sciendo

Timisoara Journal of Economics and Business TJE&B

CRYPTOCURRENCIES VOLATILITY: EMPIRICAL EVIDENCE

Avraham TURGEMAN[1] , Octavian JUDE[2]

DOI: 10.2478/ tjeb-2024-0005

Cryptocurrencies have rapidly become popular as digital assets, and as the market evolves, it is of great importance to understand their volatility and risk behavior. They present specific challenges and opportunities given that are operating within a decentralized and fast-changing ecosystem. Thus, their volatility affects risk management, investment strategies, and market stability. Cryptocurrency volatility can create both opportunities and risks. While it can provide substantial returns, it also presents challenges in terms of investment strategy, regulatory frameworks, business operations, and economic stability. As the cryptocurrency market matures, it's likely that solutions to manage volatility will evolve, but it remains a key concern for participants in the ecosystem. In this respect, the aim of the paper is to examine the volatility behavior of the main cryptocurrencies (Bitcoin, Ethereum, and Litecoin), for a recent period, i.e. from June 2018 to June 2023. Using both traditional and advanced GARCH models, the results show that these cryptocurrencies experience periods of high and low volatility, but there is no significant asymmetry effect in their responses. This suggests a balanced risk-return profile for investors. Furthermore, there is no evidence for risk premium within the sample, that is no link between risk and return. Additionally, past volatility has a greater impact on current volatility than new information, since GARCH coefficients are significantly higher than the ARCH coefficients. These insights can help investors, policymakers, and researchers to manage the cryptocurrency markets more effectively.

Keywords: **Cryptocurrency, Volatility, Heteroskedasticity, Asymmetry**

JEL Classification: **G11, G14, G15**

[1] *PhD student, Doctoral School of Economics and Business Administration, West University of Timisoara, Timisoara, Romania*

[2] *PhD student, Doctoral School of Economics and Business Administration, West University of Timisoara, Timisoara, Romania*

1. Introduction

Cryptocurrencies have rapidly become a notable asset class. As the market evolves, it is crucial to understand the volatility and risk of these digital assets. This knowledge is essential for investors making informed decisions in a dynamic environment. This study examines the volatility of Bitcoin, Ethereum, and Litecoin from June 2018 to June 2023 using various GARCH models to understand their complex dynamics and contribute to financial modeling literature on digital assets.

The unique features of cryptocurrencies and their impact on investors make analysis crucial. Operating in a decentralized and fast-changing ecosystem, cryptocurrencies present specific challenges and opportunities. Notably, their volatility affects risk management, investment strategies, and market stability. Analyzing these volatility patterns helps investors understand the risks and opportunities of digital assets.

By employing both traditional models like GARCH-M and advanced models such as TARCH-M and EGARCH-M, the findings provide valuable insights into the volatility dynamics of these cryptocurrencies. Importantly, in the conditional variance equation, the estimated GARCH coefficients substantially exceed the ARCH coefficients. This suggests that historical volatility exerts a greater impact on current volatility than new information does. Additionally, there is no significant evidence of asymmetry in the volatility response to shocks for any of the cryptocurrencies analyzed.

The rest of the paper is structured as follows. In the next section the data and the empirical methodology is explained. In Section 3 the main results are discussed, and Section 4 concludes.

2. Data and methodology

Our dataset includes daily closing prices for Bitcoin, Ethereum, and Litecoin from June 9, 2018, to June 9, 2023. These cryptocurrencies were selected due to their high market capitalization and importance in the digital asset market. The time frame reflects substantial growth and increased regulatory attention in the sector. Data was collected from Yahoo Finance, with daily returns calculated using continuous compounding to capture cryptocurrency volatility accurately.

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where R_t is the daily return; P represents daily closing price.

We use the GARCH econometric technique, developed by Engle (1982), to capture volatility nuances. Following previous studies (Guidi et al., 2011; Murinde and Poshakwale, 2002), we first estimate a GARCH-M (1,1) model with the following specification:

$$R_t = \mu + \delta \times \sigma_{t-1} + u_t, u_t \approx N(0, \sigma_t^2) \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \times u_{t-1} + \beta \times \sigma_{t-1}^2 \tag{3}$$

Following this, we conduct a series of diagnostic and misspecification tests to ensure the model's robustness. Subsequently, we perform an asymmetric test to model the volatility's asymmetric nature. The most effective extensions for capturing asymmetric volatility include TARCH-M (1,1), which is defined by the following specification:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \times u_{t-1}^2 + \beta \times \sigma_{t-1}^2 + \gamma \times u_{t-1}^2 \times I_{t-1} \tag{4}$$

Where,

$$I_{t-1} \begin{cases} = 1 \; if \; u_{t-1} < 0 \\ = 0 \; otherwise \end{cases} \tag{5}$$

and EGARCH-M (1,1) defined by the following specification:

$$ln(\sigma_t^2) = \omega + \beta \times ln(u_{t-1}^2) + \gamma \times \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \times \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{6}$$

A useful step in empirical analysis is the utilization of descriptive statistics and graphical representations. These tools not only illustrate the fundamental characteristics of data distribution but also reveal the intriguing stochastic properties inherent in the dataset. Table no. 1 showcases the descriptive statistics, revealing that the index return for all cryptocurrencies exhibits a leptokurtotic distribution, characterized by an excess of kurtosis and negative skewness, indicating more extreme negative returns than positive ones. The non-normal nature of this distribution is further validated by the Jarque-Bera statistics. In addition, the Breusch-Godfrey test, applied with 4 lags, dismisses the possibility of no serial correlation, while the ARCH test points to the presence of ARCH effects within the residuals.

DOI: 10.2478/tjeb-2023-0005

These intriguing findings make a compelling case for the use of a GARCH-M (1,1) model to accurately estimate conditional variance.

Table 1. Descriptive statistics for Daily returns

Specification	Bitcoin	Ethereum	Litecoin
Mean	0.000692	0.000618	-0.000151
Median	0.000852	0.000808	0.000211
Maximum	0.171821	0.230695	0.268725
Minimum	-0.464730	-0.550732	-0.449062
Std. Dev.	0.036727	0.048204	0.050568
Skewness	-1.151724	-1.120127	-0.765196
Kurtosis	19.43230	15.27022	11.65637
Jarque-Bera	20947.74***	11836.83***	5879.328***
BG Test (4)	12.62850**	16.32775***	12.48259**
ARCH (4)	13.89043***	37.69761***	48.05800***
Observations	1826	1826	1826

Source: Author computations using EViews12.

Note: BG represents the Breusch-Godfrey test for serial correlation applied with 4 lags. ARCH represents the autoregressive conditional heteroskedasticity test applied with 4 lags. ***, **, * represents the rejection of the null hypothesis at the 1%, 5% and 10% respectively levels of significance for statistical tests of no autocorrelation, normality, and homoscedasticity.

Table 1 shows that all indexes are highly volatile, with standard deviations exceeding the mean. Daily return plots (Appendices, Figure 1) highlight turbulence in cryptocurrencies, especially Ethereum and Litecoin, during 2020 and 2021. This indicates volatility clustering, where large price changes follow large changes, and small price changes follow small changes.

3. Results

The results from the GARCH-M (1,1) specifications, which use a normal distribution function are presented in Panel A of Table 2.

Table 2. Symmetric Volatility Models

Parameters	Bitcoin	Ethereum	Litecoin
	Panel A – GARCH-M (1,1)		
μ	0.001104 (0.5964)	0.001097 (0.6519)	-0.001161 (0.6939)
δ	0.290170 (0.8609)	0.076908 (0.9466)	0.629573 (0.6130)

Parameters	***Bitcoin***	***Ethereum***	***Litecoin***
α0	0.000113*** (0.0000)	0.000139*** (0.0000)	0.000176*** (0.0000)
α1	0.106029*** (0.0000)	0.098538*** (0.0000)	0.085846*** (0.0000)
β	0.819065*** (0.0000)	0.846407*** (0.0000)	0.847779*** (0.0000)
Panel B – GARCH-M (1,1) QML			
μ	0.001104 (0.4912)	0.001097 (0.5874)	-0.001161 (0.6419)
δ	0.290170 (0.8044)	0.076908 (0.9334)	0.629573 (0.5446)
α0	0.000113** (0.0142)	0.000139*** (0.0021)	0.000176** (0.0137)
α1	0.106029*** (0.0088)	0.098538*** (0.0071)	0.085846*** (0.0003)
β	0.819065*** (0.0000)	0.846407*** (0.0000)	0.847779*** (0.0000)
SSB Test	5.697461 (0.127294)	12.59865*** (0.005590)	16.52442*** (0.000885)

Source: Author computations using EViews12.

Note: Standard errors – Panel A. Robust standard errors (QML) – Panel B. SSB represents the Sign and Size Bias test for asymmetries in volatility. *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1.

Regarding the risk premium, the estimated parameter of the mean (δ) does not hold statistical significance for all the three cryptocurrencies under study, implying that there is no clear link between the level of risk, namely the conditional variance and the expected return, namely the conditional mean. In other words, the risk-return tradeoff, a common concept in finance, does not hold in a statistically significant way for these cryptocurrencies based on this analysis.

The ARCH (α1) and GARCH (β) coefficients show statistical significance, indicating that volatility shocks have a lasting effect on the conditional variance of cryptocurrencies. The near-unity sum of these coefficients suggests persistent future volatility. Notably, GARCH coefficients exceed ARCH coefficients, signifying that past volatility impacts current volatility more than new information does.

The conditional normality assumption was examined through a misspecification test, as shown in Figure 2 in the Appendices. The test results indicate that the assumption is rejected in all cases, showing that the standardized residuals deviate from a normal distribution. To address the issue of inconsistent standard errors, the model was re-estimated using the robust Quasi Maximum Likelihood (QML) procedure. The results, presented in Panel B of Table 2, display a noticeable difference in the robust standard errors and their associated p-values compared to the previous models. Despite this, the findings related to ARCH, GARCH, and the risk premium remain consistent, indicating their robustness and stability despite the misspecification of conditional normality.

To further assess the model's adequacy, an additional test examines the independence of standardized residuals. The plot of standardized residuals (Figure 3) and the correlogram of squared residuals (Table 4) suggest that the residuals are independent in both linear and non-linear terms.

The analysis concludes that the GARCH-M (1,1) model with robust standard errors is correctly specified. However, GARCH-M models assume symmetric volatility response to shocks, though financial markets show asymmetric reactions—larger increases in volatility due to negative shocks. The Sign and Size Bias test was conducted, showing that except for Bitcoin, the F-statistic and p-value reject the null hypothesis. This suggests extending the GARCH-M model to capture asymmetric volatility. Notably, Bitcoin's volatility does not respond asymmetrically to shocks, whereas other cryptocurrencies do, highlighting a need for more comprehensive modeling to capture their market dynamics.

Panel A of Table 3 shows the findings from the TARCH-M (1,1) model, while Panel B displays the EGARCH-M (1,1) model results.

Table 3. Asymmetric Volatility Models

Parameters	***Bitcoin***	***Ethereum***	***Litecoin***
	Panel A – TARCH-M (1,1)		
μ	0.001577 (0.2493)	0.001671 (0.4005)	-0.001120 (0.6419)
δ	-0.663924 (0.5314)	-0.399384 (0.6622)	0.520704 (0.6062)
α0	0.000132*** (0.0015)	0.000189*** (0.0006)	0.000204*** (0.0099)
α1	0.05357* (0.0758)	0.073897** (0.0106)	0.076333*** (0.0038)
β	0.797198*** (0.0000)	0.816474*** (0.0000)	0.830787*** (0.0000)

Parameters	**Bitcoin**	**Ethereum**	**Litecoin**
γ	0.122941 (0.2465)	0.062708 (0.4069)	0.030547 (0.5929)
AIC	-3.855331	-3.327134	-3.211556
SWC	-3.837226	-3.309029	-3.193451
LL	3525.917	3043.673	2938.151
	Panel B – EGARCH-M (1,1)		
μ	-0.002279 (0.2527)	0.002030 (0.3680)	-0.000968 (0.7467)
δ	2.549720 (0.1144)	-0.445925 (0.6726)	0.482990 (0.7004)
ω	-0.919010*** (0.0010)	-0.595435*** (0.0003)	-0.624531*** (0.0024)
β	0.884278*** (0.0000)	0.927133*** (0.0000)	0.918439*** (0.0000)
γ	-0.080643 (0.2259)	-0.049782 (0.3392)	-0.039733 (0.3442)
α	0.214476*** (0.0000)	0.207735*** (0.0000)	0.185163*** (0.0000)
AIC	-3.854165	-3.325297	-3.211757
SWC	-3.836061	-3.307192	-3.193653
LL	3524.853	3041.996	2938.334

Source: Authors' calculations with Eviews software

Note: Robust standard errors in parentheses. AIC, SWC and LL represent Akaike Criterion, Schwarz Criterion and Log Likelihood Ratio respectively. *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1.

The analysis of TARCH-M (1,1) and EGARCH-M (1,1) models for Bitcoin, Ethereum, and Litecoin shows no significant asymmetry in volatility response to shocks. The lack of leverage effects, indicated by the asymmetry parameter (γ), implies that these cryptocurrencies do not exhibit higher volatility increases after negative shocks compared to positive ones. This may be due to factors such as the short analysis period, market dynamics, and the evolving cryptocurrency market. As the market matures, asymmetry in volatility responses might become more evident.

5. Conclusions

This study examines the volatility dynamics of certain cryptocurrencies from June 2018 to June 2023. It explores whether volatility responds symmetrically or asymmetrically to past shocks and if it reacts differently to negative versus positive shocks. Understanding these responses is crucial for capturing market dynamics and risk characteristics.

By using both classical models like GARCH-M and flexible models such as TARCH-M and EGARCH-M, the results provide valuable insights into cryptocurrency volatility dynamics. The GARCH coefficients in the conditional variance equation are significantly higher than the ARCH coefficients, indicating that past volatility has a greater impact on current volatility than new information. No significant asymmetry in volatility response to shocks was found for any cryptocurrencies analyzed. This could be due to the unique characteristics of the cryptocurrency market, the short analysis period, or the evolving nature of the cryptocurrency ecosystem.

The study shows no significant asymmetry in the volatility of the analyzed cryptocurrencies, offering a balanced risk-return profile. This consistent volatility in response to both positive and negative shocks can enhance investor confidence by reducing fears of extreme price fluctuations. Consequently, these cryptocurrencies may appear more stable and attractive to investors due to their perceived stability and lower risk of unpredictable market movements.

References

Alexander, C., & Dakos, M. (2020). A critical investigation of cryptocurrency data and analysis. Quantitative Finance, 20(2), 173-188.

Brooks, C. 2008. Introductory econometrics for finance. 2nd ed., Cambridge: Cambridge University Press.

Botoc, C. (2014). Does Volatility Respond Asymmetric To Past Shocks? Annales Universitatis Apulensis-Series Oeconomica, 16(2).

Corbet, S., Cumming, D. J., Lucey, B. M., Peat, M., & Vigne, S. (2019). Investigating the dynamics between price volatility, price discovery, and criminality in cryptocurrency markets. Price Discovery, and Criminality in Cryptocurrency Markets (May 3, 2019).

Engle, R. F., 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variances of United Kingdom Inflation, Econometrica, 50, 987-1007.

Ghorbel, A., & Jeribi, A. (2021). Investigating the relationship between volatilities of cryptocurrencies and other financial assets. Decisions in Economics and Finance, 44, 817-843.

Guidi, F., Gupta, R., Maheshwari, S., 2011. Weak-form Market Efficiency and Calendar Anomalies for Eastern Europe Equity Markets, Journal of Emerging Market Finance, 10, 3: 337–389.

Katsiampa, P. (2019). An empirical investigation of volatility dynamics in the cryptocurrency market. Research in International Business and Finance, 50, 322-335.

Katsiampa, P. (2019). Volatility co-movement between Bitcoin and Ether. Finance Research Letters, 30, 221-227.

Katsiampa, P., Corbet, S., & Lucey, B. (2019). High frequency volatility co-movements in cryptocurrency markets. Journal of International Financial Markets, Institutions and Money, 62, 35-52.

Murinde, V., & Poshakwale, S. (2002). Volatility in the emerging stock markets in central and Eastern Europe: evidence on Croatia, Czech Republic, Hungary, Poland, Russia and Slovakia. European Research Studies, 4(3-4), 73-101.

Yi, S., Xu, Z., & Wang, G. J. (2018). Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency?. International Review of Financial Analysis, 60, 98-114.