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ASYMMETRIC RETURN-VOLATILITY NEXUS IN THE GLOBAL CRYPTO MARKET: EVIDENCE FROM BITCOIN AND ETHEREUM

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ABSTRACT

This study uses the TGARCH and PGARCH models to investigate the asymmetric volatility-return relationship in the cryptocurrency market for the period from 18/01/2018 to 26/06/2025, focusing on Bitcoin and Ethereum. We find evidence of strong persistence in both returns and volatility dimensions of crypto market performance. For both Bitcoin and Ethereum, the coefficient on one-lagged period return is negative and highly significant, while the volatility persistence parameter is approximately 1. However, we find that volatility feedback or risk-premia effect is present for Ethereum, while it is not for Bitcoin. Further, we find that although the PGARCH model outperforms the TGARCH model, both crypto assets do not exhibit asymmetric volatility effect. Hence, we conclude that while crypto market is largely inefficient and can be predicted by past events, most of the time-varying volatility properties of crypto assets can be well captured by the standard GARCH model. However, a GARCH-in mean specification is more appropriate for Ethereum compared to Bitcoin.

Keywords: Asymmetric Volatility, Volatility Feedback Effect, TGARCH, PGARCH.

1. INTRODUCTION

Cryptocurrencies have witnessed rapid growth and widespread adoption in recent times. Satoshi Nakamoto first proposed cryptocurrency in 2008 and up until this point, it has grown in popularity. The fundamental aim of crypto currencies was to create a sophisticated virtual currency with unrestricted transactional capacity, anonymous trading, and minimal transaction fees (Adrian & Rhoda, 2021). The first cryptocurrency was first released as open-source software in 2009. As of June 2023, there were more than 25,000 other cryptocurrencies in the marketplace, of which more than 40 had a market capitalization exceeding $1billion. Also, data obtained from CoinMarketCap indicates that the cryptocurrency market capitalization stood at $3.93 trillion as of July 2025.

One influential cryptocurrency that has continued to dominate the crypto market is Bitcoin. Developed in 2009, Bitcoin is not only the original cryptocurrency, but also the largest in terms of market capitalization. According to CoinMarketCap, as of July 2025, Bitcoin was traded at $109,505, with trading volume and market capitalization being $122 billion in 24 hours and $2.37trillion respectively.

Another influential cryptocurrency is Ethereum. This cryptocurrency was created in 2015 but has quickly risen to become the second-largest cryptocurrency in the world. However, it is quite different from Bitcoin as it was originally designed to serve a different purpose and now used for a variety of interesting decentralized applications. It has a market capitalization of about $463.5 billion as of July 2025, with a unit price of $2,392.92.

The question of how cryptocurrency prices and volatility evolve remains a topic of high interest in economics and financial market literature. One important aspect of this question relates to whether cryptocurrency prices are predictable and the extent of their predictability. According to Kaseke et al. (2022), while cryptocurrencies share similar characteristics with other financial assets such as volatility clustering, persistence, and asymmetric effect, it is the degree of these features that differs Zhang et al. (2018), Katsumata et al. (2019), and Hu et al. (2019) all document evidence that cryptocurrencies have much higher volatility compared to stocks and other financial assets. Besides, although the Efficient Market Hypothesis (Fama, 1970) implies that asset prices follow a random walk and are hence not predictable, the empirical evidence on the predictability of cryptocurrency prices is so far conflicting. While some studies (For example, Caporale et al. (2018)) find that cryptocurrency prices are highly predictable due to their high volatility persistence and other stylized facts, others (for example Yaya et al. (2021) document evidence supporting the efficient market theory.

This study contributes to the ongoing debate on the predictability of cryptocurrency prices by investigating the main stylized facts that characterize Bitcoin and Ethereum prices. In particular, the study employs two asymmetric GARCH models: namely, TGARCH and PGARCH models to determine the extent of asymmetry, persistence, and risk-premia or feedback effects in the return-volatility relationship for Bitcoin and Ethereum using up-to-date daily data.

Accordingly, the study has three specific objectives as follows:

1. To determine whether Bitcoin and Ethereum exhibit asymmetric effects in their return-volatility relationship.

2. To determine whether Bitcoin and Ethereum exhibit risk-premia (feedback) effect in their return-volatility relationship.
3. To determine the extent of persistence in both returns and volatility of Bitcoin and Ethereum

The remainder of this study has four sections. The next section describes the theoretical framework used in this study as well as reviews the related empirical studies. Section 3 describes the data, model, and method used in empirical analysis. Section 4 contains data analysis and discussion of findings, while the study is concluded in section 5.

2. LITERATURE REVIEW

2.1 Theoretical Framework

This study is anchored on volatility feedback theory and efficient market hypothesis. According to the volatility feedback theory, while there is tendency for asset volatility to respond differently to positive and negative shocks of similar magnitude, this asymmetric volatility response is governed by risk-premia effect (Bekaert & Wu, 2000; Campbell & Hentschel,1992; Pindyck, 1984; French et al., 1987). This theory, which is consistent with the capital asset pricing model of Sharpe (1964), implies that the market rewards investors for taking additional risks. Hence, there is a positive relationship between asset returns and their volatility.

According to the efficient market theory (EMT), financial markets are informationally efficient and hence are largely unpredictable. This implies that asset prices are driven by random shocks and cannot be predicted based on previous price information. In other words, trend analysis cannot lead to abnormal returns as there is no significant relationship between current market returns and previous market information.

2.2 Previous Empirical Studies

Nishad and Noufal (2024) investigate the asymmetric volatility in the crypto-stock market linkage in India using both the GARCH-type models and the vector error correction model (VECM). The findings demonstrate that crypto exhibits short-lived asymmetric volatility and there is a unidirectional relationship from crypto to stock. They also find cointegration between crypto and Indian stock indices and crypto prices.

Karim et al. (2024) investigate the return-volatility asymmetry in Bitcoin and Ethereum in UK (Southampton) using the asymmetric quantile regression NARDL is employed. The outcomes show that both positive and negative shocks raise volatility; behavioural biases like fear of missing out (FOMO) intensity asymmetry. Bitcoin reacts more to positive shocks, Ethereum to negative ones, driven by investors' sentiment and noise trading.

Reitalu and Bajārs (2022) examine the impact of leveraged trading on asymmetry in Latvia (SSE Riga). In this analysis, the asymmetric GARCH, Semi-Deviation Analysis was employed. The findings show that Defi-linkage coin shows upward asymmetry leverage increases systemic risk during downturns.

Yaya et al. (2021) investigate both return and volatility persistence for 12 cryptocurrencies in the context of efficient market theory. Using fractional integration models, they find that Bitcoin and most altcoins returns are largely unpredictable as they tend to follow a random walk process. In other words, their evidence indicates that crypto markets are largely efficient.

Gil-Alana, Abakah and Rojo (2020) conduct a comprehensive analysis of non-linear volatility patterns in crypto in Switzerland. The study utilizes fractional integration and co integration tests and finds that no cointegration between crypto and stock indices.

Caporale et al. (2018) analyze the degree of crypto market persistence for crypto assets: namely, Bitcoin, Dash, Ripple, and Litecoin using R/S analysis and fractional integration frameworks. Using daily data and focusing on the period from 2013 to 2017. The findings indicate strong evidence that previous and future returns are positively correlated, thereby underscoring the inefficiency in the crypto market.

Katsiampa (2017) investigates volatility dynamics in five major cryptos in the UK. In the analysis, Diagonal BEKK-GARCH is employed. The findings show that prior shock significantly affect future variance, while the degree of asymmetry varies across coins.

Liu and Serletis (2019) examine the crypto spillovers and volatility feedback in Canada. The study utilized the GARCH-in-mean model. The findings demonstrate that the volatility feedback effect exists in the crypto market, with crypto returns showing high sensitivity to its volatility.

Conrad et al. (2018) offers a scholarly examination of the volatility co-movement with macro indicators in USA. Using the GARCH-MIDAS framework, they find that Bitcoin volatility co-moves with macro indicators like vix; asymmetry varies by regime.

Baur et al. (2018) examine the asymmetric volatility in top cryptocurrencies in Australia and Germany. The study employs TGARCH, quartile AR methodology. The analysis reveals that positive shocks increase volatility more than negative shocks linked to noise trading and pump-and-dump schemes.

Bouri et al. (2017) investigate Bitcoin's changing asymmetry over time in USA. The EGARCH, GJR-GARCH are extensively employed. The findings show that asymmetries changed over time with early years having stronger leverage effects.

3. METHODOLOGY

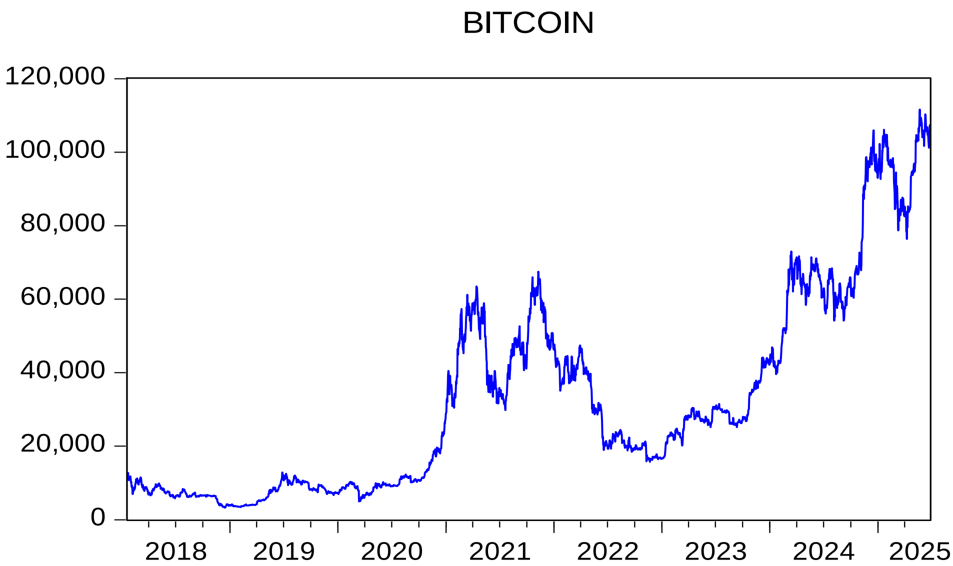
3.1 Data

The data used comprise 2717 daily observations on Bitcoin and Ethereum prices for the period 18/01/2018 to 26/06/2025. All data are sourced from www.investing.com and analyzed using EViews. Consistent with previous studies (Bollerslev, 1986; Engle, 1982; Nelson, 1991; Zakoian, 1994), we generate the returns data by taking the log difference as follows:

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

Where R_t = continuous compounded returns, ln = natural logarithm, P_t and P_{t-1}= current and previous asset prices (Bitcoin, Ethereum).

Figures 1 and 2 present the time series graphs of the data. As expected, while both Bitcoin and Ethereum prices exhibit random walk features, their returns data exhibit features of volatility clustering; that is, periods of high volatility following periods of high volatility and periods of low volatility following periods of low volatility.



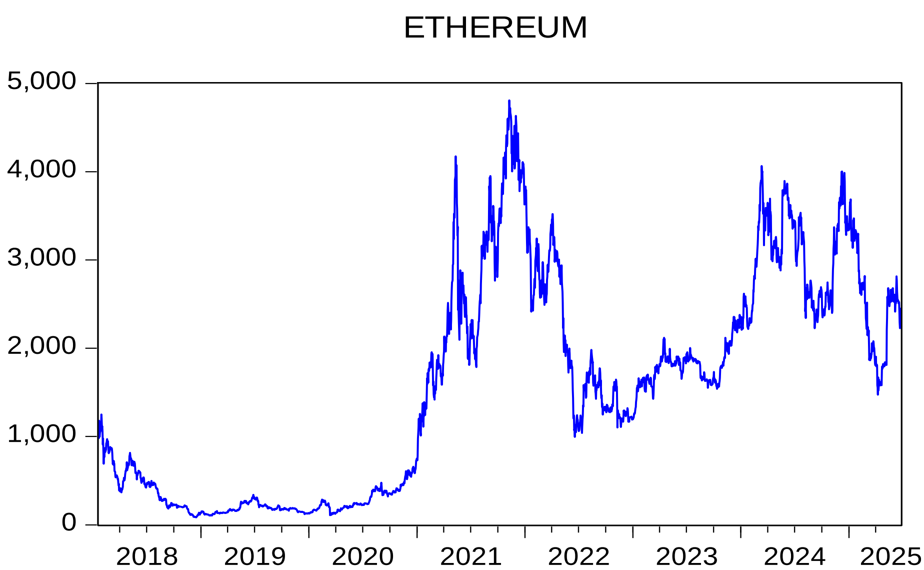


Figure 1: Daily Bitcoin and Ethereum Prices

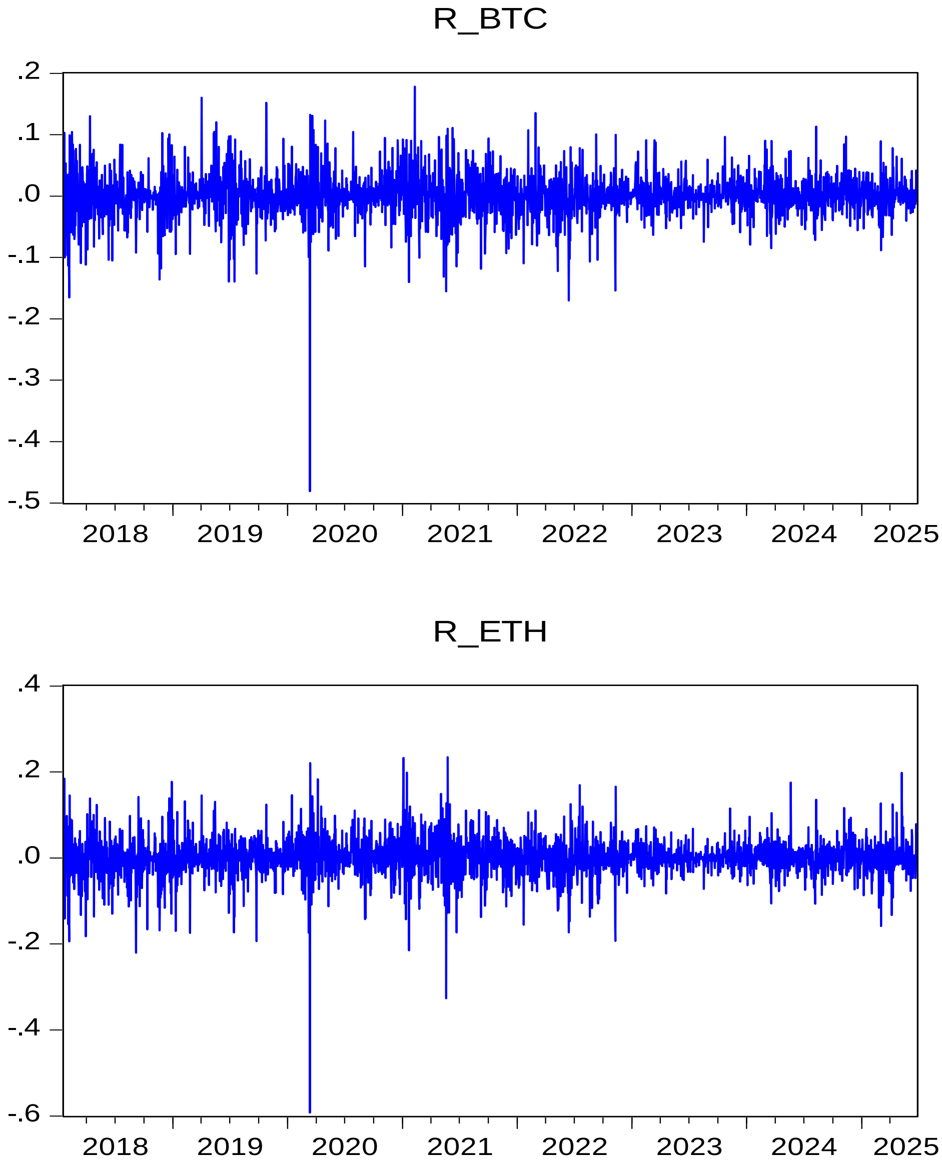


Figure 2: Daily Bitcoin and Ethereum Returns

3.2 Model Specification

To examine the asymmetric properties of crypto volatility, we employ two asymmetric volatility models: namely, Zakoian's (1994) TGARCH (Threshold Generalized Autoregressive Conditional Heteroskedasticity) and the PGARCH (Power Generalized Autoregressive Conditional Heteroskedasticity) introduced by Ding et al. (1993). The success of both models in capturing asymmetric volatility effects in daily returns data is well documented in the literature.

We specify our asymmetric GARCH models as follows:

Mean Equation

$$R_t = \phi_0 + \phi_1 R_{t-1} + \phi_2(\sigma_t) + \epsilon_t \tag{2}$$

R_t = asset returns (Bitcoin, Ethereum), ϕ_0 = model constant, ϕ_1 = coefficient capturing lagged returns, ϕ_2 = risk-premia (volatility feedback) parameter (Engle et al., 1987), and ϵ_t = error term. If ϕ_1 is significant, then returns exhibit persistence and can be predicted based on historical data which is consistent with technical analysis.

TGARCH Model

We specify the simple TGARCH model as follows

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma . d_{t-1} \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{3}$$

σ_t^2 = conditional variance (volatility), α_0= long-run conditional variance average, α_1 = $ARCH$ effect, β_1 = GARCH effect, and γ = asymmetric volatility parameter. There is no asymmetric effect in the volatility response to market innovations if $\gamma = 0$, while there is asymmetric effect if $\gamma \neq 0$.

PGARCH Model

We specify the simple PGARCH model as follows:

$$\sigma_t^{\delta} = \alpha_0 + \alpha_1(|\epsilon_{t-1}| - \gamma\epsilon_{t-1}^2)^{\delta} + \beta_1\sigma_{t-1}^{\delta} \quad (4)$$

Where δ is the power parameter, γ is the asymmetric parameter, which is expected to be significant if asymmetric effects are present in the market.

3.3 Method of Data Analysis/Distributional Assumption

To estimate the specified PGARCH model, we employ the maximum likelihood framework based on the assumption that the errors (residuals) are not conditionally normally distributed. More specifically, we assume that conditional errors have large excess kurtosis and follow a generalized error distribution.

4. DATA ANALYSIS

4.1 Descriptive Statistics

Table 1 presents the descriptive summaries for Bitcoin and Ethereum. As this Table shows, Bitcoin price averaged US$32,594.5 under the period under review, reaching an all-time high of US$111,640, and recording a minimum of US$3,282.8. On the other hand, Ethereum attained an average price of US$1,573 over the same period, with maximum and minimum values of US$4808.09 and US$83.8 respectively. In terms of returns, Bitcoin earned an average return of 0.08%, while Ethereum's average return stood at 0.03%. The maximum and minimum returns are 17.9% and -48.1% for Bitcoin, while Ethereum's maximum and minimum returns are 23.5% and -59.25%. However, Ethereum recorded much higher volatility than Bitcoin, as indicated by the coefficient of variation (CV) as well as the difference between the maximum and minimum values, with both statistics being much larger for the former than the latter. The third and fourth moment statistics show that for both Bitcoin and Ethereum, there is a significant deviation from normal distribution, which is caused by negative skewness and large excess kurtosis that characterized the data. Expectedly, the Jarque-Bera test is highly significant in all cases, thereby failing to reject the null hypothesis of normal distribution. This result is consistent with previous studies and justifies our distributional assumption that errors follow a generalized error distribution.

Table 1: Summary Statistics for BITCOIN AND ETHEREUM

Statistic	BTC	ETH	R_BTC	R_ETH
Mean	32594.46	1572.99	0.08	0.03
Maximum	111640.00	4808.09	17.87	23.48
Minimum	3282.80	83.75	-48.09	-59.25
Std. Dev.	27290.83	1223.63	3.51	4.64
Skewness	1.02	0.41	-1.00	-0.95
Kurtosis	3.20	2.03	18.42	16.21
CV	83.73	77.79	4195.31	13991.58
Jarque-Bera	477.62	181.91	27355.35	20151.98
Probability	0.0000	0.0000	0.0000	0.0000
Observations	2717	2717	2716	2716

4.2 Correlation Matrix

Table 2 shows the correlation matrix for Bitcoin and Ethereum returns. As this Table shows, both crypto assets move in similar direction and are strongly correlated. Hence, both assets increase and decrease concurrently.

Table 2: Correlation Matrix for Bitcoin and Ethereum Returns

Variables	1	2
R_BTC	1	0.8222
R_ETH	0.8222	1

4.3 Empirical Analysis

4.3.1 Test for ARCH Effect

Table 3 presents the ARCH-LM test results for R_BTC and R_ETH. As it is well documented, this test establishes the presence of ARCH effect in the data, which is a prerequisite for GARCH-type analysis (Engle, 1982). The test is implemented under the null hypothesis that ARCH effect is not present in the data.

Table 3 shows that the ARCH-LM test statistic is estimated with a zero p-value, hence, it is highly statistically significant. This result, which provides strong evidence against the null hypothesis of no ARCH effect, implies that volatility processes in the crypto market can be examined under the GARCH framework.

Table 2: ARCH LM Test Results

Statistic	ARCH LM stat.	p-value
R_BTC	36.17	0.0001
R_ETH	61.16	0.0000

4.3.2 Model Estimation and Analysis

Table 3 presents the TGARCH and PGARCH estimation results for asymmetric volatility in the crypto market. The estimation is based on OPPG BHHH optimization method. Panel A reports the results for the mean equation, Panel B provides the results for the variance equation, while the model diagnostic test results are presented in Panel C.

Table 3: TGARCH Estimation Results

Variable	TGARCH		PGARCH	
	BITCOIN	ETHEREUM	BITCOIN	ETHEREUM
Panel A: Mean Equation				
Risk-premia (ϕ_2)	0.0641 (0.1642)	0.0744 (0.1333)	0.0474 (0.2829)	0.0890 (0.0498)
Constant	-0.0013 (0.3405)	-0.0020 (0.2853)	-0.0008 (0.5318)	-0.0024 (0.1620)
R_{t-1} (ϕ_1)	-0.0852 (0.0000)	-0.1164 (0.0000)	-0.0908 (0.0000)	-0.1178 (0.0000)
Panel B: Variance Equation				
Constant (α_0)	2.05E-05 (0.0014)	4.07E-05 (0.0005)	0.0006 (0.3852)	0.0010 (0.2053)
ARCH (α_1)	0.0594 (0.0000)	0.0785 (0.0000)	0.0846 (0.0000)	0.0740 (0.0000)
ASYMMETRY (γ)	0.0102 (0.5104)	-0.0040 (0.8318)	0.0890 (0.2974)	0.0135 (0.8815)
GARCH(-1) (β_1)	0.9205 (0.0000)	0.9059 (0.0000)	0.9177 (0.0000)	0.9318 (0.0000)
Persistence $\alpha_1 + \beta_1$	0.9799	0.9844	1.0023	1.0058
POWER (δ)	–	–	1.0663 (0.0000)	0.8611 (0.0000)
Panel C: Diagnostics				
GED (r)	0.9117 (0.0000)	0.9693 (0.0000)	0.9162 (0.0000)	0.9710 (0.0000)
ARCH-LM (10)	6.4740 (0.7740)	9.8294 (0.4556)	5.0502 (0.8878)	10.589 (0.3904)
LogLk	5729.4	4946.2	5735.4	4956.8

AIC	-4.2139	-3.6370	-4.2176	-3.6440
SIC	-4.1943	-3.6174	-4.1959	-3.6223

Model Diagnostics

For all models, the value of the GED tail parameter, *r*, is significantly less than 1, which indicates a significant deviation from normal distribution. This is consistent with our modeling assumption that the distribution of conditional errors is fat-tailed. The ARCH LM test (p-value > 0.05, 0.01) is not statistically significant at all conventional levels, showing that our volatility models have no specification errors as no further ARCH effect is present in the residual series. However, comparing the performance of the two asymmetric volatility models, the log. Likelihood function (LogLk) associated with the PGARCH model is higher than that associated with the TGARCH model for both Bitcoin and Ethereum, suggesting that the former outperforms the latter. Also, for all models, the values of AIC and SIC are lower for PGARCH model compared to the TGARCH model, thereby validating the superiority of the former in capturing the time-varying volatility properties of crypto assets. Hence, our subsequent analysis would be based on P-GARCH results.

Mean Equation

From Panel A, the lagged return coefficient, ϕ_1, is negative and highly significant, indicating that both Bitcoin and Ethereum exhibit persistence in their return series and hence can be predicted based on their historical performance. This shows that, for both crypto assets, higher returns in the current period are expected to be followed by lower returns in the next period. These results provide strong evidence of market inefficiency and emphasize the importance of technical analysis in the crypto market. However, the risk-premia parameter is not significant for Bitcoin ($\phi_2 = 0.0474, p$-value = 0.2829) but significant for Ethereum ($\phi_2 = 0.0890, p$-value = 0.0498). Hence, while Ethereum returns respond to its current volatility, there is no empirical association between Bitcoin returns and its current volatility.

Variance Equation

From Panel B, both ARCH (α_1) and GARCH (β_1) parameters are significantly different from zero for both Bitcoin and Ethereum, thereby satisfying their non-negativity constraints. However, the estimated volatility persistence parameter, $\alpha_1 + \beta_1$, is approximately 1 for both crypto assets, indicating the presence of non-stationary volatility in the crypto market. Consistent with previous studies, this result implies that crypto market volatility is explosive and largely unpredictable.

Asymmetric Volatility Response

From Panel B, the results show no asymmetric effect in the return-volatility relationship in the crypto market. For both Bitcoin and Ethereum, the asymmetric parameter, γ, is not statistically significant, indicating that conditional variance responds symmetrically to positive and negative shocks in the market. Hence, there is strong evidence that the direction (sign) of market innovation does not matter in the volatility processes of crypto assets. In other words, good news and bad news of equal magnitude are equally weighted in the crypto market.

4.4 Discussion of Findings

4.4.1 Asymmetric Volatility Response to Market Innovations

First, we investigate the asymmetric effect in the volatility processes of Bitcoin and Ethereum. In theory, asset prices exhibit asymmetric effect as good news tends to increase volatility than bad news of similar magnitude (Black, 1976; Christie, 1982; Schwart, 1989). Hence, for Bitcoin and Ethereum, our expectation, *apriori*, is that the asymmetric coefficient in our volatility models would be significantly different from zero.

Contrary to our expectation, *apriori*, we find that the asymmetric coefficient (γ) in the conditional variance equation is not statistically significant for all our volatility models, suggesting that both Bitcoin and Ethereum do not exhibit asymmetric effects in their volatility processes. This finding contradicts the leverage effect theory and shows that both positive and negative shocks are equally weighted in the crypto market. In other words, market innovations do not exert differential impacts on crypto asset volatility. One implication of this finding is that a standard GARCH model would perform better in capturing most of the stylized facts of crypto market returns than an asymmetric GARCH model. This finding contradicts several previous studies including Baur and Dimpfl (2018) and Dirk et al. (2018).

4.4.2 Volatility Feedback Effect in the Crypto Market

We also investigate the extent of volatility feedback effect in the crypto market. The volatility feedback hypothesis implies a positive relationship between conditional variance and conditional returns (Bekaert & Wu, 2000; Campbell

& Hentschel,1992; Pindyck, 1984; French et al., 1987). Hence, for Bitcoin and Ethereum, our expectation, *apriori*, is that the risk-premia coefficient in our volatility models would be positive and significantly different from zero.

Our findings are mixed. The risk-premia coefficient (ϕ_2) in the conditional mean equation is positive and significant at the 5% level for Ethereum, while it is not significant for Bitcoin. This implies that the risk-return relationship in the crypto market is not general but depends on the specific asset in question. For Bitcoin, investors are not rewarded for taking additional risk, which contradicts the volatility feedback hypothesis. On the contrary, the market tends to reward Ethereum investors when they incorporate variance forecasts in their volatility model, which aligns with the volatility feedback effect hypothesis as well as the capital asset pricing model (CAPM).

4.4.3 Persistence of Shocks in the Crypto Market

Finally, we investigate the extent of return and volatility persistence in the crypto market. Theoretically, both asset volatility exhibits strong persistence and have long memory (Bolerslev, 1986; Chou, 1988; Ding & Granger, 1996). However, the persistence of shock, which is more pronounced in the crypto market, implies inefficiency of information distribution in the market, thereby contradicting the efficient market hypothesis. Hence, for Bitcoin and Ethereum, our expectation, *apriori*, is that both the lagged return coefficient (ϕ_1) in the mean equation would be significantly different from zero while the persistence volatility parameter ($\alpha_1 + \beta_1$) in the variance equation would be equal to 1.

Consistent with our expectation, *apriori*, we find that for both Bitcoin and Ethereum, the lagged return coefficient in the mean equation is highly statistically significant, while the persistence parameter in the variance equation is approximately 1. This shows that both return and volatility dimensions of Bitcoin and Ethereum performance exhibit strong persistence. In the case of returns, the persistent coefficient is negative across the two crypto assets, suggesting that higher returns in the current period are expected to be followed by lower returns in the next period. The implication is that crypto market is largely inefficient and hence can be predicted based on past shocks. This finding aligns with Caporale et al. (2018), but contradicts Yaya et al. (2021), whose findings indicate that crypto markets are largely efficient and unpredictable.

In the case of volatility, our evidence suggests that crypto market volatility has long memory while volatility shocks are explosive and not mean-reverting. While this finding contradicts Yaya et al. (2021) whose findings indicate no volatility persistence for Ethereum.

5. CONCLUSION

In this study, we employ the TGARCH and PGARCH models to investigate the asymmetric volatility-return nexus in the cryptocurrency market using daily data for the period from 18/01/2018 to 26/06/2025.

Consistent with previous studies, we find evidence of strong persistence in both returns and volatility dimensions of crypto market performance. For both Bitcoin and Ethereum, the coefficient on one-lagged period return is negative and highly significant, while the volatility persistence parameter is approximately 1. However, there is mixed evidence regarding the return-volatility relationship in the crypto market. While volatility feedback or risk-premia effect is present for Ethereum, it is not for Bitcoin.

There is evidence that although the PGARCH model outperforms the TGARCH model, both crypto assets do not exhibit asymmetric effect, hence good news and bad news of equal magnitude do not affect volatility differentially in the crypto market.

Overall, our empirical evidence aligns with the view that crypto market is informationally inefficient and suggests that trend analysis can be used to generate abnormal profits. Also, our evidence has validated the plausibility of the standard GARCH model in capturing most of the time-varying volatility properties of crypto assets. However, a GARCH-in mean specification is more appropriate for Ethereum compared to Bitcoin.

6. REFERENCES

[1] Abakah, E. J. A., Gil-Alana, L. A., Madigu, G., & Romero-Rojo, F. (2020). Volatility persistence in cryptocurrency markets under structural breaks. International Review of Economics & Finance, 69, 680-691.

[2] Adrian, T, and Rhoda W. (2021). Crypto assets as national currency? A step too far." IMF Blog, International Monetary Fund, July 26. https://blogs.imf.org/2021/ 07/26/crypto assets-as-national-currency-a-step-too-far

[3] Baur, D. G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, gold and the US dollar–A replication and extension. Finance research letters, 25, 103-110.

[4] Bekaert, G., & Wu, G. (2000). Asymmetric volatility and risk in equity markets. The Review of Financial Studies, 13(1), 1-42.

[5] Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307-327.

[6] Bouri, E., Azzi, G., & Dyhrberg, A. H. (2017). On the return-volatility relationship in the Bitcoin market around the price crash of 2013. Economics, 11(1), 2.

[7] Campbell, J. Y., & Hentschel, L. (1992). No news is good news: An asymmetric model of changing volatility in stock returns. Journal of Financial Economics, 31(3), 281-318.

[8] Caporale, G. M., Gil-Alana, L., & Plastun, A. (2018). Persistence in the cryptocurrency market. Research in International Business and Finance, 46, 141-148.

[9] Chou, R. Y. (1988). Volatility persistence and stock valuations: Some empirical evidence using GARCH. Journal of applied econometrics, 279-294.

[10] Conrad, C., Custovic, A., & Ghysels, E. (2018). Long-and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis. Journal of Risk and Financial Management, 11(2), 23. https://doi.org/10.3390/jrfm11020023

[11] Ding, Z., & Granger, C. W. (1996). Modeling volatility persistence of speculative returns: a new approach. Journal of econometrics, 73(1), 185-215.

[12] Ding, Z., Granger, C. W., & Engle, R. F. (1993). A long memory property of stock market returns and a new model. Journal of empirical finance, 1(1), 83-106.

[13] Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica: Journal of the Econometric Society, 987-1007.

[14] Hu, A. S., Parlour, C. A., & Rajan, U. (2019). Cryptocurrencies: Stylized facts on a new investible instrument. Financial Management, 48(4), 1049-1068.

[15] Karim, M. M., Noman, A. H. M., Hassan, M. K., Khan, A., & Kawsar, N. H. (2024). Volatility spillover and dynamic correlation between Islamic, conventional, cryptocurrency and precious metal markets during the immediate outbreak of COVID-19 pandemic. International Journal of Islamic and Middle Eastern Finance and Management, 17(4), 662-692.

[16] Kaseke, F., Ramroop, S., & Mwambi, H. (2022). A comparative analysis of the volatility nature of cryptocurrency and JSE market. Investment Management & Financial Innovations, 19(4), 23.

[17] Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. Economics letters, 158, 3-6.

[18] Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. Finance Research Letters, 29, 68-74.

[19] Liu, J., & Serletis, A. (2019). Volatility in the cryptocurrency market. Open Economies Review, 30(4), 779-811.

[20] Nishad, T. M., & Noufal, K. M. (2024). Modelling asymmetric volatility in the crypto currency and its dynamic relationship with stock market. Review of Finance & Banking, 16(1).

[21] Reitalu, E., & Bajārs, R. (2022). The asymmetric volatility of cryptocurrencies: What is the effect of leveraged trading. SSE Riga Student Research Papers, 4 (246), 1 – 56.

[22] Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The journal of finance, 19(3), 425-442.

[23] Wu, G. (2001). The determinants of asymmetric volatility. The Review of Financial Studies, 14(3), 837-859.

[24] Yaya, O. S., Ogbonna, A. E., Mudida, R., & Abu, N. (2021). Market efficiency and volatility persistence of cryptocurrency during pre-and post-crash periods of Bitcoin: Evidence based on fractional integration. International Journal of Finance & Economics, 26(1), 1318-1335.

[25] Zakoian, J. M. (1994). Threshold heteroskedastic models. Journal of Economic Dynamics and Control, 18(5), 931-955.

[26] Zhang, W., Wang, P., Li, X., & Shen, D. (2018). Some stylized facts of the cryptocurrency market. Applied Economics, 50(55), 5950-5965.