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VOLATILITY MODELING, TRADING VOLUME AND INVESTORS SENTIMENTS: EMPIRICAL EVIDENCE FROM CRYPTO MARKET

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Abstract
The primary objective of this study is to investigate cryptocurrency market volatility and how trading volume reflects the influence of investors sentiments on return and risk dynamics. For this purpose, the study has used daily data from January 1, 2023, to March 31, 2025, for major 10 cryptocurrencies i.e BTC and other major Altcoins. Asymmetric GARCH (1,1) is used to investigate the volatility behavior, persistency and clustering patterns over time. Confidence, Optimism, Pessimism and Rational Expectation has been modeled in Mean and Variance Equation of GARCH (1,1) model simultaneously. The results conclude that fear, greed, and sentiment-driven speculation often dominate crypto price movements. Potential misspecification has also been shown. Over optimistic sentiments increases volatility and cause to decrease returns. The pessimistic attitude reflects the contrarian behavior. However, it is concluded that trade volume significantly affects the return behavior and the volatility is due to sentiments and past shocks. Further findings suggest directions to assist portfolio managers and institutional investors in developing more effective portfolio diversification and risk mitigation strategies.

INTRODUCTION

Crypto Market is the largest market and getting popularity in the financial markets across the world. Crypto currency gets popularity with the laps of time, especially Bitcoin which is the first and famous crypto currency. Bitcoin is a uprising digital money that has revolutionized in today's financial markets (Gopane, 2018). It give the green light to international buyer to play a role in crypto currency for transaction and digital settlement (Liu and Serletis, 2019). In the crypto market, crypto currency is used as digital cash. It was established 2009 after the crises of 2008 due to uncertainty in their financial function. Since then, Lot of crypto currencies were introduced after that, in the beginning of 2020 more than 400 crypto currencies were introduced. The crypto currency market is yet comparatively new and has limited regulations, making price formation highly volatile and unpredictable. There is a strong connection between Bitcoin and investor sentiments, which play a key role in fluctuating Bit coin's returns and the fluctuations in its volatility. There are two primary perspectives explain how crypto currency markets are linked and how their prices volatile. The first is efficient market hypothesis. This first approach looks the crypto market as efficient, meaning prices reaction very fast to new information. Researcher highlights Bitcoin's leverage effect where prices down fall lead to increased more volatility (Stavroyiannis 2018; Baur and Dimpfl 2018). This study explore how the crypto currency market prices swing can help crypto investor can identify market inefficiencies and make good investment decision by using this possibility to their gain. Being calculated on a huge amount of data set it is less sensitive and it is not influenced by the crypto market assumption such as implied volatility. Optimistic investors increase their buying activity, which future drive prices up. This study look at how these market trends influences investment strategies and risk management, assisting investors in the making better financial decision based on the market conditions. Recognizing these trends is important for making sound investment choices and predicting future market shifts

In the recent years, the crypto currencies market has gained significant attention from both institutional and retail investors due to its high return potential and decentralization nature. This study will address gap in understanding how volatility market, market asymmetries and investor sentiment effects the crypto currency market trading, as present study deal with traditional financial market. Unlike conventional assets, crypto currencies operate in a decentralized and often speculative environment, making them more susceptible to emotional trading behavior. Furthermore, the rapid growth and evolving nature of the crypto currency market demand a deeper analysis of its unique dynamics. The investigation of Cryptocurrency market volatility patterns and the presence of market condition asymmetries that may have an impact on price behavior are the primary goals of this study. Additionally, the research aims to assess the impact of investor sentiments on market performance and trading decisions. Based on these findings, the study seeks to provide policy guidelines that can support investors in making more informed and strategic investment decisions in the dynamic landscape of digital assets.

One major reason is the difficulty in determining the intrinsic value of crypto currencies, as ongoing debates persist regarding whether they represent a form of currency, a speculative bubble, or merely a type of digital asset (Härdle et al., 2020). As a result, it is still not clear agreement on the factors that influence Cryptocurrency prices. Much of their valuation is shaped by public opinion, often formed through online platforms like Google and twitter. The study then changes to volatility measurements, asymmetric impacts, and the consequences of news on market sentiments. It defined how negative news affect prices more than positive news and how regularity challenges shape the market. At the end, it touches on unlawful activities and need for strict regulations to confirm security. Over all this study relates on crypto currency acceptance, market dynamics, volatility, and regulation issues, focusing the risks and possibilities for investors.

2: Literature Review

Katsiampa (2017) modeled conditional volatility for Bitcoin. The study used 2267 daily observations for the period July 2010 to Oct 2016 on daily basis. GARCH (1,1), TGARCH EGARCH and AR CGARCH model used to reveal the results. Hence he concluded that AR-CGARCH model was the most suitable to incorporate short run and long run aspects of conditional volatility. The study found that there was a high and suitable volatility in the Bitcoin, which is indicative of the existence of strong speculative behavior in its market. In general, the result indicated that Bitcoin was more of assets than a currency.

Baur and Dimpfl (2018) examined largest crypto currencies during April 20, 2013 to August 8 and 2013 and analyzed that how the crypto currency prices reacted to market changes and extreme period of volatility. They used TGARCH model to measure the volatility and QAR model to study market trends. The finding showed that, unlike stocks, crypto currency prices became more volatile after rising than after falling and it is due to engagement of a large number of inexperienced traders who bought due to excitement and experienced traders reacts towards more when price drop down and stabilize the market. However, Bitcoin and Ethereium were less affected by this behavior and they attracted more informed investments.

Li et al. (2021 investigated the relationship between the crypto market dynamic, in this case the volatility and trading volume of Bitcoin, Ethereum and investor sentiments in the us stock market. Based on the accessible data on the period between from February 2014 to December 2018. They applied vector auto regression (VAR) and ganger causality test to examine the relationship between market sentiment and cryptocurrency behavior. The finding showed that the exchange rate in the volume of the Bitcoin and Ethereum trading was lesser during period when investors were positive about US stock markets. In addition, the volatility of Bitcoin rose when investors were pessimistic about the US stock market and fell when there is investor optimism in the uncertainty of US economy policy.

Yahaya, Oyinloye, and Adams (2021) intended to predict and estimate the volatilities and returns of three key crypto currencies, Bitcoin, Ethereum, and Binance coin. They used data from 9th November 2017 to 31st December 2021 on daily basis. GARCH model used to model volatility The researchers concluded that the results may help investor to know the unique risk reward characteristics of cryptocurrencies and utilize the contributions to the allocation of investment resources and prediction of price in the future.

Fasanya et al. (2021) investigated the return and volatility spillovers among major crypto currency portfolio like Bitcoin, Ethereum, Ripple, Litcoin, and Doge coin. Data collection period from 10 august 2015 to 15 April 2018. The researcher employed the Diebold and Yilmaz 2012 spillover index based on generalized vector auto regression (VAR) framework, along with rolling sample analysis. The findings showed that substantial return and volatility spillovers across the crypto portfolios.

Das (2022) examined asymmetric volatility and spillover affects among major the crypt currencies, considering the impact of market sentiment from the CBOE VIX index on the Cryptocurrency prices. The study analyzed historical data from July 2017 to March 2019 of Bitcoin, Bitcoin cash, Ethereum, Litcoin, EOS, Staller, XRP, Tether. GARCH (1, 1), EGARCH, and TGARCH models were used to assess volatility, while the Diebold-Yilmaz technique measured connectedness. Eth and BNB showed significant asymmetric volatility. Long term spillovers were observed among all the cryptocurrencies, while short term effects were mainly seen in USDT.

Güler (2023) conducted a study analyzing the effect of investor sentiment on Bitcoin return and volatility, with a focus on COVID-19 pandemic period. The data spanned from January 2014 to August 2020. The research employed various econometric techniques, including EGARCH, CGARCH, GJR-GARCH, AP-ARCH and various models. The finding revealed that investor sentiments, particularly during the COVID-19 outbreak, positively influenced both Bitcoin returns and volatility. The study concluded that irrational behaviors, such as FOMO significant shaped Bitcoin price movement during periods of heightened uncertainty.

Idrees & Akhtar (2023) investigated the correlation of volatility among Bitcoin, Ethereum, Litecoin and Ripple in the crypto currency market. They used daily closing prices from 2017 to 2022 and applied GARCH models and the granger causality test, they found stronger volatility spillovers effects between Bitcoin and Ethereum, while Litecoin and Ripple showed different patterns. The study focused on volatility in the crypto currency market, offering insight for investor on risk and hedging strategies.

Alsulami and Raza (2025) aimed to examine how financial markets affected Bitcoin and Ethereum volatility before and after the FTX collapse. They used weekly data from January 1, 2020 to December 31, 2024. ARDL and NARDL model were applied. The study found that U.S. stock indices increased crypto prices, while Japanese markets and currency rates decrease them. The FTX collapse heightened volatility and altered these relationships.

Nechyporchuk (2025) investigated the global imperatives influencing the development of the crypto currency market segment within the international financial market. The primary objective of the study was too identified and evaluates the key trends, challenges, and opportunities shaping the growth of crypto currencies as the financial instruments. The research aimed o provides holistic understanding of how these digital assets have been integration in to the global economic landscape. Data for the study were collected from publicly accessible financial reports, the crypto currency database, and in situational research conducted over the period from 2015 to 2024. This study will contribute by exploring volatility patterns, market conditions asymmetric and the role of sentiment in trading decisions. The finding will help trader, investor and policy makers create better-informed decisions, enhances risk management strategies and upgrade market stability.

3: Data and Methodology

This study has used daily data from January 1, 2023, to March 31, 2025, for major cryptocurrencies. Price data as well as trade volume data has been used. Unit Root Test has been applied to test the stationarity of the crypto currency time series. The price data has been taken from Investing.com. Asymmetric GARCH (1,1) is used to investigate the volatility behavior, persistency and clustering patterns over time.

Table 1: Proxy Table

Variables	Symbol	Proxy	Source
Historical volatility	HV	Standard deviation of past returns	(Oprean and Tanasescu, 2014; Dhoui, 2011)
Trading Volume	TV	The daily tradingg volume of Crypto currency	(Rashid et al. 2022; Oprean and Tanasescu, 2014; Dhoui, 2011)
Confidence	CONF	The previous day's positive return (Rt-1>0).	(Rashid et al. 2022; Oprean and Tanasescu, 2014; Ullah et al. 2019; Dhoui, 2011)
Optimism	OPTM	The previous day's return exceeds the average sample return plus standard deviation. (R1->ΣR + σ).	(Ullah et al. 2019; Rashid et al. 2022; Oprean and Tanasescu, 2014; Dhoui, 2011)
Pessimism	PSM	The previous day's return exceeds the average sample return plus standard deviation. (R1->ΣR -σ).	(Rashid et al. 2022; Ullah et al. 2019; Oprean and Tanasescu, 2014; Dhoui, 2011)
Rational Expectation	R. E	Expected return calculated on the previous day's return plus an error term (E(R) = Rt-1+ 1).	(Oprean and Tanasescu, 2014; Dhoui, 2011; Rashid et al. 2022)

4: Results and Discussion

Technical Analysis of Price Trend

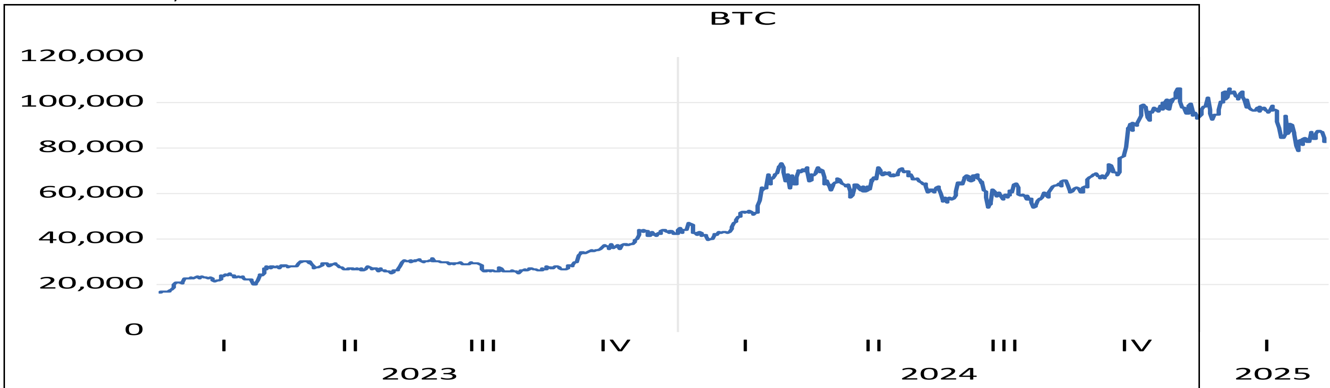

Figure: 1.1BTC PRICE TREND

Figure: 1.2 ETH PRICE TREND

Figure: 1.3SOL PRICE TREND

Figure: 1.4 XRP PRICE TREND

Figure: 1.5 UNI PRICE TREND

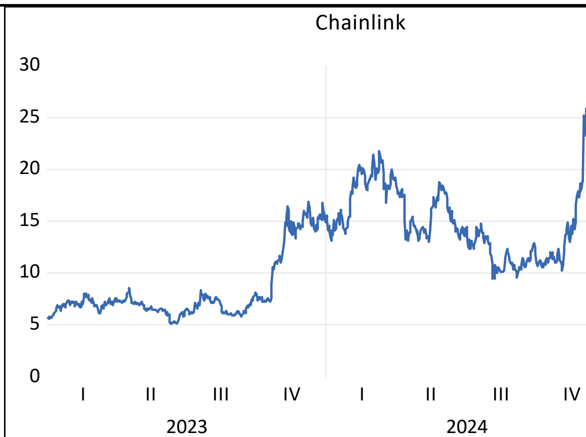

Figure: 1.6 LINL PRICE TREND

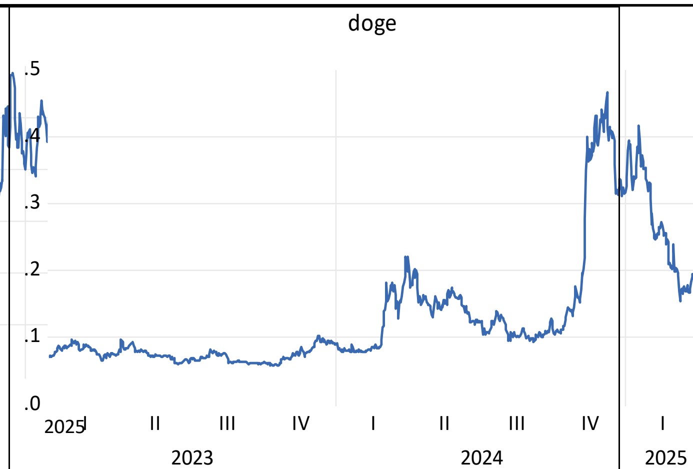

Figure: 1.7 DOGE PRICE TREND

From the above trends it has been seed that the prices of cryptocurrencies fluctuated significantly from January 2023 to March 2025 due to a combination of macroeconomic shifts, policy changes, and political events. As higher interest rates initially slowed demand for risk assets, market momentum was shaped beginning in 2023 by monetary policy tightening in major economies. On the other hand, during times of high inflation and concerns about the global banking sector, some investors saw Bitcoin and other well-established cryptocurrencies as alternative value stores, which resulted in periodic price recoveries. During April 2024 Bitcoin significantly reduced new supply, reinforcing scarcity dynamics and setting the stage for upward pressure on prices. A turning point occurred when spot Bitcoin exchange-traded funds were approved in the United States later that same year. This enabled significant inflows into the market and increased institutional participation. As a result of these developments, the prices of a number of digital assets continued to rise. Movements, particularly those that revolved around the U.S. presidential election, were amplified further during the political cycle of 2024–2025. The market saw Donald Trump's victory as a positive for the digital asset industry due to his public commitment to lowering regulatory hurdles and encouraging innovation. At the beginning of 2025, announcements such as the establishment of a "strategic crypto reserve" in the United States made up of Bitcoin, Ethereum, Solana, XRP, and Cardano sparked a rapid market rally that increased overall capitalization by hundreds of billions of dollars. Policy changes that allowed retirement accounts to hold cryptocurrencies and the appointment of industry-friendly figures to key regulatory positions increased institutional engagement and strengthened investor confidence. Even though these measures made a big difference, some financial analysts said that the rate of appreciation could make things too hot, which could cause big corrections and speculative excess. Supply-side constraints, policy liberalization, macroeconomic uncertainty, and favorable political sentiment all had an impact on the period's price dynamics. Some assets experienced substantial but moderate growth while others reached all-time highs.

Technical analysis of Return Patterns

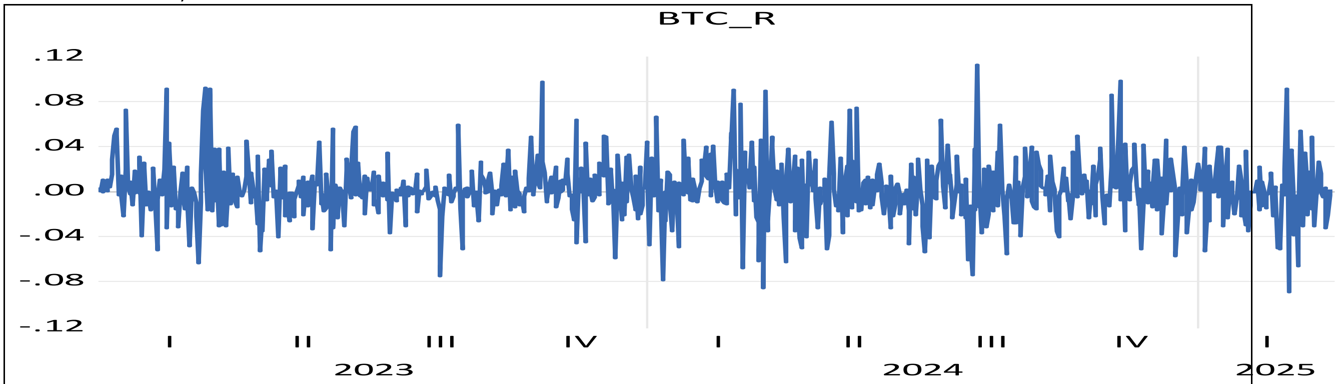

Figure: 2.1BTC RETURN PATTERNS

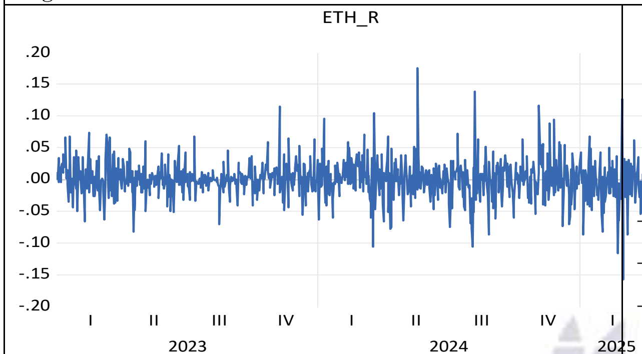

Figure: 2.2ETH RETURN PATTERNS

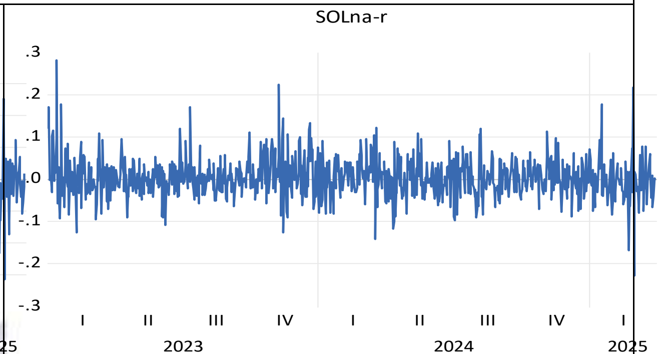

Figure: 2.3 SOL RETURN PATTERNS

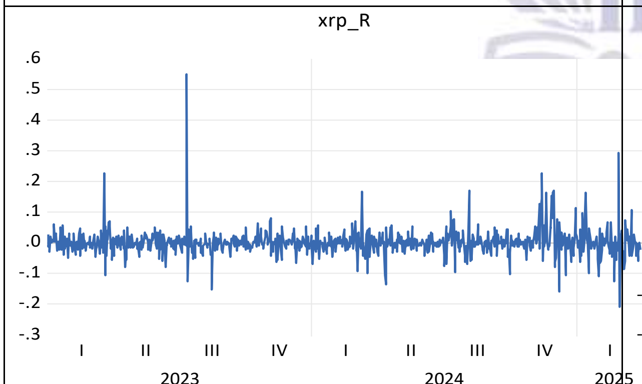

Figure: 2.4XRP RETURN PATTERNS

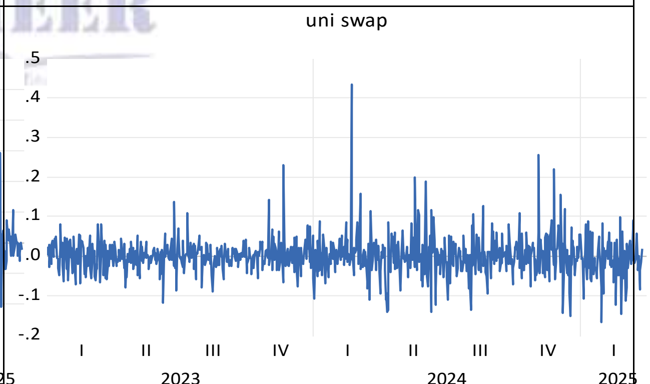

Figure: 2.5 UNISWAP RETURN PATTERNS

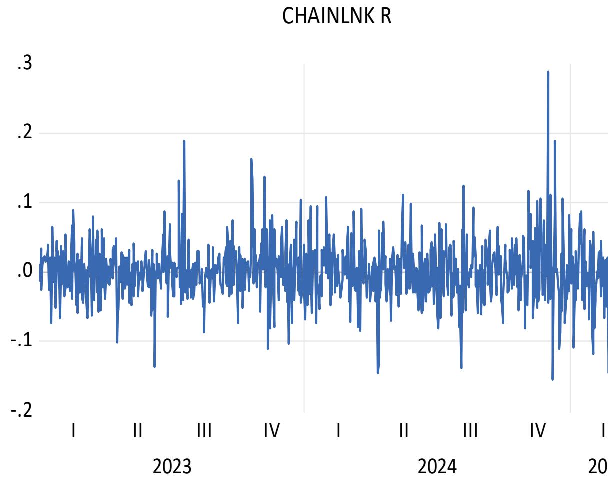

Figure: 2.6 LINK RETURN PATTERNS

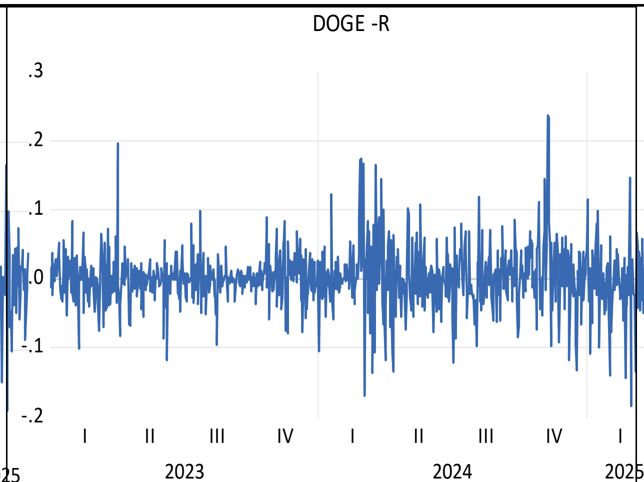

Figure: 2.7 DOGE RETURN PATTERNS

Both internal market factors and external political developments influenced the performance of major cryptocurrencies like Bitcoin (BTC), Ethereum (ETH), Solana (SOL), XRP, and Uniswap between January 2023 and March 2025. Uncertainty in the economy as a whole shaped the beginning of the 2023 phase. Investor confidence fluctuated frequently as a result of global inflationary pressures and cautious monetary policies. On the other hand, because of their higher sensitivity to liquidity conditions and speculative trading, Solana and Uniswap experienced sharper price changes. Bitcoin and Ethereum, on the other hand, had relatively stable upward movements and moderate average daily returns. However, there was a brief correction following the initial upswing, particularly in highly volatile assets like Solana and Uniswap. This shows that when big announcements are made, short-term speculation often makes gains and losses bigger. Later in the same time frame, the market experienced increased volatility as a result of the US Presidential Election in November 2024. It was thought that financial innovation and deregulation might benefit from the political climate, particularly the expectations surrounding Donald Trump's re-election. The event window's positive returns for Bitcoin and Ethereum demonstrated investor optimism for a more favorable policy environment. Altcoins, on the other hand, saw mixed results because the market responded differently to the regulatory strategy. In conclusion, the period from January 2023 to March 2025 demonstrates that cryptocurrency returns were influenced by market cycles and external political developments. The Bitcoin Spot ETF approval served as a structural catalyst by introducing institutional credibility, while Trump's election and inauguration reinforced bullish expectations. These occurrences highlight the extent to which digital asset risk-return profiles can be altered by global political and regulatory environments. Because return behavior is heavily influenced by external shocks and policy modifications, the findings demonstrate that cryptocurrencies cannot be evaluated independently of broader political and economic contexts.

Table 2: Unit oot Test at I(0) and I(1)

ADF Unit Root Test	BITCOIN		ETHEREUM		SOLANA		UNISWAP		RIPPLE (XRP)		CHAINLINK		DOGE COIN	
	t-Stat	Prob.	t-Stat	Prob.	t-Stat	Prob.	t-Stat	Prob.	t-Stat	Prob.	t-Stat	Prob.	t-Stat	Prob.
ADF at I(0)	-1.1	0.7	-2.0	0.3	-1.5	0.5	-2.3	0.2	-0.8	0.8	-2.0	0.3	-1.6	0.5
ADF at I(1)	-30.6	0.0	-29.9	0.0	-30.4	0.0	-28.5	0.0	-30.2	0.0	-28.3	0.0	-25.4	0.0
level of Significance	Critical Value	P-value		P-value		P-value		P-value		P-value		P-value		P-value
1% level	-3.4	0.0	-3.4	0.0	-3.4	0.0	-3.4	0.0	-3.4	0.0	-3.4	0.0	-3.4	0.0
5% level	-2.9	0.0	-2.9	0.0	-2.9	0.0	-2.9	0.0	-2.9	0.0	-2.9	0.0	-2.9	0.0
10% level	-2.6	0.0	-2.6	0.0	-2.6	0.0	-2.6	0.0	-2.6	0.0	-2.6	0.0	-2.6	0.0

All of the selected cryptocurrencies Bitcoin, Ethereum, Solana, Uniswap, Ripple (XRP), Chainlink, and Dogecoin are non-stationary at their level form I(0), according to the Augmented Dickey-Fuller (ADF) unit root test results. However, The t-statistics at level I(I) indicates that the price series become stationary.

Conditional Volatility and The Role of Confidence, Optimism and Pessimism in the Trading Volume

Table 3(a): GARCH (1,1) and Investors Sentiments, Mean Equation Extended

Crypto	BTC	ETH	SOL	XRP	UNI	LINK	DOGE
Mean Equation							

Variables	Co-eff	prob.	Co-eff	prob.	Co-eff	prob.	Co-eff	prob.	Co-eff	prob.	Co-eff	prob.	Co-eff	prob.
C	-0.1	0.2	-0.1	0.2	0.0	0.000***	-0.3	0.000***	0.2	0.020**	-0.1	0.093*	0.2	0.1
_TV(-1)	-0.1	0.001***	-0.2	0.000***	1.0	0.000***	-0.3	0.000***	-0.4	0.000***	-0.2	0.000***	-0.4	0.000***
CONFIDENCE	0.0	1.0	0.2	0.9	0.0	0.3	-0.4	0.000***	0.0	0.8	0.1	0.2	-1.0	0.2
OPTIMSM	-0.1	0.018**	-0.9	0.000***	0.0	0.001***	-0.6	0.000***	-0.1	0.2	-0.1	0.4	0.0	1.0
PESSIMITIC	0.1	0.089*	0.1	0.4	0.0	0.000***	0.6	0.000***	-0.1	0.089*	0.1	0.053**	0.9	0.2
ER	-0.1	0.8	6.5	0.000***	0.0	0.000***	8.4	0.000***	-0.6	0.3	0.0	0.9	-0.2	0.9
Variance Equation														
C	0.4	0.000***	0.3	0.000***	0.0	0.000***	0.2	0.000***	0.1	0.000***	0.4	0.000***	0.0	0.000***
RESID(-1)^2	-0.1	0.000***	0.6	0.000***	0.1	0.000***	0.1	0.000***	0.8	0.000***	-0.1	0.000***	0.1	0.000***
GARCH(-1)	-0.4	0.2	0.5	0.000***	0.9	0.000***	0.8	0.000***	0.6	0.000***	-0.4	0.2	0.9	0.000***

Table 3(b): GARCH (1,1) and Investors Sentiments, Variance Equation Extended

Mean Equation														
variables	Co-eff	prob.	Co-eff	prob.	Co-eff	prob.	Co-eff	prob.	Co-eff	prob.	Co-eff	prob.	Co-eff	prob.
C	0.0	0.4	0.0	0.8	0.0	0.9	-0.1	0.2	0.0	0.6	0.0	0.5	0.0	0.7
_TV(-1)	-0.1	0.000***	-0.3	0.000***	0.0	0.9	-0.4	0.000***	-0.4	0.000***	-0.2	0.000***	-0.4	0.000***
Variance Equation														
C	0.1	0.005**	2.1	0.000***	0.0	0.000***	2.8	0.000***	0.0	0.000***	0.3	0.000***	0.4	0.000***
RESID(-1)^2	-0.1	0.001***	0.3	0.000***	0.2	0.005**	0.2	0.000***	0.0	0.000***	0.1	0.000***	0.1	0.000***
GARCH(-1)	0.7	0.000***	0.5	0.000***	0.6	0.000***	0.6	0.000***	1.0	0.000***	0.1	0.054*	0.9	0.000***
CONFIDENCE	0.0	0.2	-0.3	0.118*	0.0	0.092*	-0.4	0.000***	-0.1	0.4	-0.2	0.000***	5.1	0.000***
OPTIMSM	-0.1	0.051**	0.1	0.3	0.0	0.000***	3.3	0.000***	0.0	0.000***	-0.1	0.000***	-0.3	0.000***
PESSIMITIC	0.0	0.119*	-1.9	0.000***	0.0	0.2	-2.3	0.000***	0.0	0.6	0.0	0.3	-5.6	0.000***
ER	0.3	0.116*	2.8	0.000***	0.0	0.5	-0.6	0.010**	0.1	0.000***	-0.1	0.7	1.1	0.027**

***Significant at 1% level,
** Significant at 5% level
*Significant at 10%

The outcomes of the GARCH(1,1) Table 3(a) estimation shows that the returns of most cryptocurrencies, especially BTC, ETH, XRP, UNI, LINK, and DOGE, have significant negative impact by the past trading volume. This suggests that lower present returns are frequently the result of higher past market activity. Pessimism has a large negative impact on ETH, UNI, and DOGE, whereas optimism has beneficial effects on SOL and UNI and a negative impact on BTC and ETH. These sentiment indicators exhibit asset-specific effects. External returns have a negative correlation with UNI but an upward relationship with ETH, XRP, and DOGE. A consistent base level of volatility is reflected in the variance equation by the relevance of the constant term for all assets. The high and significant GARCH coefficients across a large number of assets indicate great volatility persistence, whereas the ARCH term validates that recent shocks significantly contribute to volatility. Overall, the findings show that past market shocks, trading activity, and mood all have a significant influence on Bitcoin price dynamics, with different assets having fluctuated awareness

Table 4(a): Mean Diagnostics

	BTC	ETH	SOL	XRP	UNI	LINK	DOGE
$(R)^2$	0.0	0.1	-1.1	0.1	0.2	0.1	0.2
ARS	0.0	0.0	-1.2	0.1	0.2	0.1	0.2
SER	0.5	1.6	0.1	1.9	1.4	0.6	2.4
SSR	230.4	1962.6	10.5	2942.6	1493.4	286.0	4803.3
LLH	-630.8	-1310.2	9075.6	-1476.6	-954.1	-618.8	-1793.5
MDV	2.0	2.3	2.7	2.1	2.3	2.5	2.1
SDV	0.0	0.0	0.0	0.0	0.0	0.0	0.0
AIC	0.5	1.6	0.1	2.0	1.5	0.6	2.6
SC	1.6	3.2	-22.1	3.6	2.4	1.5	4.4
HQC	1.6	3.3	-22.1	3.7	2.4	1.6	4.5
DVS	1.6	3.2	-22.1	3.7	2.4	1.6	4.4

Table 4(b) Variance Diagnostics

Crypto	BTC	ETH	SOL	XRP	UNI	LINK	DOGE
$(R)^2$	0.0	0.1	0.0	0.1	0.2	0.1	0.2
ARS	0.0	0.1	0.0	0.1	0.2	0.1	0.2
SER	0.5	1.5	0.1	1.9	1.4	0.6	2.4
SSR	233.1	1849.7	4.9	2820.5	1499.0	285.5	4726.9
LLH	-636.3	-1251.4	1269.0	-1455.4	-934.6	-630.5	-1731.7
MDV	2.1	2.2	2.1	2.2	2.3	2.5	2.1
SDV	0.0	0.0	0.0	0.0	0.0	0.0	0.0
AIC	0.5	1.6	0.1	2.0	1.5	0.6	2.6
SC	1.6	3.1	-3.1	3.6	2.3	1.6	4.3
HQC	1.6	3.1	-3.0	3.6	2.4	1.6	4.3
DVS	1.6	3.1	-3.1	3.6	2.3	1.6	4.3

The mean equation's diagnostic results show that all cryptocurrencies have a generally low explanatory power; the R-squared values range from 0.0 to 0.2, indicating that the independent variables in the model only partially account for the variation in returns. This pattern is reflected in adjusted R-squared values, which support the limited fit. BTC has the lowest standard error of regression (S.E.) at 0.5, while DOGE has the highest at 2.4, suggesting that DOGE's residuals are more volatile. The log likelihood values differ significantly; XRP (-1476.6) and DOGE (-1793.5) have very negative values, which indicate a poorer model fit than BTC (-630.8). the majority of Durbin watson statistics are in the optimal range of 2, indicating low residual auto correlation. For Bitcoin and Link, the information criteria (Akaike, Schwarz, and Hannan-Quinn) are the lowest, suggesting that these assets have comparatively more effective model specifications. The R-squared values for the variance equation are likewise low (0.0–0.2), suggesting that the model only partially accounts for volatility variation. In line with the mean equation results, the standard error of regression is highest for DOGE (2.4) and lowest for BTC (0.5), underscoring DOGE's greater volatility risk. Log likelihood values once more reveal significant disparities, with assets like XRP (-1455.4) and DOGE (-1731.7) performing comparatively worse than BTC (-636.3) and LINK (-630.5). In general, Durbin-Watson statistics are near 2, indicating minimal residual autocorrelation. Further confirming that BTC and LINK models are more economical and well-defined than others with higher values, like DOGE and XRP, are information criteria values (AIC, SIC, and HQC). While some cryptocurrencies show better model fit and lower residual volatility than others, the results generally show weak model explanatory power across both mean and variance equations.

1. Conclusion

The study discovered and concluded that the pattern of the cryptocurrency volatility was well defined, and the volatility clustering and assets specific pattern existed. Although Solana, Uniswap and Doge coins portrayed more swings in specifications, Bitcoin turned out to be comparatively consistent, which implies a set of substantial volatility interactions. Second, the asymmetries of the market condition were affirmed with Bitcoin and Ethereum benefiting most in bearish markets due to optimism and policy changes and leading to low returns across the board and positive though uneven return in the bullish markets. Thirdly, optimism and pessimism and trading activity were also discovered to affect the return dynamic significantly but in the market specific manners. These dynamic were the external shocks and investor sentiment. The explore of the digital assets to the political and macroeconomics event were brought in to focus with the success of the Bitcoin ETF, the election of the trump, and regulatory changes, which increased the bullish and bearish market cycles. As it can show the evidence, the volatility pattern, market asymmetries and sentiment dynamics were well explained even with the moderate explanatory powers of the models. Therefore, the objectives of the study were largely met, which give investors and policy makers in the crypto currency market practical suggestion and empirical justification. The study could be enhanced in future research by adding intra-day high frequency data to allow the capture the short term volatility dynamics that could not fully capture in the daily data. The comparative weakness of the explanatory power of the econometric models is a significant drawback of this research and may be modelled with advanced GARCH family models, which suggests that the return of the crypto currency could also be exploded to the external factors that are not observed. The implication of the findings includes the fact that political developments, sentiment changes, and trading activity are important volatility drives that investors and policymakers should take in to account to make informed investment or regulatory decisions.

References:

Alsulami, F. And A. Raza. 2025. Financial Markets Effect on Cryptocurrency Volatility: Pre- and Post-Future Exchanges Collapse Period in USA and Japan. International Journal of Financial Studies 13:24

Baur, D.G. and T. Dimpfl. 2018. Asymmetric volatility in cryptocurrencies. Economics Letters 173:148–151.

Dhoui, A. 2011. What does matter in economy today: Between rationality and animal spirits. Faculty Soc. Sci. Manage. 11-12.

Das, A. 2022. Asymmetric volatility and volatility spillover : A study of major asymmetric volatility and volatility Spillover : A study of major cryptocurrencies. Journal of Commerce & Accounting Research 11:71–88.

Fasanya, I.O., O. Oyewole and T. Odudu. 2021. Returns and volatility spillovers among cryptocurrency portfolios. International Journal of Managerial Finance 17:327-341.

Gopane, T. 2018. The likelihood of financial inclusion in e-banking: A biprobit sample-selection modeling approach. International Conference on Digital Economy 1:1–14.

Güler, D. 2023. The Impact of investor sentiment on bitcoin returns and conditional volatilities during the era of Covid-19. Journal of Behavioral Finance 24:276-289.

Härdle, W. K., Harvey, C. R., & Reule, R. C. 2020. Understanding cryptocurrencies. *Jonuarl of Finance Econometrics.*

Idrees, M.A. and S. Akhtar. 2023. An investigative analysis of volatility in the cryptocurrency market. International Journal of Trends and Innovations in Business & Social Sciences 1:80–86.

Katsiampa, P., 2017. Volatility estimation for Bitcoin: A comparison of GARCH models. Economics letters, 158, pp.3-6.

Liu, J. And A. Serletis. 2019. Volatility in the cryptocurrency market. Open Economies Review 30:779–811.

Nechyporchuk, M. 2025. Global Imperatives for the Development of the Cryptocurrency Segment of the Global Financial Market. Economics & Education 10:39-46.

Oprean, C. and C. Tanasescu. 2014. Effects of behavioural finance on emerging capital markets. Procedia Econ. Finance 15:1710-1716.

Oprean, C. and C. Tanasescu. 2014. Effects of behavioural finance on emerging capital markets. Procedia Econ. Finance 15:1710-1716.

Stavroyiannis, S. 2018. A note on the Nelson-Cao inequality constraints in the Gjr-Garch model: Is there a leverage effect? International Journal of Economics and Business Research 16:442–452.

Yahaya, H.U., Oyinloye, J.S. and Adams, S.O., 2022. Modeling and Forecasting Cryptocurrency Returns and Volatility: An Application of GARCH Models. Universal Journal of Finance and Economics, 2, p.497.

Ullah, I., M. Zahid and Z. Ullah. 2019. The impact of behavioural biases on stock volatility: Evidence from Pakistan Stock Exchange. J. Bus. Tourism 05:1-12.