Are Crypto-Assets More Resilient to Financial Shocks than Conventional Assets?

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Citation: Steli, E. M., & Ouchen, A. (2026). Are crypto-assets more resilient to financial shocks than conventional assets? *Theoretical and Practical Research in Economic Fields, 17*(1), 112–132. https://doi.org/10.14505/tpref.v17.1(37).09

Article info: Received 24 August 2025; Received in revised form 26 September 2025; Accepted for publication 2 November 2025; Published 30 March 2026.

Abstract: This article examines the resilience of crypto-assets and that of conventional assets to financial shocks. It uses GARCH models to analyze the volatility of daily returns of crypto-assets (*i.e.*, BTC, ETH, BNB, XRP, ADA) and conventional assets (*i.e.*, AAPL, MSFT, GOOG, AMZN, NVDA), with their respective benchmarks (*i.e.*, CRIX and S&P500). The total study period runs from March 16, 2018, to June 30, 2023, divided into three sub-periods: the pre-COVID-19 period (March 16, 2018, to November 29, 2019), the post-COVID-19 period (December 02, 2019, to February 09, 2022), and the Russo-Ukrainian war period (February 10, 2022, to June 30, 2023). The results indicate that crypto-assets are more volatile than conventional assets over the full study period, confirming their status as risky assets. Furthermore, all assets experienced a significant increase in volatility during the COVID-19 pandemic, with particularly high levels for crypto-assets compared to conventional assets. During the Russo-Ukrainian war period, crypto-assets experienced high levels of volatility, which were slightly lower than those observed during the post-COVID-19 period. Compared to crypto-assets, conventional assets are more resilient to financial shocks. Our research could help investors build their portfolios while also allowing them to understand the role of digital assets in risk management.

Keywords: crypto-assets; conventional assets; GARCH models; COVID-19; Russo-Ukrainian war; volatility; resilience.

JEL Classification: G15; C22; C58.

Introduction

Over the past decade, cryptocurrencies have rapidly emerged on the global financial landscape. Many hedge funds and asset managers have begun to incorporate cryptocurrency-related assets into their investment portfolios (Fang *et al.* 2022). Bitcoin has distinguished itself as the market leader among these assets. It is considered a kind of digital currency and payment mechanism, operating online via decentralized, distributed networks (Hayes, 2017). Its value is not based on the economy of any country and relies instead on the security of the algorithm and the traceability of transactions (Platanakis and Urquhart, 2020). Although created as a digital currency, Bitcoin is also used as an asset (Baur *et al.* 2018). As such, several authors have examined Bitcoin in relation to other conventional financial instruments, including its utility as a safe-haven asset, hedging tool, or means of diversification (Abdelmalek, 2023; Bouri *et al.* 2017; Rashid *et al.* 2023; Stensås *et al.* 2019).

Designed to function as a cryptographically secure means of exchange (Nakamoto, 2008), cryptocurrencies have revolutionized the financial world by offering a decentralized alternative to traditional financial assets. Their growing adoption has been fuelled by their potential for direct peer-to-peer transactions, eliminating the need for financial intermediaries (Peters *et al.* 2015; Steli and Ouchen, 2024; Swartz, 2014). With the explosive rise of cryptocurrencies and their growing integration into investment strategies, it is essential to assess their ability to offer resilience against financial shocks compared to conventional assets.

The COVID-19 pandemic and the Russo-Ukrainian war have exacerbated the volatility of global financial markets and raised concerns about the stability of conventional assets and crypto-assets (Chen and Yu, 2025; Mgadmi *et al.* 2023; Ouchen, 2022; Özdemir, 2022; Shaik *et al.* 2023). During periods of intense uncertainty, characterized by high volatility in financial asset prices, some investors view crypto-assets as a safe-haven (Corbet *et al.* 2020; Dwita Mariana *et al.* 2021; Tarchella *et al.* 2024; Yatie, 2022). Corbet *et al.* (2020) find that bitcoin offers diversification benefits and plays a similar role to gold as a safe-haven during the COVID-19 crisis. Indeed, Dwita Mariana *et al.* (2021) analyze the safe-haven properties of crypto-assets (*i.e.*, Bitcoin and Ethereum) for equities during the COVID-19 pandemic. The results indicate that Bitcoin and Ethereum can serve as short-term safe havens. In addition, Tarchella *et al.* (2024) examine the safe-haven, hedging, and diversification properties of oil, gold, and two cryptocurrencies (*i.e.*, Bitcoin and Ethereum) for G7 stock markets. The results show that cryptocurrencies have safe-haven potential during the COVID-19 crisis. Finally, Yatie (2022) analyzes the safe-haven properties of crypto-assets and gold for European assets during the COVID-19 crisis. The results show that crypto-assets such as Tether, Cardano, and Dogecoin exhibited safe-haven characteristics, proving to outperform gold. While Bitcoin, Ethereum, Litecoin, and Ripple performed particularly well as diversification tools for European indices.

However, some researchers put forward arguments against the idea that crypto-assets can be considered safe-havens during periods of financial crisis (Ballis *et al.* 2025; Conlon *et al.* 2020; Conlon and McGee, 2020; Karamti and Belhassine, 2022; Li and Miu, 2023; Yuyama *et al.* 2023). Ballis *et al.* (2025) show that cryptocurrencies cannot serve as safe-havens in times of crisis and may begin to behave similarly to traditional assets during difficult times. Conlon *et al.* (2020) indicate that Bitcoin and Ethereum do not fulfill this safe-haven function for global stock market indices during the COVID-19 crisis. Conlon and McGee (2020), Karamti and Belhassine (2022) state that Bitcoin cannot be considered a safe-haven since its price varies closely with the S&P500. Li and Miu (2023) find that cryptocurrencies are not a safe-haven for equity investors, since they fail to play their risk-mitigating role during market downturns. Yuyama *et al.* (2023) conclude that crypto-assets do not fulfill the role of "digital gold" or safe-haven in times of crisis. They demonstrate that the correlation between Bitcoin and the S&P500 increased significantly during COVID-19, the Russo-Ukrainian invasion, and the crypto winter.

This debate surrounding the status of crypto-assets as safe-havens, due to their resilience to shocks, leads us to the following question: Are crypto-assets more volatile than conventional assets? What about their respective resilience during the COVID-19 crisis and the Russo-Ukrainian war?

To provide some answers to this research question, we apply GARCH models to the daily returns of five crypto-assets, *i.e.*, Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), and Cardano (ADA); five US equities, *i.e.*, Apple (AAPL), Microsoft (MSFT), Google (GOOG), Amazon (AMZN), and Nvidia (NVDA); and their respective benchmark indices, *i.e.*, CRIX and S&P500. The study period runs from March 16, 2018, to June 30, 2023, divided into three sub-periods: the pre-COVID-19 period (March 16, 2018, to November 29, 2019), the post-COVID-19 period (December 02, 2019, to February 09, 2022), and the Russo-Ukrainian war period (February 10, 2022, to June 30, 2023).

This study contributes to the literature on the resilience of crypto-assets and conventional assets to financial shocks. It proposes a framework for examining the responsiveness of both asset classes during periods of crisis. The research highlights that crypto-assets are more volatile and therefore less resilient to financial shocks than conventional assets. This perspective will provide investors with valuable recommendations for managing the risks of their portfolios and exploiting opportunities for diversification in digital assets.

The remainder of this paper is structured as follows. The first section is devoted to a literature review on the resilience of crypto-assets relative to conventional assets during crisis periods. The second section presents the GARCH model and its extensions, suitable for modeling the volatility of the daily return series of the financial assets studied. The final section focuses on the analysis and discussion of the results.

1. Literature Review: Resilience of Crypto-Assets versus Traditional Assets During Crisis Periods

The COVID-19 pandemic and the Russo-Ukrainian war caused major fluctuations in financial assets, highlighting their resilience in the face of crises. Against this backdrop, the literature falls into three broad categories. The first category of research shows the resilience of crypto-assets during periods of crisis. The second concludes, on the contrary, that conventional assets are more resilient. On the other hand, the third highlights a significant absence of resilience for both asset classes.

1.1 Resilience of Crypto-Assets Compared to Conventional Assets

Numerous studies have analyzed the issue of the comparative volatility of digital assets compared to their conventional counterparts during periods of crisis (Maghyereh and Abdoh, 2022; Ullah, 2025; Terraza *et al.* 2024). Some have demonstrated the resilience of crypto-assets, highlighting their role as a safe-haven. Melki and Nefzi (2022) examined the hedging and safe-haven characteristics of the three main cryptocurrencies (*i.e.*, Bitcoin, Ripple, and Ethereum) against three traditional indices (*i.e.*, MSCI World, Gold Bullion LBM, and EUR/USD) during the COVID-19 pandemic. The results show that cryptocurrencies, in particular Bitcoin and Ethereum, exhibit strong safe-haven characteristics due to their resilience to external shocks. Nguyen (2022) analyzes the relationship between the stock market and Bitcoin during periods of uncertainty, notably during the COVID-19 pandemic. The results indicate that Bitcoin could function as a safe-haven due to the high correlation between traditional assets and cryptocurrencies in times of crisis. This shows its resilience to economic shocks and its potential to diversify portfolios. Taera *et al.* (2023) examined the volatility of traditional assets, the Fintech index, and cryptocurrencies during the COVID-19 pandemic and the Russo-Ukrainian war. They demonstrate that all financial and alternative market assets retained in this study experienced significant volatility, except for Bitcoin, over the total study period. Mejri *et al.* (2025) examined the impact of geopolitical risk on Bitcoin, gold, and green bonds using quantile wavelet analysis. The results show Bitcoin's resilience to stress conditions, highlighting its hedging capacity within diversified portfolios. Marobhe (2022) examines the sensitivity of cryptocurrencies to the COVID-19 crisis, comparing them to the main stock market indices. His study reveals that cryptocurrencies showed greater resilience in these difficult times, managing to recover rapidly as early as April 2020, shortly after the onset of the pandemic. In contrast, indices such as the S&P500, FTSE 100, and SSE Composite continued to be affected by the COVID-19-related panic until June 2021.

1.2 Resilience of Conventional Assets Against Crypto-Assets

Conversely, other research challenges the perception of crypto-assets as resilient during turbulent times. Lahmiri and Bekiros (2020) compare the behavior of 45 cryptocurrencies with global stock markets during the COVID-19 crisis. The results show that cryptocurrency markets are more impacted by the pandemic than global stock markets. Certainly, there is greater instability in the cryptocurrency market compared to the equity market. Yarovaya *et al.* (2022) also analyzed the financial market response and recovery of four financial asset classes (*i.e.*, stock market, precious metals, bonds, and cryptocurrencies) during the COVID-19 pandemic. The results show that stock markets are more predictable and therefore less risky, while cryptocurrencies are considered the riskiest asset class in the long term. Kayani *et al.* (2024) examined quantile connectivity in digital and traditional asset markets with the renewable energy price index. The study period from January 2, 2018, to December 4, 2023, covered various economic crises. The results show that the volatility of digital assets is higher than that of traditional and energy assets. Bampinas and Panagiotidis (2024) studied the links between six international stock markets and the two main cryptocurrency markets during the COVID-19 pandemic and the Russo-Ukrainian war. The results show that Bitcoin and Ethereum possess diversification and limited safe-haven properties during COVID-19, which further diminish during the war. In their research into the resilience of cryptocurrencies during the Russo-Ukrainian war, Khalfaoui *et al.* (2023) show that cryptocurrencies, particularly Bitcoin, were affected by the war and are not entirely resilient to geopolitical crises.

1.3 Absence of Significant Resilience of Crypto and Traditional Assets

However, some studies highlight the fact that the volatility of both asset classes was particularly affected during periods of crisis. Jeribi and Kammoun Masmoudi (2021) studied the relationship between the volatility of traditional and digital assets before and during the COVID-19 pandemic. They show that stock markets reacted to the COVID-19 pandemic as did the cryptocurrency market, with worrying volatility. Zhu *et al.* (2025) provided an econometric modeling of volatility and estimation of extreme risk for Bitcoin, stock indices, gold, and crude oil. The results show that extreme risk levels for all asset classes increased significantly during the COVID-19 pandemic, confirming the disruptive effect of crises on financial stability. Hamouda *et al.* (2024) show that cryptocurrency markets became more closely linked to equity markets after February 2022. Gaies and Chkili (2023) studied the dynamic relationship between Bitcoin volatility and stock market volatility during the Russo-Ukrainian war. They also show that the correlation between the two markets increased during the war, and, consequently, Bitcoin was not a safe-haven during this period. However, in a portfolio context, their findings indicate that integrating Bitcoin into an equity portfolio can reduce risk without compromising expected returns.

2. Methodological Framework

2.1 Variables and Study Period

This study takes the daily return series of five crypto-assets, *i.e.*, Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), and Cardano (ADA); five U.S. market stocks, *i.e.*, Apple (AAPL), Microsoft (MSFT), Google (GOOG), Amazon (AMZN), and Nvidia (NVDA); as well as their respective benchmark indices, *i.e.*, CRIX and S&P500, during the period from March 16, 2018, to June 30, 2023. The selection criteria for these assets are market capitalization and data availability. The daily return of an asset i on date t is calculated using the following formula:

$$R_{it} = \ln \left(\frac{P_{it}}{P_{i,t-1}}\right) \quad (1)$$

2.2 Volatility Analysis

2.2.1 GARCH Models

In 1986, Bollerslev (1986) developed Engle's ARCH model into the GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) model. We have used the well-known GARCH (1,1) econometric model to model risk and volatility in our study. This model is frequently used to analyze time series data with volatility clusters, meaning that large changes in the time series tend to be followed by other significant changes. The GARCH (1,1) model also provides a more accurate representation of volatility clustering than simpler models such as the constant variance model or the ARCH (n) model (Bollerslev, 1986; Chou, 1988).

2.2.1.1 ARCH Models

The ARCH (AutoRegressive Conditional Heteroskedasticity) model introduced by Engle (1982) can be used to model chronicles (mainly financial) that have an instantaneous variability that depends on the past. This makes it possible to develop a dynamic forecast of the chronicle in terms of mean and variance.

The ARCH (1) model equation is then written as follows:

$$r_t = \delta + \varepsilon_t = \delta + n_t\sqrt{h_t} \quad (2)$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2$$

With $\alpha_0 > 0$ and $\alpha_1 \geq 0$; $\varepsilon_t = n_t\sqrt{h_t}$ (where $n_t \sim N(0,-1)$) as the error term of the AR (1) model: $r_t = \emptyset_1 y_{t-1}$ of our study variable; and h_t as the conditional variance.

2.2.1.2 GARCH Model

The GARCH (1, 1) model equation is written as:

$$r_t = \delta + \varepsilon_t = \delta + n_t\sqrt{h_t}$$

The residual conditional variance equation is defined as:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (3)$$

Where: $\alpha_0 > 0$, $\sim \alpha_1 \geq 0$, and $\sim \beta_1 \geq 0$.

2.2.1.3 EGARCH Model

The EGARCH model introduced by Nelson (1991) was developed to incorporate the impact of asymmetry between positive and negative shocks on the conditional variance of future observations. The model also takes into account the leverage effect, whereby negative shocks have a greater impact on conditional variance than positive shocks of the same magnitude.

The equation of the EGARCH (1,1) model is written as follows:

$$\log(h_t) = \alpha_0 + \alpha_1 \left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \alpha_2 \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_1 \log(h_{t-1}) \quad (4)$$

Where α_1 denotes the ARCH effect, estimating the response to any market shock or news;
α_2 represents the coefficient identifying the presence of the asymmetric effect;
β_1 represents the GARCH effect, identifying the persistence of volatility.

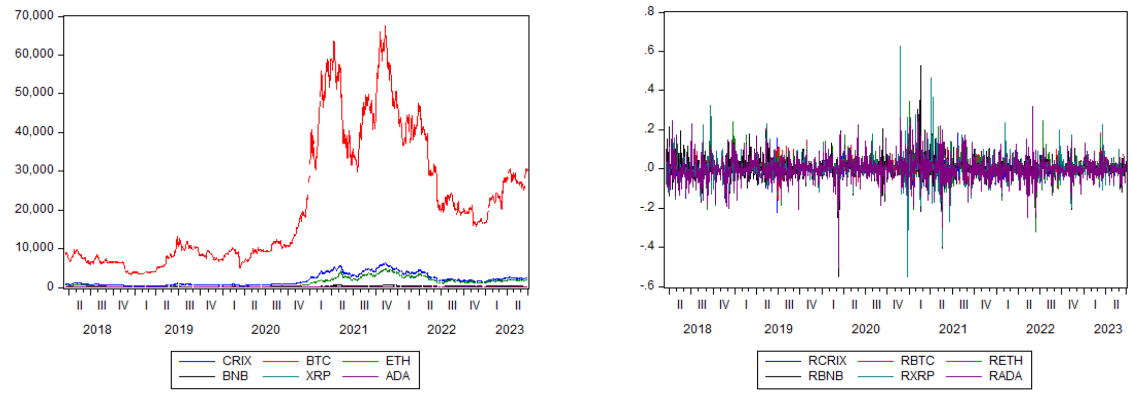
3. Results

3.1 Graphical and Statistical Examination of the Series of Daily Returns on the Assets of Our Interest

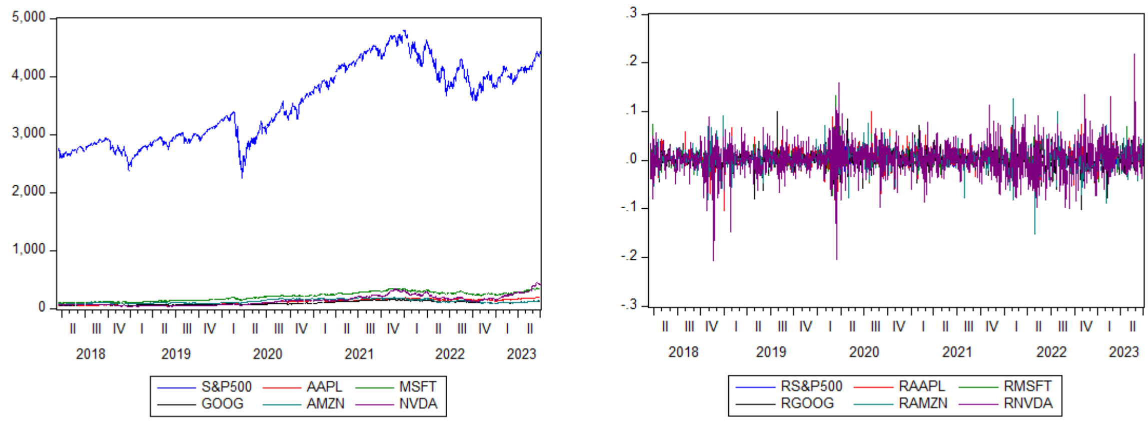
Figure 1 below shows the graphical evolution of the series of prices and daily returns on the assets of our study over the full study period from March 16, 2018, to June 30, 2023.

Figure 1. Daily asset prices and returns

(a) Crypto-assets



(b) Conventional assets



Source: Eviews software, Authors

Graphical analysis of the variables in our study and unit root tests, namely the increased Dickey–Fuller, Phillips–Perron, and KPSS (Kwiatkovski, Phillips, Schmidt and Shin), show that the daily prices of the five crypto-assets, *i.e.*, Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), and Cardano (ADA); the five U.S. market stocks, *i.e.*, Apple (AAPL), Microsoft (MSFT), Google (GOOG), Amazon (AMZN), and Nvidia (NVDA); as well as their respective benchmark indices, *i.e.*, CRIX and S&P500, are not stationary I(1). In contrast, the daily return series for the same assets: RBTC, RETH, RBNB, RXRP, RADA, RAAPL, RMSFT, RGOOG, RAMZN, RNVDA, RCRIX, and RS&P500, are stationary and therefore I(0), throughout the full study period (Figure 1). This stationary characteristic is also verified over the three distinct sub-periods (pre-COVID-19, post-COVID-19, and the Russo-Ukrainian war period). Tables 1, 2, 3, and 4 below present the statistical indicators of the daily return series of our interest assets for the full study period (between March 16, 2018 and June 30, 2023) as well as its three sub-periods, namely, the pre-COVID-19 sub-period (between March 16, 2018 and November 29, 2019), the post-COVID-19 sub-period (between December 2, 2019 and February 9, 2022), and the Russo-Ukrainian war sub-period (between February 10, 2022 and June 30, 2023).

Table 1. Statistical indicators of daily asset return series for the full study period

	RCRIX	RBTC	RETH	RBNB	RXRP	RADA
Mean	0.000691	0.000976	0.000879	0.002464	-0.000282	0.000356
Median	0.001639	0.000973	0.000881	0.001722	-0.000361	-6.66E-05
Maximum	0.189390	0.203046	0.343523	0.529218	0.626741	0.316747
Minimum	-0.272552	-0.464730	-0.550732	-0.543084	-0.550503	-0.503638
Std. Dev.	0.045015	0.044203	0.058590	0.060253	0.066097	0.065918
Skewness	-0.431010	-0.983517	-0.765685	-0.222714	0.449244	-0.050890
Kurtosis	6.728078	14.81685	12.23142	15.73495	18.42266	7.713621
Jarque-Bera (Probability)	810.1709 (0.000000)	7940.730 (0.000000)	4845.217 (0.000000)	8984.885 (0.000000)	13206.18 (0.000000)	1229.982 (0.000000)
Observations	1328	1328	1328	1328	1328	1328
	RS&P500	RAAPL	RMSFT	RGOOG	RAMZN	RNVDA
Mean	0.000362	0.001109	0.000965	0.000569	0.000381	0.001439
Median	0.000819	0.001243	0.001005	0.000862	0.001080	0.002385
Maximum	0.089683	0.113157	0.132929	0.099380	0.126949	0.218088
Minimum	-0.127652	-0.137708	-0.159453	-0.117667	-0.151398	-0.207712
Std. Dev.	0.013571	0.020760	0.019564	0.019981	0.022760	0.033321
Skewness	-0.762157	-0.235582	-0.210616	-0.154119	-0.146223	-0.199795
Kurtosis	16.20253	7.738534	9.768400	6.639625	6.895875	7.601898
Jarque-Bera (Probability)	9773.551 (0.000000)	1254.722 (0.000000)	2544.707 (0.000000)	738.2508 (0.000000)	844.5728 (0.000000)	1180.655 (0.000000)
Observations	1328	1328	1328	1328	1328	1328

Source: Eviews software, Authors

Table 2. Statistical indicators of daily asset return series for the pre-COVID-19 sub-period

	RCRIX	RBTC	RETH	RBNB	RXRP	RADA
Mean	-0.001272	-0.000167	-0.003150	0.001349	-0.002550	-0.003402
Median	-0.000930	0.000910	-0.001829	0.001068	-0.003625	-0.005175
Maximum	0.189390	0.203046	0.247451	0.213333	0.322005	0.246724
Minimum	-0.224789	-0.159026	-0.206860	-0.192859	-0.188028	-0.208078
Std. Dev.	0.048122	0.043194	0.056754	0.056547	0.056560	0.064245
Skewness	-0.077698	0.100427	-0.095643	0.167175	0.771679	0.156437
Kurtosis	5.753549	5.959420	5.329934	4.440054	7.274881	4.639329
Jarque-Bera (Probability)	136.2774 (0.000000)	157.6400 (0.000000)	97.91788 (0.000000)	39.15771 (0.000000)	370.0968 (0.000000)	49.90313 (0.000000)
Observations	430	430	430	430	430	430

	RS&P500	RAAPL	RMSFT	RGOOG	RAMZN	RNVDA
Mean	0.000307	0.000945	0.001093	0.000323	0.000316	-0.000336
Median	0.000762	0.001647	0.001552	0.000416	0.001343	0.000851
Maximum	0.048403	0.068053	0.072977	0.099380	0.090254	0.089504
Minimum	-0.033416	-0.104924	-0.055870	-0.080089	-0.081423	-0.207712
Std. Dev.	0.009321	0.017876	0.015543	0.016625	0.019546	0.029682
Skewness	-0.372962	-0.609645	-0.021953	-0.018403	-0.202877	-1.337071
Kurtosis	6.254113	7.328999	5.539545	8.007192	6.000290	10.38571
Jarque-Bera (Probability)	199.6930 (0.000000)	362.3986 (0.000000)	115.5843 (0.000000)	449.2304 (0.000000)	164.2309 (0.000000)	1105.453 (0.000000)
Observations	430	430	430	430	430	430

Source: Eviews software, Authors

Table 3. Statistical indicators of daily asset return series for the post-COVID-19 sub-period

	RCRIX	RBTC	RETH	RBNB	RXRP	RADA
Mean	0.003729	0.003275	0.005598	0.006046	0.002505	0.006267
Median	0.005829	0.002410	0.004788	0.006054	0.001601	0.004732
Maximum	0.185811	0.191527	0.343523	0.529218	0.626741	0.279436
Minimum	-0.272552	-0.464730	-0.550732	-0.543084	-0.550503	-0.503638
Std. Dev.	0.045642	0.047903	0.064715	0.071707	0.081119	0.073712
Skewness	-0.627328	-1.664714	-1.175558	-0.283132	0.354816	-0.268015
Kurtosis	6.715640	20.16415	15.32755	16.82391	17.63128	8.395706
Jarque-Bera (Probability)	352.4616 (0.000000)	7005.471 (0.000000)	3609.288 (0.000000)	4386.737 (0.000000)	4917.408 (0.000000)	673.7724 (0.000000)
Observations	550	550	550	550	550	550
	RS&P500	**RAAPL**	**RMSFT**	**RGOOG**	**RAMZN**	**RNVDA**
Mean	0.000704	0.001785	0.001332	0.001428	0.001078	0.002964
Median	0.001534	0.001332	0.001230	0.002325	0.001171	0.003340
Maximum	0.089683	0.113157	0.132929	0.089856	0.126949	0.158340
Minimum	-0.127652	-0.137708	-0.159453	-0.117667	-0.082535	-0.203979
Std. Dev.	0.016090	0.023138	0.021341	0.020004	0.021088	0.032314
Skewness	-1.033940	-0.225911	-0.453384	-0.274476	0.226487	-0.353969
Kurtosis	18.12024	8.608635	13.08276	7.966613	7.039588	7.438995
Jarque-Bera (Probability)	5337.239 (0.000000)	725.5630 (0.000000)	2348.596 (0.000000)	572.1968 (0.000000)	378.6626 (0.000000)	463.0507 (0.000000)
Observations	550	550	550	550	550	550

Source: Eviews software, Authors

Table 4. Statistical indicators of daily asset return series for the Russo-Ukrainian war sub-period

	RCRIX	RBTC	RETH	RBNB	RXRP	RADA
Mean	-0.001444	-0.001033	-0.001344	-0.001579	-0.001619	-0.004018
Median	0.000745	-0.001311	-0.000125	0.001087	0.000706	-0.000913
Maximum	0.177088	0.181200	0.247058	0.130593	0.226182	0.316747
Minimum	-0.244354	-0.257227	-0.323717	-0.251202	-0.217138	-0.249988
Std. Dev.	0.039536	0.038971	0.049602	0.041849	0.048180	0.053079
Skewness	-0.780904	-0.900139	-0.761879	-1.519334	-0.235551	0.042550
Kurtosis	9.006690	10.92154	10.82752	11.14029	8.162436	8.870215
Jarque-Bera (Probability)	555.3238 (0.000000)	951.3819 (0.000000)	916.7837 (0.000000)	1088.428 (0.000000)	387.4145 (0.000000)	496.8945 (0.000000)
Observations	346	346	346	346	346	346
	RS&P500	**RAAPL**	**RMSFT**	**RGOOG**	**RAMZN**	**RNVDA**
Mean	-3.47E-05	0.000345	0.000343	-0.000393	-0.000574	0.001426
Median	-0.000712	0.000697	-0.000997	-0.000884	0.000253	0.001178
Maximum	0.053953	0.085236	0.079059	0.074606	0.114915	0.218088
Minimum	-0.044199	-0.060472	-0.080295	-0.101313	-0.151398	-0.099518
Std. Dev.	0.013668	0.020118	0.021057	0.023481	0.028411	0.038710
Skewness	-0.103686	0.014043	0.111267	-0.068926	-0.313831	0.561886
Kurtosis	3.814657	4.169291	4.069672	4.238169	5.804046	5.757680
Jarque-Bera (Probability)	10.18780 (0.006134)	19.72244 (0.000052)	17.20945 (0.000183)	22.37560 (0.000014)	119.0331 (0.000000)	127.8421 (0.000000)
Observations	346	346	346	346	346	346

Source: Eviews software, Authors

During the total study period from March 16, 2018, to June 30, 2023, containing both crisis and stability phases, crypto-assets show higher volatility compared to conventional assets. The standard deviations of the daily returns of crypto-assets, ranging between 0.04 and 0.06, are significantly higher than those of conventional assets, which vary between 0.01 and 0.03. Furthermore, the average daily returns of both asset classes are generally positive and very close to 0.

During the pre-COVID-19 sub-period, most crypto-assets showed negative average returns and were very close to 0. In contrast, conventional assets presented positive average returns. The standard deviations of crypto-asset daily returns, ranging from 0.04 to 0.06, recorded higher volatility than conventional assets, whose standard deviations were generally lower, varying from 0.009 to 0.02.

During the post-COVID-19 sub-period, both crypto-assets and conventional assets recorded a significant increase in their volatilities compared to the pre-COVID-19 sub-period. However, crypto-assets, such as Ethereum, Binance Coin, Ripple, and Cardano, recorded higher levels of volatility and higher average returns compared to conventional assets during this post-COVID-19 sub-period. On the other hand, conventional assets recorded an increase in their positive average returns compared to the pre-COVID-19 sub-period.

During the Russo-Ukrainian war sub-period, the average returns of both crypto-assets and conventional assets were generally negative. Standard deviations of daily returns on conventional assets ranged from 0.01 to 0.03, demonstrating a degree of stability compared with crypto-assets. The latter showed higher volatility, with standard deviations ranging from 0.03 to 0.05. This observation highlights the increased sensitivity of crypto-assets to geopolitical crises compared with conventional assets.

Furthermore, over the full study period, it is remarkable that these series show leptokurtic distributions, with kurtosis coefficients exceeding 3, indicating a high probability of extreme points occurring. This characteristic is more pronounced in the post-COVID-19 period than in the pre-COVID-19 period, underlining an increase in volatility and uncertainty in financial markets following the pandemic. There is also non-linearity in these series. Except for the RXRP returns series, the distributions of the daily asset return series of our interest have skewness coefficients below 0, are asymmetric, and spread to the left. This asymmetry is consistent with lower volatility after an increase in returns than after a decrease. In other words, yields react more to a negative shock than to a positive one. What's more, the Jarque-Bera test shows that yield distributions do not follow a normal distribution. These results underline the complexity and dynamics of financial markets, with important implications for risk management and investor decision-making.

3.2 Results of the GARCH (1,1) Model Estimation

Tables 5, 6, 7, and 8 below show the results of the GARCH (1, 1) model estimation for the daily return series of crypto-assets and conventional assets during the total study period from March 16, 2018, to June 30, 2023; the pre-COVID-19 sub-period (March 16, 2018, to November 29, 2019); the post-COVID-19 sub-period (December 2, 2019, to February 9, 2022); and the Russo-Ukrainian War sub-period (February 10, 2022, to June 30, 2023), respectively.

Table 5. Results of the GARCH (1,1) model estimation over the full study period

	Equation for the conditional variance of the GARCH (1, 1) model residuals: $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ Where: $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$.					
	RCRIX	**RBTC**	**RETH**	**RBNB**	**RXRP**	**RADA**
α_0	0.000305*** (0.0000)	0.000254*** (0.0000)	0.000255*** (0.0000)	0.000187*** (0.0000)	0.000336*** (0.0000)	0.000296*** (0.0000)
α_1	0.096393*** (0.0000)	0.128882*** (0.0000)	0.110642*** (0.0000)	0.161979*** (0.0000)	0.245520*** (0.0000)	0.134873*** (0.0000)
β_1	0.752924*** (0.0000)	0.752053*** (0.0000)	0.822585*** (0.0000)	0.796947*** (0.0000)	0.729875*** (0.0000)	0.803650*** (0.0000)
$\alpha_1 + \beta_1$	0.849317	0.880935	0.933227	0.958926	0.975395	0.938523
LL	2271.135	2303.770	1941.699	2005.146	1860.132	1806.606
AIC	-3.413919	-3.463105	-2.917407	-3.013030	-2.794472	-2.713800
BIC	-3.390450	-3.439636	-2.893937	-2.989561	-2.771002	-2.690331
	Equation for the conditional variance of the GARCH (1, 1) model residuals: $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ Where: $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$.					
	RS&P500	**RAAPL**	**RMSFT**	**RGOOG**	**RAMZN**	**RNVDA**
α_0	4.65E-06*** (0.0000)	1.39E-05*** (0.0000)	9.13E-06*** (0.0000)	1.43E-05*** (0.0000)	1.65E-05*** (0.0000)	4.08E-05*** (0.0000)
α_1	0.200210*** (0.0000)	0.123827*** (0.0000)	0.126808*** (0.0000)	0.067754*** (0.0000)	0.136766*** (0.0000)	0.108468*** (0.0000)
β_1	0.778835*** (0.0000)	0.846054*** (0.0000)	0.850880*** (0.0000)	0.894726*** (0.0000)	0.837007*** (0.0000)	0.859392*** (0.0000)
$\alpha_1 + \beta_1$	0.979045	0.969881	0.977688	0.96248	0.973773	0.96786
LL	4188.245	3408.188	3533.861	3403.716	3274.641	2727.989
AIC	-6.303308	-5.127638	-5.317048	-5.120898	-4.926362	-4.102470
BIC	-6.279838	-5.104168	-5.293578	-5.097428	-4.902892	-4.079000

Source: Eviews software, Authors

Note: *** indicates coefficient significance at the 1% threshold; ** indicates coefficient significance at the 5% threshold; and * indicates coefficient significance at the 10% threshold.

α_1: the ARCH effect, which estimates the response to any shock or news in the market; β_1 : the GARCH effect, which identifies the persistence of volatility; $\alpha_1 + \beta_1$: the persistence of the shock within the market; LL: Log Likelihood; AIC: Akaike Information Criterion; and BIC: Bayesian Information Criterion.

Table 6. Results of the GARCH (1,1) model estimation during the pre-COVID-19 sub-period

	Equation for the conditional variance of the GARCH (1, 1) model residuals: $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ Where: α_0> 0, α_1≥ 0, and β_1 ≥ 0.					
	RCRIX	**RBTC**	**RETH**	**RBNB**	**RXRP**	**RADA**
α_0	0.000860*** (0.0074)	0.000329*** (0.0008)	0.000492** (0.0266)	0.000355** (0.0181)	0.000914*** (0.0000)	0.000485** (0.0246)
α_1	0.125194*** (0.0011)	0.128992*** (0.0023)	0.066214*** (0.0084)	0.109909*** (0.0005)	0.217863*** (0.0000)	0.099980*** (0.0024)
β_1	0.494399*** (0.0043)	0.694373*** (0.0000)	0.778604*** (0.0000)	0.776955*** (0.0000)	0.500247*** (0.0000)	0.783475*** (0.0000)
$\alpha_1 + \beta_1$	0.619593	0.823365	0.844818	0.886864	0.71811	0.883455
LL	706.0690	757.9463	630.9214	637.3265	647.7875	580.5365
AIC	-3.263725	-3.505577	-2.913386	-2.943247	-2.992016	-2.678492
BIC	-3.206922	-3.448774	-2.856583	-2.886444	-2.935213	-2.621688
	Equation for the conditional variance of the GARCH (1, 1) model residuals: $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ Where: α_0> 0, α_1≥ 0, and β_1 ≥ 0.					
	RS&P500	**RAAPL**	**RMSFT**	**RGOOG**	**RAMZN**	**RNVDA**
α_0	3.85E-06*** (0.0003)	1.58E-05*** (0.0001)	1.26E-05*** (0.0011)	1.70E-05 (0.1934)	1.07E-05** (0.0129)	2.13E-05*** (0.0096)
α_1	0.231975*** (0.0000)	0.166656*** (0.0000)	0.132499*** (0.0006)	0.015688 (0.1378)	0.165989*** (0.0001)	0.106696*** (0.0008)
β_1	0.739162*** (0.0000)	0.798137*** (0.0000)	0.807209*** (0.0000)	0.917936*** (0.0000)	0.806439*** (0.0000)	0.872184*** (0.0000)
$\alpha_1 + \beta_1$	0.971137	0.964793	0.939708	0.933624	0.972428	0.97888
LL	1461.828	1148.200	1226.740	1159.692	1153.120	947.1495
AIC	-6.787076	-5.324944	-5.691098	-5.378518	-5.347880	-4.387643
BIC	-6.730273	-5.268140	-5.634294	-5.321714	-5.291076	-4.330840

Source: Eviews software, Authors

Table 7. Results of the GARCH (1,1) model estimation during the post-COVID-19 sub-period

	Equation for the conditional variance of the GARCH (1, 1) model residuals: $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ Where: α_0> 0, α_1≥ 0, and β_1 ≥ 0.					
	RCRIX	**RBTC**	**RETH**	**RBNB**	**RXRP**	**RADA**
α_0	0.000136*** (0.0028)	0.000226*** (0.0000)	0.000294*** (0.0002)	0.000251*** (0.0003)	0.000415*** (0.0000)	0.000550*** (0.0002)
α_1	0.076910*** (0.0000)	0.132762*** (0.0000)	0.144958*** (0.0000)	0.215772*** (0.0000)	0.332084*** (0.0000)	0.169037*** (0.0000)
β_1	0.860799*** (0.0000)	0.785423*** (0.0000)	0.803634*** (0.0000)	0.760931*** (0.0000)	0.725020*** (0.0000)	0.743053*** (0.0000)
$\alpha_1 + \beta_1$	0.937709	0.918185	0.948592	0.976703	1.057104	0.91209
LL	936.8136	912.1408	755.5367	759.4755	649.9671	685.0255
AIC	-3.390942	-3.301059	-2.730553	-2.744902	-2.345964	-2.473681
BIC	-3.343859	-3.253976	-2.683470	-2.697819	-2.298881	-2.426598

	Equation for the conditional variance of the GARCH (1, 1) model residuals: $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ Where: $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$.					
	RS&P500	RAAPL	RMSFT	RGOOG	RAMZN	RNVDA
α_0	7.64E-06*** (0.0000)	1.82E-05** (0.0124)	1.12E-05** (0.0182)	1.69E-05*** (0.0060)	2.88E-05*** (0.0004)	4.77E-05** (0.0137)
α_1	0.261905*** (0.0000)	0.130560*** (0.0000)	0.148308*** (0.0000)	0.142509*** (0.0000)	0.109033*** (0.0000)	0.121885*** (0.0001)
β_1	0.710450*** (0.0000)	0.835426*** (0.0000)	0.826992*** (0.0000)	0.818205*** (0.0000)	0.830585*** (0.0000)	0.830644*** (0.0000)
$\alpha_1 + \beta_1$	0.972355	0.965986	0.9753	0.960714	0.939618	0.952529
LL	1723.863	1377.437	1471.006	1450.361	1381.159	1174.567
AIC	-6.258152	-4.996127	-5.336999	-5.261790	-5.009687	-4.257074
BIC	-6.211069	-4.949044	-5.289916	-5.214707	-4.962604	-4.209991

Source*:* Eviews software, Authors

Table 8**.** Results of the GARCH (1,1) model estimation during the Russo-Ukrainian war subperiod

	Equation for the conditional variance of the GARCH (1, 1) model residuals: $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ Where: $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$.					
	RCRIX	RBTC	RETH	RBNB	RXRP	RADA
α_0	0.000422*** (0.0006)	0.000472** (0.0104)	0.000257*** (0.0073)	8.79E-05*** (0.0000)	0.000626*** (0.0001)	0.000669*** (0.0001)
α_1	0.321293*** (0.0001)	0.198357*** (0.0032)	0.304291*** (0.0000)	0.053149*** (0.0006)	0.247954*** (0.0019)	0.349280*** (0.0000)
β_1	0.472679*** (0.0003)	0.525186*** (0.0006)	0.658947*** (0.0000)	0.898362*** (0.0000)	0.485262*** (0.0001)	0.465326*** (0.0000)
$\alpha_1 + \beta_1$	0.793972	0.723543	0.963238	0.951511	0.733216	0.814606
LL	635.9066	635.4984	564.6929	616.8374	584.3970	547.6066
AIC	-3.651632	-3.649266	-3.238800	-3.541086	-3.353026	-3.139748
BIC	-3.584788	-3.582422	-3.171955	-3.474242	-3.286182	-3.072904

	Equation for the conditional variance of the GARCH (1, 1) model residuals: $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ Where: $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$.					
	RS&P500	RAAPL	RMSFT	RGOOG	RAMZN	RNVDA
α_0	-3.52E-07 (0.7687)	3.27E-06 (0.4351)	5.55E-05 (0.4815)	7.92E-05 (0.3391)	0.000212*** (0.0072)	0.000338 (0.4688)
α_1	0.041036** (0.0134)	0.069805*** (0.0079)	0.015530 (0.6010)	0.036511 (0.2810)	0.275100*** (0.0001)	-0.025582 (0.3895)
β_1	0.959028*** (0.0000)	0.922533*** (0.0000)	0.857136*** (0.0000)	0.819841*** (0.0000)	0.491704*** (0.0000)	0.794443*** (0.0065)
$\alpha_1 + \beta_1$	1.000064	0.992338	0.872666	0.856352	0.766804	0.768861
LL	1009.843	876.6339	846.9016	807.8492	749.1431	635.8788
AIC	-5.819379	-5.047153	-4.874792	-4.648401	-4.308076	-3.651471
BIC	-5.752535	-4.980309	-4.807948	-4.581557	-4.241232	-3.584627

Source: Eviews software, Authors

Over the full study period and the pre-COVID-19 sub-period, the results of the GARCH (1,1) model show that crypto-assets exhibit lower β coefficients than conventional assets, indicating less persistent volatility. For example, over the full study period, the β coefficient for Bitcoin is (0.752053), for Binance Coin (0.796947), and

Ripple (0.729875). In contrast, conventional assets show significantly higher β coefficients (0.850880, 0.894726, 0.859392) for Microsoft, Google, and Nvidia, respectively (Table 5). Similarly, during the pre-COVID-19 sub-period, the β coefficient of crypto-assets ranged from (0.500247) for Ripple to (0.783475) for Cardano, while those of conventional assets ranged from (0.798137) for Apple to (0.917936) for Google (Table 6). The sum of coefficients (α + β) representing shock persistence is also higher for conventional assets, showing that volatility shocks persist more for conventional assets than for crypto-assets.

The post-COVID-19 sub-period shows an increase in volatility persistence for crypto-assets, although conventional assets maintain high levels of persistence. For example, crypto-assets display high β coefficients (0.785423, 0.803634, 0.760931) for Bitcoin, Ethereum, and Binance Coin, respectively. Although these coefficients show a persistence of high volatility for crypto-assets, they remain lower than those for some conventional assets such as Apple (0.835426), Amazon (0.830585), and Nvidia (0.830644). The sum of coefficients (α + β) also increases for crypto-assets, indicating a more pronounced persistence of volatility shocks, but it remains lower than that observed for some conventional assets. Indeed, many assets recorded an increase in their α coefficients compared to the pre-COVID-19 sub-period, with high levels for crypto-assets. This reveals that crypto-assets show greater reactivity during the COVID-19 pandemic than conventional assets (Table 7).

Finally, the war sub-period is characterized by a decrease in β coefficients for the majority of crypto-assets, showing an attenuation of volatility persistence. Comparatively, conventional assets continue to exhibit relatively high persistence, reaching (0.922533) for Apple. Furthermore, crypto-assets tend to display high α values following a similar dynamic to that observed during the post-COVID-19 sub-period. For example, Ethereum displays an α coefficient of (0.304291), Ripple of (0.247954), and Cardano of (0.349280). This indicates that crypto-assets have continued to be highly sensitive to geopolitical crises (Table 8).

It should be noted that, unlike crypto-assets, the GARCH (1,1) model used to model conventional assets during the Russo-Ukrainian war is not statistically validated. We also estimated the EGARCH (1,1) model for the same assets. However, this model is not as statistically robust. Consequently, it is very difficult to compare the volatility of the two asset classes solely during the Russo-Ukrainian war period based on the GARCH (1.1) and EGARCH (1.1) models.

In summary, crypto-assets tend to have lower β coefficients than conventional assets during all the periods studied, indicating less persistent volatility. However, the post-COVID-19 period shows an increase in volatility persistence for crypto-assets, although conventional assets maintain high levels of persistence. These observations show that, although crypto-assets can react more quickly to new information with higher α coefficients, their markets exhibit less persistent volatility in the long term compared with conventional assets.

3.3 Statistical Indicators of Conditional Volatility for the Assets Studied

According to the extent values (Max-Min), for the full study period and the pre-COVID-19 sub-period, crypto-assets tend to display higher values than conventional assets. For example, over the full study period, Bitcoin displays an extent of (0.029078), Ethereum of (0.035982), Binance Coin of (0.06126), and Ripple of (0.099971). In contrast, conventional assets show lower extent values (0.005692, 0.0067853, 0.003823, 0.008114) for Apple, Microsoft, Amazon, and Nvidia, respectively (Table A1 in Appendix). Similarly, the pre-COVID-19 sub-period is marked by high extent values for crypto-assets compared to conventional assets, but with less variation than the previous period. For example, Binance Coin has an extent of (0.008418), Ripple of (0.024826), and Cardano of (0.010895) (Table A2 in Appendix).

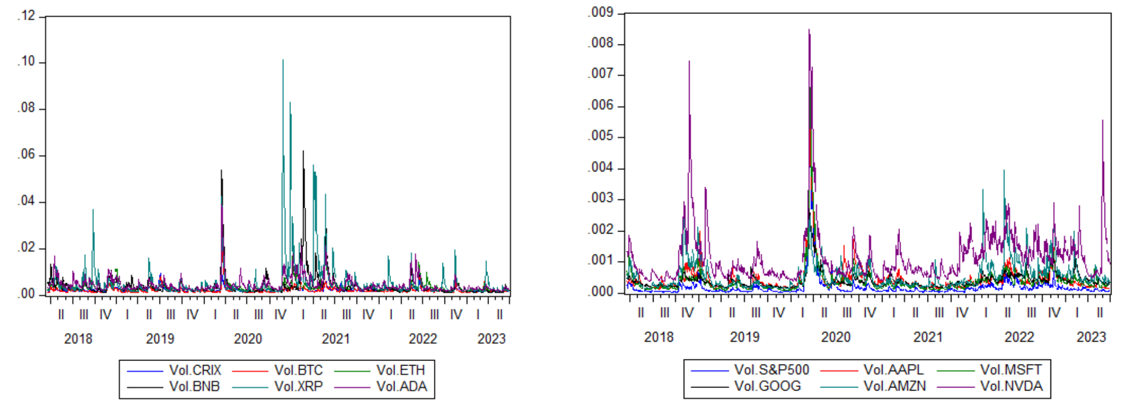
In the post-COVID-19 sub-period, extent values increased compared to the previous two periods for all the assets studied, with high levels for crypto-assets. The latter show higher extent values (0.03049, 0.049327, 0.077291, 0.135872) for Bitcoin, Ethereum, Binance Coin, and Ripple, respectively. While conventional assets show values well below those of crypto-assets, which do not exceed 0.008561 for Nvidia (Table A3 in Appendix). Similarly, during the war sub-period, crypto-assets continue to display higher extent values, but they are still lower than those observed during the post-COVID-19 sub-period (Table A4 in Appendix). This shows that crypto-assets react more strongly to economic and geopolitical crises than conventional assets.

Indeed, over the full study period and the pre-COVID-19 sub-period, the extent of volatility for crypto-assets is greater than that for conventional assets. For example, the spread observed for crypto-assets varies between 0.00 and 0.12, while that for conventional assets is between 0.000 and 0.009 over the full study period. Similarly, for the pre-COVID-19 sub-period, crypto-assets show high spreads over conventional assets. Furthermore, during both crisis periods (e.g., the COVID-19 pandemic and the Russo-Ukrainian war), crypto-assets recorded significant volatility deviations from their conventional counterparts, underlining their sensitivity to crises. For example, the extent of volatility for crypto-assets varies between 0.00 and 0.14 during the post-COVID-19 sub-period and between 0.000 and 0.040 during the war sub-period. However, conventional assets show generally lower spreads between 0.000 and 0.009 during the post-COVID-19 sub-period and between 0.000 and 0.008 during the war sub-period (Figure 2).

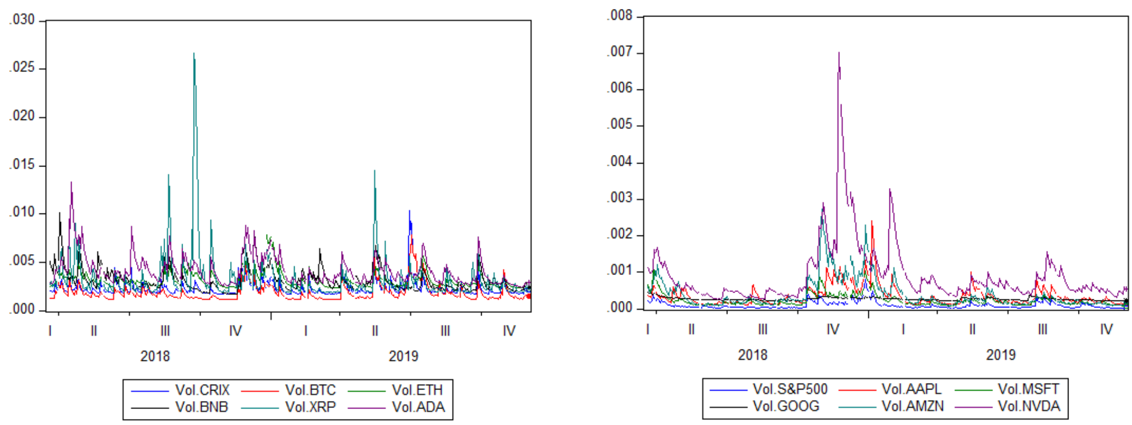
In sum, these results show that the gap between the volatility of crypto-assets and that of conventional assets becomes wider during periods of crisis than during periods of stability. This reveals that conventional assets are more resilient to financial shocks than crypto-assets.

Figure 2. Conditional volatility

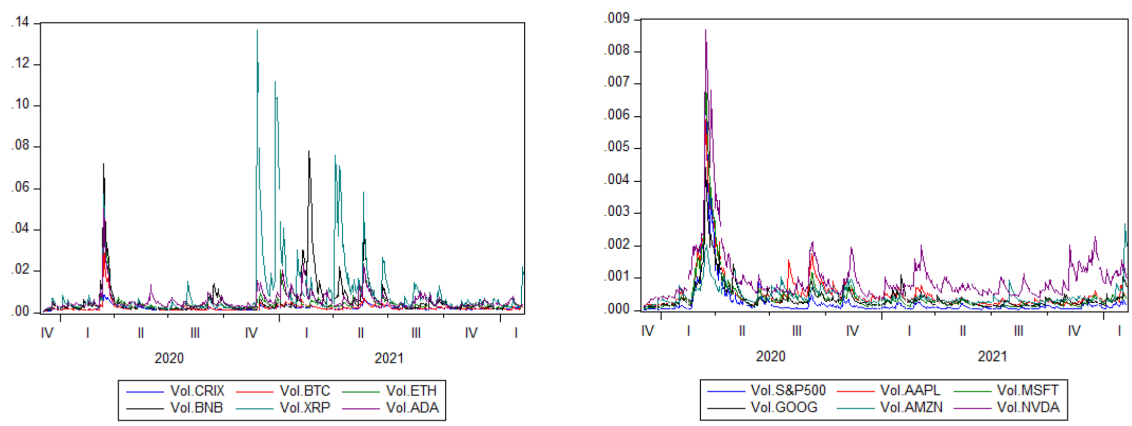
(a) Conditional asset volatility for the full study period



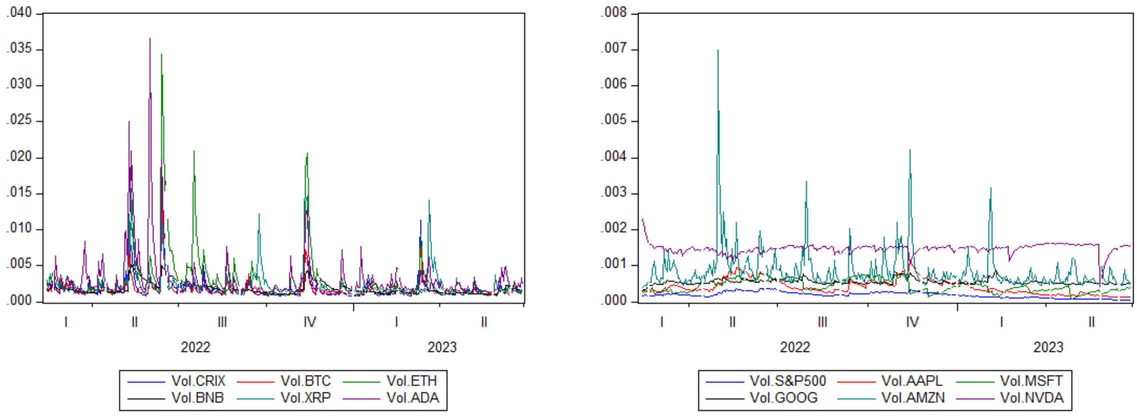
(b) Conditional asset volatility for the pre-COVID-19 sub-period



(c) Conditional asset volatility for the post-COVID-19 sub-period



(d) Conditional asset volatility for the war sub-period



Source*:* Eviews software, Authors

4. Discussion and Concluding Remarks

The results of our study show that crypto-assets are more volatile than conventional assets over the entire study period, including both crisis and stability phases. This finding calls into question the idea that crypto-assets can be considered safe-havens during crisis periods, thanks to their high correlation with conventional assets (Ballis *et al.* 2025; Conlon *et al.* 2020; Conlon and McGee, 2020; Karamti and Belhassine, 2022; Li and Miu, 2023; Yuyama *et al.* 2023). This means they don't offer protection within portfolios in turbulent times but rather tend to increase risk. The volatility of crypto-assets is particularly highlighted in our study, confirming their reputation as highly volatile assets and therefore very risky for investments (Botte and Nigro, 2021; Omane-Adjepong *et al.* 2019; Yaya *et al.* 2021). Their speculative nature and high dependence on external factors, regulatory uncertainties, and changes in market conditions may explain this high volatility (Bajra and Aliu, 2023; Fry and Cheah, 2016; Naeem *et al.* 2021).

The COVID-19 pandemic disrupted global financial markets, leading to a widespread increase in the volatility of financial assets (Jeribi and Kammoun Masmoudi, 2021; Ouchen, 2022; Özdemir, 2022; Shaik *et al.* 2023; Taera *et al.* 2023). In this light, crypto-assets were strongly affected, displaying high volatility compared to conventional assets, during the COVID-19 pandemic (Bampinas and Panagiotidis, 2024; Kayani *et al.* 2024; Lahmiri and Bekiros, 2020; Yarovaya *et al.* 2022). In addition, the Russo-Ukrainian war period, for its part, amplified the volatility of financial assets, confirming the destabilizing effect of geopolitical crises on financial markets (Bampinas and Panagiotidis, 2024; Gaies and Chkili, 2023; Hamouda *et al.* 2024; Kayani *et al.* 2024; Khalfaoui *et al.* 2023; Taera *et al.* 2023). During this period, crypto-assets recorded high volatility, but it remains lower than that seen in the post-COVID-19 period. These results confirm that crypto-assets are more volatile than conventional assets during the COVID-19 pandemic and the Russo-Ukrainian war period. Their sensitivity to crises confirms their status as risky assets despite their ability to offer high returns and diversification opportunities (Bampinas and Panagiotidis, 2024; Bossman *et al.* 2024). This phenomenon highlights the importance of considering asset volatility levels when making investment decisions, particularly for assets with higher levels of risk (*i.e.*, crypto-assets). In conclusion, it can be said that crypto-assets are more volatile and therefore less resilient to financial shocks compared to conventional assets (Bampinas and Panagiotidis, 2024; Kayani *et al.* 2024; Khalfaoui *et al.* 2023; Lahmiri and Bekiros, 2020; Yarovaya *et al.* 2022). This underlines the need for investors to manage their portfolios in a prudent manner, thus considering crypto assets as risky investments rather than alternatives.

From an academic point of view, our results are of great importance in the field of finance and portfolio management. Firstly, they enrich the existing literature, highlighting the crucial importance of understanding the responsiveness of different asset types to financial shocks. By analyzing the responses of crypto-assets and conventional assets to periods of crisis, our study offers valuable insights into the diversification of investment portfolios and the management of their risks.

On a managerial level, our findings could offer valuable recommendations to investors in order to make the right investment decision. This involves taking proactive measures, such as rebalancing their portfolios, which involves divesting financial assets with higher levels of risk (*i.e.*, crypto-assets) during periods of crisis and increasing the share of conventional assets.

To consolidate, a future study could focus on optimizing a hybrid portfolio integrating both cryptographic and traditional assets using machine learning methods. This study aims to determine the optimal composition of such a portfolio in different economic contexts, both during stable and crisis periods. This originality lies in our desire to exploit the predictive and optimization capabilities of machine learning algorithms. This could provide investors with recommendations for reducing portfolio risk while improving returns.

Declarations

Acknowledgments: The authors would like to thank the support of the National Centre for Scientific and Technical Research (CNRST) as part of the "PhD-Associate Scholarship-PASS" Program.

Credit Authorship Contribution Statement: This article is the result of collaborative work.

Declaration of Competing Interest: The authors declare no conflicts of interest in this paper.

Declaration of use of generative AI and AI-assisted technologies: The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Appendices

Table A1. Statistical indicators of conditional asset volatility for the full study period

	Vol.CRIX	Vol.BTC	Vol.ETH	Vol.BNB	Vol.XRP	Vol.ADA
Mean	0.002025	0.002041	0.003577	0.003847	0.005217	0.004492
Median	0.001760	0.001656	0.002877	0.002516	0.002947	0.003420
Maximum	0.009597	0.030131	0.037591	0.062264	0.101305	0.039116
Minimum	0.001266	0.001053	0.001609	0.001004	0.001334	0.001664
Extent	0.008331	0.029078	0.035982	0.06126	0.099971	0.037452
Std. Dev.	0.000872	0.001598	0.002695	0.005031	0.007975	0.003277
Skewness	3.588448	8.988619	5.900381	6.186113	6.042767	3.921993
Kurtosis	22.14141	125.5300	56.20233	53.48183	50.61589	28.88418
Jarque-Bera (Probability)	23106.47 (0.000000)	847995.9 (0.000000)	164202.2 (0.000000)	149369.7 (0.000000)	133437.2 (0.000000)	40446.90 (0.000000)
Observations	1327	1327	1327	1327	1327	1327

	Vol.S&P500	Vol.AAPL	Vol.MSFT	Vol.GOOG	Vol.AMZN	Vol.NVDA
Mean	0.000184	0.000436	0.000381	0.000392	0.000536	0.001145
Median	9.92E-05	0.000319	0.000280	0.000333	0.000377	0.000891
Maximum	0.006220	0.005819	0.006872	0.002709	0.003949	0.008486
Minimum	2.52E-05	0.000127	8.67E-05	0.000159	0.000126	0.000372
Extent	0.0061948	0.005692	0.0067853	0.00255	0.003823	0.008114
Std. Dev.	0.000407	0.000450	0.000491	0.000248	0.000442	0.000876
Skewness	8.580403	5.501822	7.214854	3.719759	2.520197	3.651582
Kurtosis	93.46526	46.24255	72.12379	24.13319	12.13592	22.56940
Jarque-Bera (Probability)	468788.0 (0.000000)	110085.6 (0.000000)	275701.7 (0.000000)	27754.11 (0.000000)	6019.633 (0.000000)	24123.63 (0.000000)
Observations	1327	1327	1327	1327	1327	1327

Source: Eviews software, Author

Table A2. Statistical indicators of conditional asset volatility for the pre-COVID-19 sub-period

	Vol.CRIX	Vol.BTC	Vol.ETH	Vol.BNB	Vol.XRP	Vol.ADA
Mean	0.002276	0.001862	0.003178	0.003169	0.003215	0.004122
Median	0.001993	0.001570	0.002945	0.002793	0.002516	0.003738
Maximum	0.010386	0.007835	0.007839	0.010087	0.026672	0.013298
Minimum	0.001702	0.001096	0.002292	0.001669	0.001846	0.002403
Extent	0.008684	0.006739	0.005547	0.008418	0.024826	0.010895
Std. Dev.	0.000877	0.000931	0.000836	0.001221	0.002378	0.001497
Skewness	4.580714	2.631978	2.194157	1.691499	5.570644	1.872703
Kurtosis	33.54701	11.94096	9.918051	6.786524	46.18514	8.140385
Jarque-Bera (Probability)	18179.80 (0.000000)	1924.243 (0.000000)	1199.711 (0.000000)	460.8612 (0.000000)	35554.88 (0.000000)	723.0729 (0.000000)
Observations	429	429	429	429	429	429
	Vol.S&P500	Vol.AAPL	Vol.MSFT	Vol.GOOG	Vol.AMZN	Vol.NVDA
Mean	9.39E-05	0.000345	0.000230	0.000265	0.000388	0.000904
Median	5.15E-05	0.000243	0.000168	0.000250	0.000225	0.000597
Maximum	0.000802	0.002413	0.001080	0.000451	0.002720	0.007032
Minimum	1.78E-05	0.000110	7.97E-05	0.000220	8.10E-05	0.000256
Extent	0.0007842	0.002303	0.0010003	0.0002309	0.0026392	0.006776
Std. Dev.	9.86E-05	0.000276	0.000168	4.00E-05	0.000400	0.000852
Skewness	2.587230	2.820686	2.238370	1.529389	2.436640	3.475191
Kurtosis	12.51347	15.78669	8.783824	5.909750	10.17406	18.95518
Jarque-Bera (Probability)	2096.399 (0.000000)	3491.425 (0.000000)	956.2020 (0.000000)	318.5819 (0.000000)	1344.487 (0.000000)	5413.900 (0.000000)
Observations	429	429	429	429	429	429

Source*:* Eviews software, Authors

Table A3. Statistical indicators of conditional asset volatility for the post-COVID-19 sub-period

	Vol.CRIX	Vol.BTC	Vol.ETH	Vol.BNB	Vol.XRP	Vol.ADA
Mean	0.002098	0.002473	0.004565	0.005689	0.009417	0.005688
Median	0.001780	0.001939	0.003312	0.003114	0.004367	0.004282
Maximum	0.008573	0.031112	0.050046	0.078173	0.136837	0.049916
Minimum	0.000444	0.000621	0.000719	0.000882	0.000965	0.001010
Extent	0.008129	0.030491	0.049327	0.077291	0.135872	0.048906
Std. Dev.	0.001012	0.002441	0.004574	0.008704	0.015328	0.004457
Skewness	2.794291	7.382333	5.587671	4.802709	4.362830	4.477722
Kurtosis	14.19119	70.51328	43.68387	30.94350	25.94194	33.60706
Jarque-Bera (Probability)	3579.365 (0.000000)	109251.9 (0.000000)	40719.00 (0.000000)	19972.23 (0.000000)	13781.49 (0.000000)	23263.69 (0.000000)
Observations	549	549	549	549	549	549
	Vol.S&P500	Vol.AAPL	Vol.MSFT	Vol.GOOG	Vol.AMZN	Vol.NVDA
Mean	0.000245	0.000524	0.000424	0.000393	0.000437	0.000995
Median	8.67E-05	0.000342	0.000258	0.000267	0.000339	0.000736
Maximum	0.007110	0.005892	0.007149	0.004417	0.002692	0.008676
Minimum	2.04E-05	0.000142	3.38E-05	9.83E-05	6.12E-05	0.000114
Extent	0.0070896	0.00575	0.0071152	0.0043187	0.0026312	0.008561
Std. Dev.	0.000626	0.000620	0.000693	0.000437	0.000284	0.000910
Skewness	6.449991	4.442522	5.627288	4.528183	3.284333	4.469760
Kurtosis	52.81342	27.68841	41.35005	30.11117	18.77301	28.87187
Jarque-Bera (Probability)	60568.11 (0.000000)	15748.56 (0.000000)	36540.33 (0.000000)	18689.63 (0.000000)	6678.016 (0.000000)	17139.52 (0.000000)
Observations	549	549	549	549	549	549

Source*:* Eviews software, Authors

Table A4. Statistical indicators of conditional asset volatility for the Russo-Ukrainian war sub-period

	Vol.CRIX	Vol.BTC	Vol.ETH	Vol.BNB	Vol.XRP	Vol.ADA
Mean	0.001753	0.001634	0.002962	0.001776	0.002324	0.003080
Median	0.001255	0.001290	0.001975	0.001512	0.001680	0.002065
Maximum	0.019927	0.014538	0.034375	0.005130	0.015717	0.036584
Minimum	0.000811	0.001005	0.000838	0.000955	0.001247	0.001290
Extent	0.019116	0.013533	0.033537	0.004175	0.01447	0.035294
Std. Dev.	0.001663	0.001170	0.003442	0.000817	0.002024	0.003385
Skewness	5.920680	6.011798	4.644442	1.944775	4.173058	5.368682
Kurtosis	52.00235	53.05341	31.50017	6.574725	22.49590	41.08862
Jarque-Bera (Probability)	36533.32 (0.000000)	38092.46 (0.000000)	12916.55 (0.000000)	401.1670 (0.000000)	6465.123 (0.000000)	22511.73 (0.000000)
Observations	345	345	345	345	345	345
	Vol.S&P500	**Vol.AAPL**	**Vol.MSFT**	**Vol.GOOG**	**Vol.AMZN**	**Vol.NVDA**
Mean	0.000186	0.000412	0.000437	0.000547	0.000852	0.001471
Median	0.000184	0.000348	0.000394	0.000527	0.000681	0.001494
Maximum	0.000384	0.001143	0.000785	0.000865	0.006979	0.002299
Minimum	4.76E-05	0.000114	7.29E-05	0.000299	0.000399	0.000403
Extent	0.0003364	0.001029	0.0007121	0.0005656	0.006579	0.0018967
Std. Dev.	8.15E-05	0.000209	0.000175	7.63E-05	0.000576	0.000145
Skewness	0.168825	0.836104	0.262063	1.462849	5.309193	-1.496925
Kurtosis	2.258874	3.114960	1.883602	6.876912	45.58661	19.22833
Jarque-Bera (Probability)	9.534576 (0.008503)	40.38652 (0.000000)	21.86512 (0.000018)	339.1084 (0.000000)	27691.56 (0.000000)	3914.624 (0.000000)
Observations	345	345	345	345	345	345

Source: Eviews software, Authors