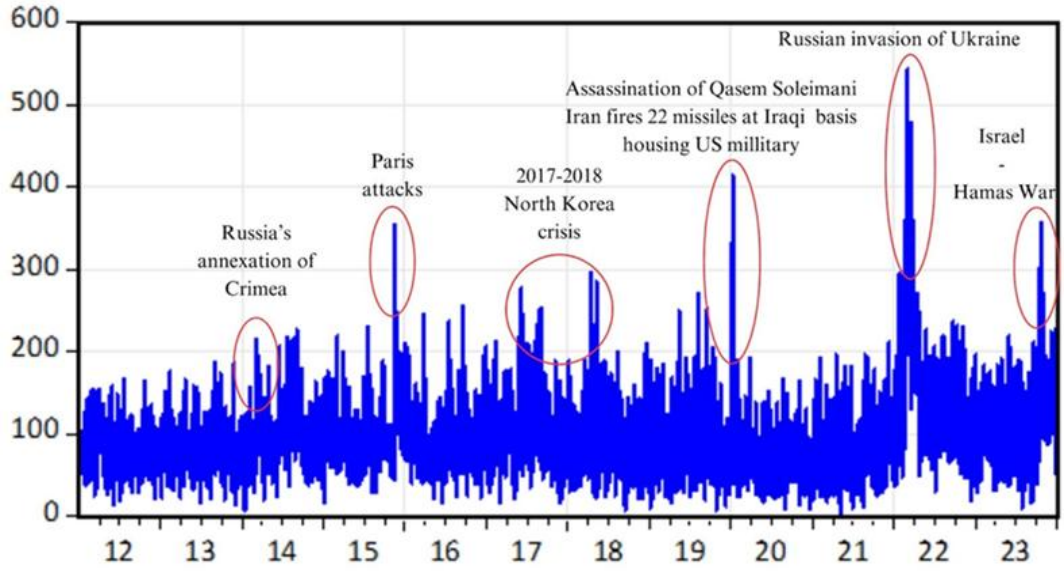
1. Introduction

Geopolitical risks (GPR) encompass conflicts, terrorism, and political tensions, significantly influencing investment decisions and impacting economic growth and financial markets (Caldara & Iacoviell, 2022). A series of events have geopolitical risks recently including conflicts like Russia-Ukraine, Israel-Hamas, Korean peninsula tensions, China-Taiwan disputes, and recent US-UK attacks on Houtin forces in the Red Sea. The ongoing conflict between Ukraine and Russia, stemming from Russia's annexation of Crimea in 2014, has led to a prolonged war in Eastern Ukraine, straining relations between Russia and the West and resulting in economic sanctions against Russia. The conflict between Russia and Ukraine has greatly fluctuated fossil energy markets (Maneejuk et al., 2023) and caused negative impacts on global financial markets (Assaf et al., 2023). In November 2015, a series of terrorist attacks occurred in Paris, France, it was one of the deadliest acts of terrorism in French history. The terrorist attacks have a negative impact on stock market returns (Arfaoui & Naoui, 2022). Similarly, in 2022, the Israeli-Palestinian conflict intensified with an attack on Hamas. Hamas relies on Gaza's tunnel

network for movement, storage, and command. Israel targets these tunnels, leading to Palestinian terrorist attacks and casualties. This event leads to an increase in oil prices due to widespread conflict, which will increase global inflation. Increased inflation will reduce people's purchasing power, reduce GDP growth, and at the same time reduce the purchasing power of money and negatively impact other major markets (Yoganandham, 2023). These events, along with various other geopolitical incidents over the past decade, serve as a global warning sign, impacting investors and businesses amidst the economic downturn triggered by the Russia-Ukraine war and the Federal Reserve's continuous interest rate hikes in 2022. This poses a significant challenge to all stakeholders in the market, especially investors, who are most exposed to the market risks.

Figure 1

Trend in Geopolitical Risk



Source. Author's compilation from policyuncertainty.com

In times of rising geopolitical risks and economic downturns, currencies like the Swiss franc, Japanese Yen, and US Dollar are considered safe haven assets alongside traditional investments. Investors and currency traders often shift to these currencies in volatile markets to protect their assets. Additionally, central banks also hold these currencies as a protective measure against global financial risks. However, the Japanese Yen's status as a safe haven asset has diminished due to differences in monetary policies compared to other major central banks. While most of the world moved to tighten interest rates to control inflation, the Bank of Japan kept interest rates near zero. That caused the Yen to be heavily shorted on the market. Amidst declining savings interest rates and volatile stock markets, investors face challenges in finding secure and stable investment options. Typically, an increase in geopolitical risk will cause most asset values to decline, but not all asset classes react equally, some will be more resilient than others (Będowska-Sójka et al., 2022). Traditional safe-haven assets include gold, silver, government bonds, etc. (Naqvi et al., 2022).

In recent times, a type of financial asset that has emerged with a very large capitalization is cryptocurrency (Riahi et al., 2024). A cryptocurrency is a form of digital or virtual currency that relies on cryptographic techniques to make it impossible to double-spend on a distributed network. In today's world, there are over 1,600 cryptocurrencies available, which can be utilized for conducting payment transactions such as bitcoin, bitcoin cash, LTC, LINK, tether, etc.

(Aggarwal & Kumar, 2021). There have been many studies related to cryptocurrency that show that this is a high-risk asset, such as Yang et al. (2023) or Gunay et al. (2023). Many previous studies have largely focused on Economic Policy Uncertainty (EPU) on cryptocurrency-related volatility (Colon et al., 2021; Raza et al., 2023; Y. Zhang et al., 2023) rather than explicitly discussing the impact of geopolitical risks (GPR) on cryptocurrency. The evidence above demonstrates that political risks create instability in the global financial market and lead to significant volatility in traditional financial assets. Therefore, undertaking this topic is both appropriate and urgent. The question raised is whether cryptocurrency, a high-risk but highly valued market asset, is a safe haven asset for investors during times of increasing geopolitical risks at present, the objective of this research is to examine and provide empirical evidence on the relationship between geopolitical risk and cryptocurrency market volatility over the period from 2014 to 2023, at a daily frequency. The research findings may serve as a foundation for future studies to further investigate models related to cryptocurrency market volatility during times of economic instability and its impact on financial decisions and investments by individuals or businesses. This objective will be achieved by addressing the following research questions: Firstly, does a relationship exist between geopolitical risk and cryptocurrency market volatility? Consequently, should cryptocurrencies be considered as a safe haven asset during periods of geopolitical instability? Secondly, what is the impact of sustainable development - specifically, green cryptocurrencies - on the market? Thirdly, does cryptocurrency truly provide hedging capabilities throughout all time periods or only during periods of market instability?

This study aims to address this gap by specifically examining the correlation between geopolitical risk and cryptocurrencies. Additionally, we also find that cryptocurrencies are not effective as a hedge all the time but can only act as a hedge during periods of high risk. Besides, this study uses the more advanced model GARCH-M-GJR-LEV to measure cryptocurrency volatility instead of commonly used models such as GJR-GARCH (1,1), GARCH-in Mean (1,1), or GARCH (1,1). By using the GARCH-M-GJR-LEV model, this study aims to overcome the limitations and improve the accuracy of volatility estimates in the cryptocurrency market.

We hope that this research will serve as a comprehensive reference document to aid investors in evaluating the role of cryptocurrencies in safeguarding their asset values during periods of heightened political risk. Furthermore, policymakers can leverage the benefits of cryptocurrencies as investment tools rather than just transaction methods. They can also utilize these research outcomes to inform regulatory policies within the cryptocurrency market, emphasizing the power of green cryptocurrencies for their efficiency and alignment with the sustainable development goals pursued globally. In addition, we also suggest strategies for central banks in selecting haven assets amidst geopolitical tensions and currency volatility.

The remainder of this paper proceeds as follows. Section 2 recaps the theoretical background and empirical literature on the effectiveness of governance characteristics. Section 3 presents the data and the econometric approach used in this research. Section 4 discusses the main findings, while Section 5 concludes the paper.

2. Literature review

2.1. Theoretical framework

Markowitz's (1952) portfolio selection model analyzes risk and return to allocate investments optimally. It aims to create efficient portfolios based on specific assumptions, such as that investors are rational (they seek to maximize returns while minimizing risk), investors will accept increased risk only if compensated with higher expected returns, investors receive all

pertinent information regarding their investment decisions in a timely manner, and investors can borrow or lend an unlimited amount of capital at a risk-free rate of interest. An efficient portfolio has either the highest expected return for a given risk level or the lowest risk for a given expected return. The set of efficient portfolios is illustrated as the efficient frontier. Markowitz's (1952) theory suggests that diversifying across asset classes can reduce individual asset risk. Research supports the idea that a diversified portfolio, especially with low-correlation assets, can lower overall risk and enhance resilience to market fluctuations. However, Feng et al. (2018) argue that even diversified portfolios may not fully manage risks from geopolitical factors affecting global markets. In such conditions, safe-haven assets gain importance. Cryptocurrencies are seen as attractive safe havens due to their decentralized nature, value preservation, and ability to withstand systemic risks independently from traditional assets (Feng et al., 2018).

Kahneman and Tversky (1979) offer a critique of expected utility theory as a descriptive model for decision-making under risk and propose an alternative framework known as prospect theory. This theory identifies several common patterns in risky decision-making that contradict the assumptions of utility theory. One such pattern is the certainty effect, where individuals tend to underweight probable outcomes compared to certain ones, leading to risk aversion when faced with guaranteed gains and risk seeking when confronted with guaranteed losses. Another key pattern is the isolation effect, where individuals disregard components shared by all options, resulting in inconsistent preferences when identical choices are framed differently. Prospect theory shifts the focus from final outcomes to changes in wealth, assigning value to gains and losses rather than to overall assets. Additionally, probabilities are replaced by decision weights, which are typically lower than actual probabilities, except in the case of low probabilities, where individuals tend to overweight them. This overweighting can explain the appeal of both insurance and gambling. The value function in prospect theory is generally concave for gains, convex for losses, and steeper for losses than for gains, reflecting people's tendency to be more sensitive to losses than to equivalent gains. This theory highlights the impact of emotions on investment choices, particularly during volatile times influenced by geopolitical risks, leading to a preference for safe-haven assets like cryptocurrencies (Yen & Cheng, 2021).

Salience theory (Bordalo et al., 2013) suggests that decision-makers tend to overestimate the likelihood of extreme events they are aware of, shaping subjective probability distributions and challenging traditional rationality. It explains the preference for skewness, where assets with positive skew are overvalued, and those with negative skew are undervalued. Cryptocurrencies, perceived as safe havens, can draw investors' attention during high volatility. This increased focus on cryptocurrency safety in turbulent markets reflects investors' capital preservation concerns, especially amid geopolitical risks.

Herding occurs when investors ignore personal signals and follow the majority in the market, either through observed interactions or deliberate imitation (da Gama Silva et al., 2019). This behavior is seen across various asset classes, but its prevalence in traditional cryptocurrency markets, especially during uncertain times like geopolitical risks, remains debated. Some studies support the existence of herd behavior in cryptocurrency markets, indicating that investors may view cryptocurrencies as safe havens when market consensus is strong. Conversely, other research suggests herding is minimal, while a third group proposes that investors act in opposition to herding tendencies.

2.2. Literature review of the relationship between geopolitical risks and

cryptocurrency volatility

While previous studies have predominantly centered on Economic Policy Uncertainty (EPU), a more direct exploration of geopolitical risks' impact on cryptocurrency volatility remains relatively scarce. Yen and Cheng (2021) conducted a study delving into the correlation between the Economic Policy Uncertainty Index (EPU) and cryptocurrency volatility. They discovered that Bitcoin and Litecoin function as protective measures against EPU in China, although this effect was not observed in the United States and Japan. Colon et al. (2021) examined the impact of political and economic uncertainty on the cryptocurrency market, suggesting cryptocurrencies as reliable hedges against geopolitical risks, though potentially less effective during bull markets. Jiang et al. (2021) embarked on an investigation into the intricate connections between EPU, the Covid-19 pandemic, and cryptocurrencies. Their findings underscored the efficacy of cryptocurrencies as hedging tools against high EPU, with Stellar (XLM) demonstrating particularly strong hedging properties. Raza et al. (2023) delved into the impact of uncertainty surrounding financial regulatory policies on cryptocurrency volatility, employing the GARCH-MIDAS model. Their research revealed a discernible decrease in cryptocurrency volatility amidst heightened levels of uncertainty in financial regulation policies.

Zhang et al. (2024) echoed similar sentiments, positing cryptocurrencies as secure investment options during periods characterized by economic policy uncertainty. Meanwhile, Nouir and Hamida (2023) utilized the ARDL model and quantile regression to delve into the nuanced relationship between uncertainty and bitcoin volatility across various scenarios. Furthermore, P. Zhang et al. (2023) conducted an insightful examination into the repercussions of regulatory policies amid the Covid-19 pandemic on cryptocurrency market volatility. Their research illuminated a notable surge in volatility following the announcement of regulations targeting cryptocurrencies by Chinese policymakers, particularly accentuated during the pandemic. Kamal et al. (2023) conducted a specific investigation into the geopolitical impact on cryptocurrency volatility during the Russia-Ukraine war. Their study revealed a discernible negative impact on liquidity and returns in the cryptocurrency market, particularly following escalations in the conflict.

While existing research has provided valuable insights, there is a need for more detailed analyses focusing on the impact of geopolitical risks on cryptocurrency volatility Moreover, a broader consideration of multiple measurement methods for assessing geopolitical risk volatility could enhance the depth and reliability of future research findings. Such endeavors hold significant implications not only for investors but also for policymakers navigating the intricate interplay between geopolitical risks and cryptocurrency markets.

2.3. Research hypothesis

2.3.1. Geopolitical risks and Cryptocurrencies volatility

Most previous studies only focus on the impact of EPU on the volatility of the crypto market (Colon et al., 2021; Jiang et al., 2021; Raza et al., 2023; Yen & Cheng, 2021; Zhang et al., 2024). All studies have shown a common result that with greater uncertainty in economic policy, the stability of cryptocurrency returns is also higher. Meanwhile, geopolitical risk acts as one of the most potent transmission channels for other risk factors. While previous research predominantly analyzes the impact of global economic policy uncertainty on the cryptocurrency market, this study aims to explore more directly how geopolitical risks influence the crypto market. Drawing on the findings of prior research, we formulate the first research hypothesis as follows:

H1: Geopolitical risks have a negative correlation with cryptocurrencies volatility

2.3.2. Geopolitical risks and Cryptocurrencies volatility: The impact of green feature

The transition to cleaner energy sources has influenced various markets, including cryptocurrencies. The complex process of blockchain and mining requires a significant amount of electricity, leading to increased environmental damage when producing e-waste (Ali et al., 2024). In response to environmental concerns, the green crypto market has emerged. However, the green crypto market is particularly sensitive to environmental policies, governmental decisions, international organizations, and corporate environmental commitments and regulatory changes, leading to significant price fluctuations. Based on these factors, we propose the hypothesis:

H2: Geopolitical risks have a stronger negative correlation with volatility in green cryptocurrencies than in non-green cryptocurrencies

2.3.3. Geopolitical risks and cryptocurrencies volatility in a different context

Research by Colon et al. (2021) finds that the cryptocurrency market can serve as a strong hedge against geopolitical risks in most cases but may function as a weaker hedge and safe haven amid economic policy uncertainty during a bull market. This is attributed to investors' risk-seeking behavior in favorable market conditions, diminishing the appeal of cryptocurrencies. Furthermore, cryptocurrencies have many security-related disadvantages, making them easy targets for cybercriminals (Reddy, 2020) and cryptocurrency transactions consume a lot of energy. Consequently, in times of low geopolitical risk, cryptocurrencies are not typically favored as safe haven assets by investors. As a result, we propose the third research hypothesis:

H3: The negative relationship between geopolitical risk and cryptocurrencies volatility just appears in uncertain times

3. Methodology

3.1. Data and sample selection

Research data includes 10 cryptocurrencies, including 05 cryptocurrencies with the largest market capitalization including Bitcoin (BTC), Binance Coin (BNB), Ethereum (ETH), Solana (SOL), Tether (USDT) and the 05 green cryptocurrencies with the highest market capitalization include Ripple (XRP), Stellar (XLM), Cardano (ADA), Nano (XNO) and IOTA (MIOTA). The authors chose the period from November 10, 2017, to December 31, 2023, specifically for Bitcoin, the authors used data from September 17, 2014, to December 31, 2023. The chosen time period captures significant developments in the cryptocurrency market, including its rapid growth, increased adoption, and major geopolitical events that may influence market volatility. For Bitcoin, extending the data back to September 17, 2014, allows for a longer historical perspective, as it is the oldest and most established cryptocurrency. The independent variables, which are geopolitical risk (GPR), geopolitical ask (GPA), and geopolitical threat (GPT) are calculated by Caldara and Iacoviell (2022) and collected from policyuncertainty.com. The dependent variable and other control variables are collected from Yahoo Finance, Investing.com, and West Texas Intermediate. The selected data sources ensure reliability and relevance for the study. PolicyUncertainty.com provides trusted geopolitical risk indices (GPR, GPA, GPT) from Caldara and Iacoviello (2022), making it a credible source for measuring geopolitical factors. YahooFinance and Investing.com are widely recognized

platforms for accurate historical data on cryptocurrency prices, ensuring consistency in financial analysis. Additionally, West Texas Intermediate (WTI) is included as a control variable due to its role as a global oil price benchmark, reflecting broader macroeconomic conditions that may influence both traditional and cryptocurrency markets.

3.2. Model and methodology

Regarding cryptocurrency volatility, they use the GARCH-M-GJR-LEV (1,1) model Trifonov and Potanin (2024), which is commonly applied in financial time series analysis, to measure the volatility of the following cryptocurrencies:

$$y_t = \mu + \lambda_1\sigma^2_{t-1} + \lambda_2\, d_{t-1}\sigma^2_{t-1} + \varepsilon_t \quad (1)$$

$$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \gamma d_{t-1}\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} \quad (2)$$

$$with\ d_{t-1} := \begin{cases} 0, if\ r_{t-1} \geq \mu \\ 1, if\ r_{t-1} < \mu \end{cases} \quad (3)$$

$$and\ d_{t-1} := \begin{cases} 0, if\ \varepsilon_{t-1} \geq \mu\ (\text{Good News}) \\ 1, if\ \varepsilon_{t-1} < \mu\ \ (\text{Bad News}) \end{cases} \quad (4)$$

Where y_t is the return of cryptocurrencies and is calculated by $\ln(S_t/S_{t-1})$, ε_t is zero mean and need not be serially independent, σ^2_t is the conditional forecast variance at time t. Parameters λ_1 and λ_2 define the influence of conditional variance on returns. The presence of $\lambda_2 d_{t-1}\sigma^2_{t-1}$ allows differentiating between "good" and "bad" volatility periods while defining the risk premium.

To test the assumed relationship between the Geopolitical Risk, Geopolitical Acts, Geopolitical Threat and the volatility of the cryptocurrencies for all sample and also for the for each group of green and non-green cryptocurrencies, the authors estimate the following models:

$$VOL_{i,t} = \beta_0 + \beta_1 RISK_{i,t} + \varphi V_{i,t} + \delta_t + \alpha_i + \mu_{i,t} \quad (5)$$

Where i refers to coin and t refers to periods; δt is the error term in correlation to time specific effects; α_i is the error term associated with coin-specific effects which include unobservable coin-specific characteristics, and $\mu_{i,t}$ is the random error term. $V_{i,t}$ denotes a vector of macro-level control variables which are the Morgan Stanley Capital International (MSCI) index, Texas Crude oil price in USD (Oil), S&P 500 index (SP500), EUR/USD exchange rate (EX) that potentially affect cryptocurrencies' volatility. The MSCI reflects global market sentiment, potentially affecting cryptocurrency investments (Singh et al., 2019). Oil prices have shown spillover effects on Bitcoin's role as a hedge against economic uncertainty (Li et al., 2022). The S&P 500 index impacts investor sentiment and can lead to shifts toward alternative assets like Bitcoin during market volatility (Just & Echaust, 2023). Lastly, the EUR/USD exchange rate captures the relationship between fiat and digital currencies, impacting demand for cryptocurrencies (Aloui, 2021).

To evaluate the impact of Geopolitical Risk, Geopolitical Acts, and Geopolitical Threat to the volatility of cryptocurrencies in risky condition and nonrisky conditions, the authors estimate the model:

$$VOL_{i,t} = \beta_0 + \beta_1 RISK_{i,t} + \beta_2 RISK_{i,t}*HIGH + \beta_3 HIGH + \varphi V_{i,t} + \delta_t + \alpha_i + \mu_{i,t} \quad (6)$$

$$VOL_{i,t} = \beta_0 + \beta_1 RISK_{i,t} + \beta_2 RISK_{i,t}*LOW + \beta_3 LOW + \varphi V_{i,t} + \delta_t + \alpha_i + \mu_{i,t} \quad (7)$$

The LOW variable has a value of 1 at the time when the GPR, GPA, and GPT score was smaller than the first quartile of GPR, GPA, and GPT score, and vice versa is equal to 0. The High variable has a value of 1 at the time when the GPR, GPA, and GPT score was bigger than the third quartile of the GPR, GPA, and GPT score, and vice versa is equal to 0.

The study utilizes the GARCH-M-GJR-LEV model to examine cryptocurrency return volatility (VOL) as the dependent variable, reflecting fluctuations in cryptocurrency rates of return. Key independent variables include Geopolitical Risk (GPR), Geopolitical Act (GPA), and Geopolitical Threat (GPT), represented by the natural logarithm of their scores. GPR, derived from extensive news article analysis, encompasses threats like wars and terrorism and is divided into GPT and GPA. Control variables include macro factors like exchange rates, oil prices (proxied by Texas Crude oil prices), and stock indices (such as the S&P 500). These variables aim to enhance model stability and ensure the reliability of results by accounting for economic policy uncertainty, market information, and investor sentiment.

Table 1

Descriptive Variables

Variables	Definitions	Sources
Dependent variable		
VOL	Daily log-return volatility measured by conditional variance calculated from the asymmetric GARCH-M-GJR-LEV model for coins i at time t	Calculations based on data from yahoofinance.com
Key independent variables		
RISK	The natural logarithm of GPR, GPA, GPT score at time t	Calculations based on data from https://www.matteoiacoviello.com/gpr.htm
High	The value equals 1 on the day when GPR, GPA, GPT scores go beyond its third quartile value, and 0 otherwise	Calculations based on data from https://www.matteoiacoviello.com/gpr.htm
Low	The value equals 1 with the day has GPR, GPA, GPT scores are below its first quartile value, and 0 otherwise	Calculations based on data from https://www.matteoiacoviello.com/gpr.htm
Control variables		
MSCI	Log return between the MSCI index time t and t-1	Calculations based on data from yahoofinance.com
Oil	Log return between the Oil price time t and t-1	Calculations based on data from fred.stlouisfed.org/series/DCOILWTICO
SP500	Log return between the S&P500 time t and t-1	Calculations based on data from yahoofinance.com
EX	Log return between the MSCI index time t and t-1	Calculations based on data from investing.com

Source. The researcher's data analysis

4. Research results

4.1. Descriptive statistics

Table 2

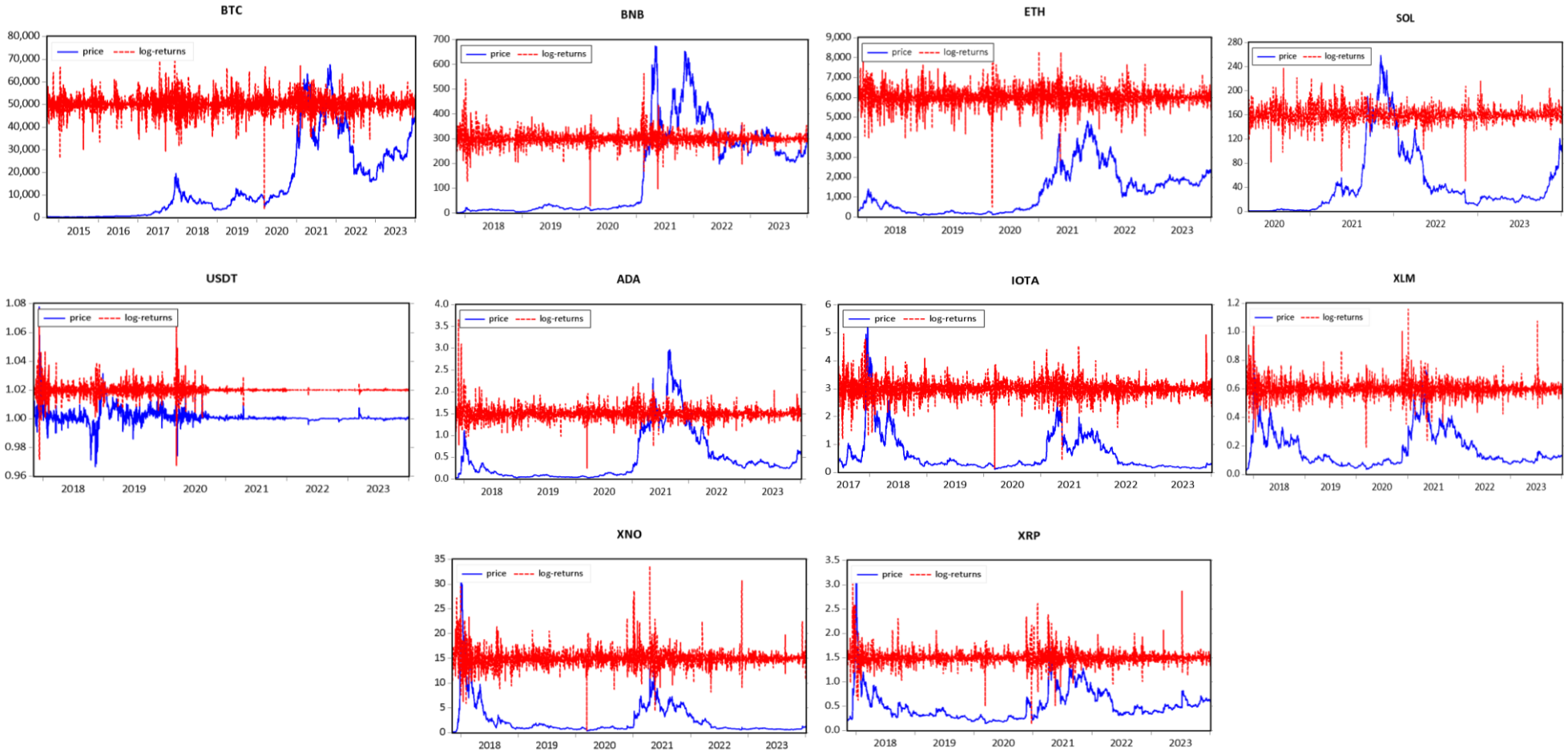
Descriptive Statistics

Sample		Variable							
	VOL	**GPR**	**GPA**	**GPT**		**MSCI**	**OIL**	**SP500**	**EX**
Total sample	Obs.	22,844	22,844	22,256	22,804	15,680	15,560	15,721	16,243
	Mean	0.0034	4.5010	4.1504	4.6660	0.0000	-3.77e-06	0.0005	-9.19e-06
	Standard deviation	0.0057	0.5636	0.7603	0.6220	0.0073	0.0131	0.0126	0.0048
	Min	6.71e-08	1.2724	1.8034	1.7811	-0.3074	-0.3114	-0.1198	-0.0281
	Max	0.1592	6.2965	6.3121	6.7046	0.0300	0.1779	0.0510	0.0938
Non-green currency	Obs.	11,481	11,481	11,194	11,461	7,883	7,822	8,163	7,902
	Mean	0.0022	4.5051	4.1740	4.6597	0.0001	-7.50e-06	0.0001	-0.0000
	Standard deviation	0.0037	0.5594	0.7584	0.6186	0.0065	0.0132	0 .0123	0 .0049
	Min	6.71e-08	1.2724	1.8034	1.7811	-0.2720	-0.3114	-0.0281	-0.1198
	Max	0.0588	6.2965	6.3121	6.7046	0.0300	0.1779	0.0938	0.0510
Green currency	Obs.	11,363	11,363	11,062	11,343	7,797	7,738	8,080	7,819
	Mean	0.0046	4.4968	4.1265	4.6725	6.23e-20	1.15e-18	0.0005	3.60e-19
	Standard deviation	0.0069	0.5679	0.7615	0.6254	0.0080	0.0131	0.0128	0.0047
	Min	0.0008	1.2725	1.8035	1.7811	-0.3074	-0.2847	-0.1198	- 0.0281
	Max	0.1592	6.2965	6.1186	6.7046	0.0300	0.1779	0.0510	0.0938

Source. Authors' calculation

Figure 2

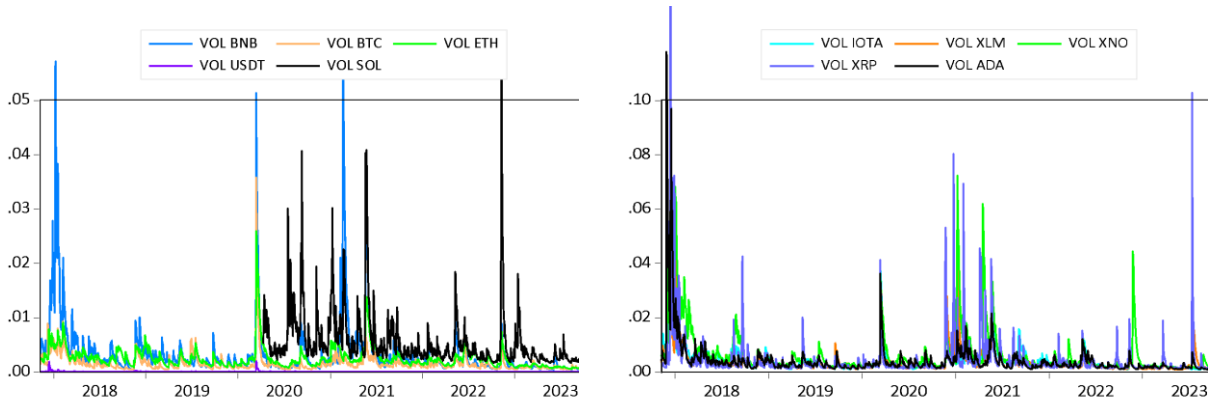
Trend in Price and Return of Cryptocurrencies



Source. Data analysis result of the research

Figure 3

Trend in Volatility of Cryptocurrenices



Source. Author's compilation

Table 2 provides descriptive statistics for variables in the research model, encompassing 10 cryptocurrencies and a total of 22,844 observations. The sample consists of the top 05 cryptocurrencies by market capitalization as of December 31, 2023, and the largest 05 green cryptocurrencies from 2014 to 2023, with daily frequency. The primary dependent variable, VOL, measures the volatility of cryptocurrency yield rates on a given day. Key independent variables include Geopolitical Risk (GPR), Geopolitical Ask (GPA), and Geopolitical Threat (GPT), all logarithmically transformed. Control variables comprise the logarithmically transformed Morgan Stanley Capital International (MSCI) index, Texas Crude oil price in USD (Oil), S&P 500 index (SP500), and EUR/USD exchange rate (EX).

The analysis reveals that green cryptocurrencies exhibit higher volatility compared to other groups. Their association with emerging technologies and environmental initiatives makes them speculative investments, prone to price fluctuations based on market sentiment and opinions regarding long-term viability and adoption. USDT stands out with the least volatility due to its peg to the USD at a 1:1 ratio, providing stability distinct from other cryptocurrencies. Notably, during periods of instability like the Covid-19 pandemic and wartime conflicts, cryptocurrencies like Bitcoin exhibit an upward trend. This is attributed to their role as alternative investments during severe global economic downturns, as they are independent of public monetary policy.

4.2. Research results

4.2.1. Analyze the impact of geopolitical risks on cryptocurrencies volatility

Table 3

Regression Results by all Samples

Dependent variable:VOL	Model 1 (GPR)	Model 1 (GPA)	Model 1 (GPT)
GPR	-0.0864***	-	-
	(-9.53)		
GPA	-	-0.0425***	-
		(-7.35)	
GPT	-	-	-0.0611***

Dependent variable:VOL	Model 1 (GPR)	Model 1 (GPA)	Model 1 (GPT)
			(-7.62)
MSCI	0.0014	0.0194	0.0823
	(0.00)	(0.03)	(0.13)
OIL	-0.6608**	-0.7301**	-0.7093**
	(-1.99)	(-2.20)	(-2.14)
EX	-0.8534	-0.9276	-0.8838
	(-0.96)	(-1.03)	(-0.99)
SP500	1.3784***	1.3998***	1.3429***
	(3.77)	(3.82)	(3.67)
Constant	0.7377***	0.5149***	0.6299***
	(17.37)	(20.66)	(16.15)
Time fixed effect	Yes	Yes	Yes
Coin fixed effect	Yes	Yes	Yes
Adjust R-Squared	0.1294	0.1275	0.1276
F-test	22.05***	14.79***	15.45***
Observations	15,453	15,336	15,453

Notes. The symbols ***, **, and * represent the coefficients' statistical significance at 1%, 5%, and 10%, respectively, the regression coefficient is multiplied by 100. The data are from Authors' calculation

The regression results of the study model using the Multi-way Fixed Effect method on the entire sample data set reveal that geopolitical risk has a negative correlation with cryptocurrency market volatility at the 1% significance level. This indicates that as geopolitical risk increases, the cryptocurrency market tends to become more stable. These findings align with the study by Raza et al. (2023), which suggests that cryptocurrencies experience a surge during uncertain times regarding financial regulatory policies, especially geopolitical risks, becoming independent of regulatory agencies and hence more attractive for investment during such periods. Our findings are valuable for investors and traders in terms of portfolio asset allocation for risk minimization, suggesting that cryptocurrencies may offer opportunities for investment and risk control during global economic and financial crises. Jiang et al. (2021) also argue that cryptocurrencies, being unrelated directly to any government or central bank, could be viewed positively during times of increasing geopolitical risk tensions. Moreover, geopolitical risk is also a contributing factor to economic instability, such as oil price hikes leading to global supply chain disruptions (Chortane & Pandey, 2022; Nerlinger & Utz, 2022; Umar et al., 2022) as evidenced by the case of Russia and Ukraine in 2022, with Russia facing economic sanctions resulting in retaliatory measures, leading to continuous global commodity price increases and current recession. In response, governments worldwide are implementing consecutive policies to stabilize the current economic and political landscape (Liadze et al., 2023). Therefore, as geopolitical risk increases, indicating growing uncertainty, investors may allocate their funds to cryptocurrencies if they perceive them as safe-haven assets.

4.2.2. Analyze the impact of geopolitical risks on cryptocurrencies volatility: The impact of green feature

Table 4

Regression Results by Coin Group

Dependent variable:VOL	Green cryptocurrencies			Non-green cryptocurrencies		
	Model 1 (GPR)	Model 1 (GPA)	Mode 1 (GPT)	Model 1 (GPR)	Model 1 (GPA)	Model 1 (GPT)
GPR	-0.1074***	-	-	-0.0634***	-	-
	(-6.65)			(-7.98)		
GPA	-	-0.0515***	-	-	-0.0324***	-
		(-4.97)			(-6.48)	
GPT	-	-	-0.0747***	-	-	-0.0466***
			(-5.21)			(-6.65)
MSCI	-0.1082	-0.1421	-0.0077	0.0697	0.1596	0.1293
	(-0.10)	(-0.14)	(-0.01)	(0.11)	(0.25)	(0.20)
OIL	-0.6001	-0.6614	-0.6667	-0.7317**	-0.8098***	-0.7630***
	(-1.02)	(-1.12)	(-1.13)	(-2.50)	(-2.79)	(-2.60)
EX	-1.2580	-1.3439	-1.3025	-0.5101	-0.5825	-0.5296
	(-0.77)	(-0.82)	(-0.80)	(-0.67)	(-0.77)	(-0.69)
SP500	1.8400***	1.8472***	1.7923***	0.8906***	0.9216***	0.8668***
	(2.90)	(2.89)	(2.82)	(2.68)	(2.80)	(2.61)
Constant	0.9511***	0.6680***	0.8121	0.5164***	0.3581***	0.4454***
	(12.56)	(15.03)	(11.61)	(13.85)	(16.51)	(13.08)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Coin fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjust R-Squared	0.0703	0.0656	0.0658	0.2221	0.2223	0.2202
F-test	10.83***	6.90***	7.40***	15.54***	11.61***	11.65***
Observations	7,685	7,625	7,685	7,768	7,711	7,768

Notes. The symbols ***, **, and * represent the coefficients' statistical significance at 1%, 5%, and 10%, respectively, the regression coefficient is multiplied by 100. The data are from Authors' calculation

Through the results obtained from the main model above, it is evident that when geopolitical risk increases, cryptocurrencies tend to become more stable. However, a question arises: how does the impact of geopolitical risk differ between specific types of cryptocurrencies, namely green and non-green ones?

To address this question, the authors proceed with subgroup regression analysis by grouping 05 cryptocurrencies into one group and the remaining 05 green cryptocurrencies into another. Through the regression results from Table 4, it can be observed that all three variables representing geopolitical risk (GPR, GPA, and GPT) have negative correlations with the volatility of both green and non-green cryptocurrencies at the 1% significance level. However, it

is more specifically apparent that geopolitical risk has a more pronounced dampening effect on volatility in the group of green cryptocurrencies. This phenomenon can be attributed to the increasing investor interest driving investors to seek financial instruments aligning with their environmental values. Therefore, studying and comparing green cryptocurrencies with conventional ones may provide favorable conditions to identify and evaluate their potential as investment options aligned with sustainability goals amidst geopolitical instability.

Farid et al. (2023) discovered a weak connection between clean and dirty energy markets in short-term investments, indicating limited coordination. Green cryptocurrencies could provide a unique diversification opportunity during times of tension, such as political instability. The sustainability of green cryptocurrencies is crucial in today's investment landscape due to concerns about climate change and geopolitical risks. Ren and Lucey (2022) found that clean energy can act as a hedge and safe haven during price declines of unsustainable cryptocurrencies, while Naeem and Karim (2021) stated that it could mitigate the price risk of Bitcoin. Unsustainable cryptocurrencies rely on PoW algorithms, consuming significant energy and generating carbon emissions. In contrast, green cryptocurrencies employ energy-saving methods and consensus algorithms, resulting in lower energy consumption. Recent technological advancements have made it possible to transform unsustainable cryptocurrencies into green ones through algorithmic changes.

4.2.3. Analyze the impact of geopolitical risks on cryptocurrencies volatility in different contexts

Table 5

Regression Result in different Cases

Dependent variable:VOL	High-Risk			Dependent variable:VOL	Low-Risk		
	Model 2 (GPR)	**Model 2 (GPA)**	**Model 2 (GPT)**		**Model 3 (GPR)**	**Model 3 (GPA)**	**Model 3 (GPT)**
GPR	-0.0559***	-	-	**GPR**	-0.1261***	-	-
	(-3.65)				(-10.13)		
GPR*High	-0.096***	-	-	**GPR*Low**	0.1239***	-	-
	(2.94)				(2.71)		
GPA	-	-0.0056***	-	**GPA**	-	-0.0896***	-
		(-0.65)				(-9.39)	
GPA*High	-	-0.1328***	-	**GPA*Low**	-	0.0905***	-
		(-4.82)				(3.74)	
GPT	-	-	-0.0333**	**GPT**	-	-	-0.1105***
			(-2.53)				(-9.74)
GPT*High	-	-	-0.0804***	**GPT*Low**	-	-	0.2021***
			(-2.71)				(5.48)
High	0.4676***	0.6014***	0.4020***	**Low**	-0.5546***	-0.3841***	-0.8891***
	(2.85)	(4.39)	(2.58)		(-3.05)	(-4.65)	(-5.90)
MSCI	0.0091	0.0214	0.0722	**MSCI**	0.0481	-0.0158	-0.0792
	(0.01)	(0.03)	(0.11)		(0.08)	(-0.02)	(0.12)
OIL	-0.6703**	-0.6880**	-0.7109**	**OIL**	-0.6761**	-0.7340**	-0.6768**

Dependent variable:VOL	High-Risk			Dependent variable:VOL	Low-Risk		
	Model 2 (GPR)	**Model 2 (GPA)**	**Model 2 (GPT)**		**Model 3 (GPR)**	**Model 3 (GPA)**	**Model 3 (GPT)**
	(-2.02)	(-2.07)	(-2.14)		(-2.04)	(-2.21)	(-2.04)
EX	-0.9811	-1.0183	-1.0261	**EX**	-0.8933	-1.1207	-1.0151
	(-1.10)	(-1.14)	(-1.15)		(-1.00)	(-1.25)	(-1.13)
SP500	1.3714***	1.3263***	1.3524***	**SP500**	1.3193***	1.3337***	1.2895***
	(3.75)	(3.62)	(3.70)		(3.61)	(3.64)	(3.53)
Constant	0.6048***	0.3787***	0.5061***	**Constant**	0.9328***	0.7355***	0.8815***
	(8.90)	(11.24)	(8.39)		(15.60)	(16.90)	(15.54)
Time fixed effect	Yes	Yes	Yes	**Time fixed effect**	Yes	Yes	Yes
Coin fixed effect	Yes	Yes	Yes	**Coin fixed effect**	Yes	Yes	Yes
Adjust R-Squared	0.1298	0.1298	0.1280	**Adjust R-Squared**	0.1306	0.1296	0.1301
F-test	17.12***	16.52***	12.35***		18.98***	16.16***	17.86***
Observations	15,453	15,336	15,453	**Observations**	15,453	15,336	15,453

Notes. The symbols ***, **, and * represent the coefficients' statistical significance at 1%, 5%, and 10%, respectively, the regression coefficient is multiplied by 100. The data are from Author's compilation

The regression results indicate that geopolitical risk affects green and non-green cryptocurrencies in opposite directions, with a stronger impact on the green cryptocurrency group. Despite previous studies suggesting high risk in cryptocurrencies, this study finds that cryptocurrencies can serve as safe haven assets during periods of geopolitical risk. However, the authors aim to address whether cryptocurrencies can act as safe havens and hedge assets in both high and low geopolitical risk scenarios.

Analyzing the regression results, the study categorizes the HIGH-RISK group as observations above the third quartile and the LOW-RISK group as observations below the first quartile. It is observed that geopolitical risk reduces cryptocurrency volatility only in high geopolitical risk market conditions. Conversely, in stable low geopolitical risk periods, geopolitical risk increases cryptocurrency volatility. These findings suggest that global regulations on cryptocurrencies are more stringent during stable market conditions, resulting in insignificant effects of geopolitical risk on cryptocurrencies when major systemic risks are absent.

The Efficient Market Hypothesis (EMH) suggests that market prices are determined by fundamental factors (Fama, 1970), but behavioral finance research has demonstrated that investor psychology and behavior play a role in influencing asset prices, challenging the assumption of market efficiency (Ichev & Marinč, 2018). Empirical evidence shows that investors often behave irrationally, especially during times of recovering from the Covid-19 pandemic and facing geopolitical conflicts like the Russia-Ukraine conflict. As a result, the value of the cryptocurrency market relies more on individual beliefs and decisions rather than fundamental factors (Kumar, 2020). This phenomenon provides investors with more incentives to invest in cryptocurrencies during high geopolitical risk periods, leading to increased liquidity and reduced volatility in the crypto market.

4.3. The effect of the wars on the volatility of different financial markets

Table 6

Futher Analysis DIS-PSM Estimation

Dependent Variable: VOL	Model (4) Crypto vs Stock martket	Model (5) Crypto vs Forex market
TREAT	0.3755***	0.3775***
	(26.66)	(26.91)
POST1	0.0111	0.0127
	(0.40)	(0.46)
POST2	0.0537	0.0551
	(1.03)	(1.06)
TREAT*POST1	-0.0811***	-0.0821***
	(-2.60)	(-2.63)
TREAT*POST2	-0.1530***	-0.1557***
	(-2.73)	(-2.78)
MSCI	1.7643	1.5119
	(1.39)	(0.08)
OIL	-0.7307**	-0.7454**
	(-2.11)	(-2.14)
EX	-1.8024*	-
	(-1.70)	
SP500	-	1.3809 (1.10)
Constant	-0.0016	-0.0037
	(-0.12)	(-0.29)
Time fixed effects	Yes	Yes
Coin fixed effects	Yes	Yes
Obs.	6244	6244
Adjust R-squared	0.1500	15.05
F-statistic	108.79**	110.34***

Notes. The symbols ***, **, and * represent the coefficients' statistical significance at 1%, 5%, and 10%, respectively, the regression coefficient is multiplied by 100. The data are from Author's compilation

To further investigate the impact of geopolitical risks on the cryptocurrency market and provide additional empirical evidence, the authors employed a combination of Difference-in-Differences (DID) estimation and Propensity Score Matching (PSM) with two recent war events: the Russia-Ukraine conflict and the Hamas-Israel conflict.

The output variable, VOL, is employed in this research as an indicator to measure the impact of wars on the volatility of the difference layer of financial assets. To validate the parallel trends assumption, the pre-treatment dividend payouts of the treated and control groups are compared. The main regressions equation for the DID estimator:

$$VOL_{i,t} = B_0 + B_1*TREAT_i + B_2*POST1_t + B_3*POST1_t + B_4*POST1_t*TREAT1_i + B_5*POST2_t*TREAT1_i + B_6MSCI_{i,t} + B_7*OIL_{i,t} + B_8*EX_{i,t} + \delta_t + \alpha_i + \mu_{i,t} \quad (8)$$

$$VOL_{i,t} = B_0 + B_1*TREAT_i + B_2*POST1_t + B_3*POST1_t + B_4*POST1_t*TREAT1_i + B_5*POST2_t*TREAT1_i + B_6MSCI_{i,t} + B_7*OIL_{i,t} + B_8*SP500_{i,t} + \delta_t + \alpha_i + \mu_{i,t} \quad (9)$$

Where TREAT is a dummy variable that equals 1 if with the volatility of green cryptocurrencies and equals 0 with the volatility of the S&P 500 index (model 10) and the volatility of the EUR/USD exchange rate (model 11), POST1 is a dummy variable that equals 1 if day t is in the first posttreatment period (from 24 February 2022 to the end of 2022) represent for the Russia and Ukraine war, POST2 is a dummy variable that equals 1 if day t is in the second posttreatment period (from 07 October 2023 to the end of 2023) represent for the Hamas and Israel War. (TREAT x POST1) is the interaction term between the treated group and the first post-treatment period, indicating the impact of the Russia and Ukraine war on the volatility of the green crypto market when TREAT x POST2 indicates the impact of the Hamas and Israel war on the volatility of the green crypto market. The coefficient of interest is β_4 and β_5 in both model 10 and model 11, which capture the average treatment effect on the treated (ATT) (Caliendo & Kopeinig, 2008). A negative and statistically significant β_4, β_5 indicates that the two recent wars have a negative impact on the volatility of the green cryptocurrencies market, which means the green cryptocurrencies market will be more sustainable during the uncertainty.

5. Conclusion

The research confirms that Geopolitical Risk (GPR), Geopolitical Ask (GPA), and Geopolitical Threat (GPT) have a negative influence on cryptocurrency volatility. This means that during times of increased uncertainty caused by war, terrorism, or political tension, the cryptocurrency market becomes more stable, and cryptocurrencies can serve as new safe haven assets. The influence of these geopolitical factors on green cryptocurrencies' volatility is stronger than on non-green cryptocurrencies, indicating a growing emphasis on sustainability. The relationship between geopolitical risk and cryptocurrency market stability only appears during periods of high risk and uncertainty.

The implications of the research suggest that cryptocurrency markets can be a refuge for investors seeking stability during times of heightened geopolitical risk. It also highlights the importance of considering geopolitical factors in cryptocurrency regulations and policies. Investors may increasingly favor green cryptocurrencies due to sustainability considerations, leading to shifts in investment behavior. Risk management strategies should incorporate geopolitical risk assessments to navigate uncertainty better.

However, the study's focus on a limited number of cryptocurrencies and reliance on established indices for measuring geopolitical risk introduces limitations. The use of daily data neglects intraday fluctuations and fails to capture specific nuances or localized geopolitical events. The study acknowledges the presence of bidirectional relationships between variables and the potential impact of unobserved factors, which may introduce bias. The absence of a ranking system for green cryptocurrencies leaves a gap in the analysis.

Future research can expand the sample size, employ qualitative methodologies to understand investor perspectives, integrate high-frequency intraday data, utilize machine learning algorithms, conduct cross-country analyses, and focus on specific geopolitical crises to enhance our understanding of the relationship between geopolitical factors and cryptocurrency markets.

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