



Research Article

**Assessing the Best Cryptocurrencies for Long-Term Investment
Using Mean Reversion and Half-Life Volatility Models**

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ABSTRACT

This study aims to evaluate optimal cryptocurrencies for both short-term and long-term investment through the use of volatility mean reversion and half-life models. The study analyzes the volatility of daily closing prices for twelve cryptocurrencies: Bitcoin, Ethereum, Cardano, Dogecoin, Litecoin, Binance, Ripple, Bitcoin Cash, Stellar, Chainlink, Monero, and Tether over the period from January 14, 2014, to July 16, 2021. The study employs various statistical methods, including summary statistics, normality measures, Augmented Dickey-Fuller unit root test, heteroskedasticity test for ARCH effects, and symmetric GARCH (1,1) models. Findings reveal non-Gaussian, leptokurtic log returns with volatility clustering and high shock persistence across cryptocurrency returns, indicating stable, mean-reverting, and predictable log returns. The study found that all cryptocurrencies exhibit mean reversion to their historical mean values after specific periods. Dogecoin, Litecoin, Ripple, Monero, Ethereum, Cardano, Bitcoin Cash, Chainlink, and Binance exhibit faster mean reversion and smaller volatility half-lives of 2, 5, 8, 10, 13, 14, 22, 24, and 35 days respectively, while Bitcoin and Stellar have slower mean reversion rates and larger volatility half-lives of 1454 and 624 days respectively. The study suggests short-term trading and investment in Dogecoin, Litecoin, Ripple, Monero, Ethereum, Cardano, Bitcoin Cash, Chainlink, and Binance due to their faster mean reversion and smaller volatility half-lives, and long-term investment in Bitcoin and Stellar due to their slower mean reversion and larger volatility half-lives. Recommendations include the use of heavy-tailed error distributions in modeling cryptocurrency returns and caution against excessive trading to mitigate market volatility.

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INTRODUCTION

The evolution of money is a fascinating journey that spans thousands of years and has undergone significant transformations (Weatherford, 1997). Before the advent of money, people engaged in barter, exchanging goods and services directly (O'Sullivan *et al.*, 2003). Over time, societies transitioned to commodity money, where items with intrinsic value (such as gold, silver, or salt) were used as a medium of exchange (Weatherford, 1997). The first standardized metal coins were introduced by the Lydians in the 7th century BC. These coins, made of precious metals like gold and silver, facilitated trade and became widely adopted (Weatherford, 1997). The Chinese were among the first to use paper money during the Tang Dynasty (7th century AD). Paper money provided a more convenient form of currency than metal coins (O'Sullivan *et al.*, 2003). In the 17th century, European banks began issuing banknotes as promissory notes, representing a promise to pay the bearer a specified amount of precious metal on demand (Weatherford, 1997). With the abandonment of the gold standard in the 20th century, most countries shifted to fiat currency. Fiat money has no intrinsic value and was not backed by a physical commodity but was accepted as a form of payment due to government decree (Weatherford, 1997).

In the late 20th century, the emergence of computers and the internet spurred the evolution of digital currency. Electronic transactions and online banking became common, representing a shift towards a more intangible form of currency (Menger, 2007). Bitcoin, established in 2009 by an individual or collective under the pseudonym Satoshi Nakamoto, introduced the notion of a decentralized digital currency founded upon blockchain technology. Other cryptocurrencies followed, each with its unique features and use cases (Nakamoto, 2008).

Cryptocurrency refers to a form of digital or virtual currency that utilizes cryptographic

methods to ensure the security of financial transactions, regulate the generation of new units, and validate asset transfers. Unlike traditional currencies issued by governments and central banks, cryptocurrencies operate on decentralized networks based on blockchain technology (Narayanan *et al.*, 2016). Cryptocurrencies are characterized by their operation on decentralized computer networks, commonly referred to as blockchains. This structure ensures that no central authority, such as a government or financial institution, possesses absolute control over the currency. Utilizing blockchain technology—a distributed ledger recording all transactions across a network of computers—cryptocurrencies guarantee transparency, security, and the unalterable nature of transaction records. Cryptographic methods are employed to safeguard transactions and regulate the generation of new currency units. Public and private keys enable secure and verifiable transactions between parties (Narayanan *et al.*, 2016).

Numerous cryptocurrencies feature a finite supply, indicating a predetermined maximum number of units that can exist. For instance, Bitcoin is capped at 21 million coins, a measure intended to manage inflation. Despite the transparency of blockchain transactions, the identities of participants are typically pseudonymous, as users are identified by cryptographic addresses rather than personal details, ensuring a degree of privacy. Cryptocurrencies enable global accessibility and transactions without reliance on traditional banking infrastructure. This feature facilitates financial inclusion for individuals who may not have access to traditional banking services (Narayanan *et al.*, 2016).

The prices of cryptocurrencies are prone to significant and swift fluctuations, displaying high volatility. This volatility is influenced by factors such as market demand, regulatory

developments, and technological advancements (Narayanan *et al.*, 2016).

Cryptocurrency markets are renowned for their notable volatility. While this volatility can offer profit opportunities, it also escalates the risk for investors. Sudden and significant price fluctuations can lead to both substantial gains and losses (Dwyer, 2015). Cryptocurrency markets often attract speculative trading due to the potential for quick and sizable returns. However, the speculative nature of the market can amplify volatility as prices are influenced by sentiment, news, and market dynamics (Ciaian *et al.*, 2016). High volatility can present challenges for the mainstream adoption of cryptocurrencies. Merchants and businesses may be hesitant to accept cryptocurrencies as a means of payment if the value is subject to rapid and unpredictable changes (Foley *et al.*, 2019). Regulatory authorities may be cautious about embracing or endorsing cryptocurrencies in environments where prices are highly volatile. Concerns about market manipulation, fraud, and investor protection may be exacerbated in volatile market conditions. Cryptocurrencies are often criticized for their lack of price stability, a characteristic that traditional fiat currencies typically provide (Yelowitz and Wilson, 2015). The volatility can hinder the ability of cryptocurrencies to function as a stable medium of exchange or store of value. Businesses and individuals using cryptocurrencies may face challenges in managing the risks associated with volatile price movements. Effective risk management strategies become crucial in such an environment (Dyhrberg, 2016).

Modeling the volatility of cryptocurrencies is crucial for several reasons, including risk management, investment decision-making, and understanding the dynamics of these unique financial assets. Understanding and quantifying the volatility of cryptocurrencies helps in assessing and managing risk for investors, traders, and financial institutions (Ciaian *et al.*,

2016). Investors often consider volatility as a key factor in decision-making. Volatility models can provide insights into potential price movements and assist in portfolio optimization (Dyhrberg, 2016).

Studying volatility helps researchers and market participants understand the efficiency of cryptocurrency markets and how information is reflected in prices (Baur and Lucey, 2010). Volatility models contribute to forecasting future price movements, aiding traders and investors in making informed decisions (Bouri *et al.*, 2017a). Volatility modeling provides insights into the microstructure of cryptocurrency markets, helping to understand the behaviour of market participants (Cheah *et al.*, 2019). Understanding volatility is essential for assessing whether cryptocurrencies, such as Bitcoin, exhibit characteristics of a safe-haven asset or can be used for risk hedging (Bouri *et al.*, 2017b). GARCH models are widely used to model and forecast volatility, assisting in risk management strategies for cryptocurrency traders and investors (Dyhrberg, 2016). GARCH models contribute to portfolio optimization by providing estimates of the conditional volatility of cryptocurrencies, helping investors construct well-diversified portfolios (Ciaian *et al.*, 2016). Financial institutions use GARCH models to assess the risk associated with exposure to cryptocurrencies in their portfolios (Conlon *et al.*, 2018).

Mean reversion models on the other hand, help identify potential market inefficiencies in cryptocurrency prices, guiding traders in developing mean-reverting trading strategies (Kristoufek, 2015). Mean reversion models contribute to understanding the impact of investor sentiment on cryptocurrency prices and whether deviations from mean values are driven by psychological factors (Balcilar *et al.*, 2017). Mean reversion models are applied to analyze the microstructure of cryptocurrency markets, exploring how prices revert to their historical

mean over time (Cheah *et al.*, 2019). These applications highlight the versatility of GARCH models in capturing volatility dynamics and mean reversion models in understanding market behaviour and trading strategies in the cryptocurrency space.

Cryptocurrency investment refers to the act of allocating funds to cryptocurrencies with the expectation of generating returns. Investment in cryptocurrency could be long-term or short-term. Long-term investments are maintained over an extended period, often spanning several years or even decades. Investors with long-term strategies seek to capitalize on the potential growth of their investments over time. Conversely, short-term investments are held for shorter durations, typically ranging from a few days to a few years. Short-term investors are often more focused on capital preservation and liquidity. Investing in cryptocurrencies involves acquiring digital assets in the hope that their value will increase over time. Many investors adopt a "buy and hold" strategy, where they purchase cryptocurrencies and hold onto them for an extended period, anticipating that their value will rise over time. Some investors engage in active trading, buying and selling cryptocurrencies in the short term to take advantage of price fluctuations. This strategy necessitates a comprehensive grasp of market trends, technical analysis, and effective risk management. Additionally, there are Initial Coin Offerings (ICOs) and token sales. ICOs emerged as a favoured fundraising avenue in the nascent stages of cryptocurrencies, enabling projects to secure funds through the issuance of new tokens. Investors could participate in ICOs by purchasing these tokens in the hope that their value would increase. Some cryptocurrencies offer staking or yield farming opportunities where investors can lock up their coins to support the network and, in return, receive additional tokens as rewards.

It is important to note that cryptocurrency investments come with inherent risks. Cryptocurrencies often exhibit significant volatility in value, while their legality and usage can be influenced by regulatory frameworks. Furthermore, the cryptocurrency market, being relatively nascent, is susceptible to a range of factors such as technological advancements, market sentiment, and macroeconomic trends. This study is an attempt to extend the existing literature and contribute to the existing body of knowledge by assessing the best cryptocurrencies for both short-term and long term investment decisions using lower symmetric GARCH, volatility mean reversion and half-life models.

EMPIRICAL LITERATURE

Dyhrberg (2016) utilized GARCH models to examine the volatility of Bitcoin, gold, and the U.S. dollar. The research compared Bitcoin's volatility to traditional assets, highlighting periods of fluctuation. The findings offered insights into Bitcoin's risk and potential as an investment compared to gold and fiat currencies. Yelowitz and Wilson (2015) utilized Google search data to examine the characteristics of Bitcoin users. By analyzing search queries related to Bitcoin, the study aims to discern demographic and geographic patterns among individuals interested in the cryptocurrency. This innovative approach provides insights into the user base and sheds light on the factors influencing Bitcoin adoption during the period studied.

Foley *et al.* (2019) examined the connection between cryptocurrencies, particularly Bitcoin, and illegal activities such as the trade of illicit goods and services. The study seeks to quantify the extent to which cryptocurrencies facilitate unlawful transactions. Through their analysis, the authors provided insights into the role of cryptocurrencies in financing illegal activities, contributing to the broader understanding of the potential challenges and implications of digital

currencies. Ciaian *et al.* (2016) delved into the economics of Bitcoin price formation. The study explored the various economic factors that contribute to the valuation of Bitcoin. By employing economic models and analysis, the authors aim to uncover the determinants that drive the pricing dynamics of Bitcoin. The research contributed to the understanding of the economic forces shaping the value of the cryptocurrency. Dwyer (2015) investigated the economic dimensions of Bitcoin and similar private digital currencies. The study delved into the economic mechanisms that underlie the functioning of these digital currencies. It likely covers aspects such as the role of decentralized systems, the impact on traditional financial systems, and the potential implications for monetary policy. Dwyer's research enhanced comprehension of the economic dynamics and hurdles linked to the rise of digital currencies. Naimy and Hayek (2018) centered their study on the application of GARCH models to model and predict the volatility of Bitcoin. The study examined the efficacy of GARCH models in depicting Bitcoin's volatility patterns, outlined the prediction methodology, and discussed the implications of the findings for comprehending and mitigating Bitcoin price volatility. Katsiampa (2017) specifically addressed the issue of volatility estimation in the context of Bitcoin. The study compared various GARCH models, which are commonly used in financial econometrics for modeling time-varying volatility. The comparison involved assessing the performance of different GARCH specifications in capturing the unique volatility patterns exhibited by Bitcoin. The paper contributed insights into the effectiveness of GARCH models for estimating and understanding Bitcoin's price volatility. Ngunyi *et al.* (2019) examined the volatility dynamics of eight major cryptocurrencies using GARCH models for the period of 2015 to 2018. The research examined Bitcoin, Ethereum,

Litecoin, Ripple, Monero, Dash, Stellar, and NEM. Various distributions were applied to fit GARCH-type models to the data, and their appropriateness was assessed through diagnostic tests. Results showed that the optimal in-sample GARCH-type models differed from those chosen for out-of-sample Value at Risk (VaR) forecasts. Asymmetric GARCH models featuring long memory and heavy-tailed innovations demonstrated superior performance in forecasting cryptocurrency volatility overall. Gronwald (2014) studied various GARCH models, including multiple threshold-GARCH and Asymmetric-power GARCH to measure and estimate Bitcoin price volatility. The research employed model selection criteria, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Information Criterion (HQC), to accommodate leverage and regime-switching characteristics in the conditional variance. The conclusion drawn from the analysis was that the Bitcoin market was deemed not yet matured. On the other hand, Bouri (2013) conducted a study that focused on assessing the safe-haven property of Bitcoin and its relationship before and after the Bitcoin price crash in December 2013. Employing an asymmetric-GARCH model, the study found evidence supporting Bitcoin's status as a safe haven asset prior to the crash. However, this safe haven characteristic was reported to be absent in the post-crash period. Liu and Tsyvinski (2018) assessed the risks and returns of cryptocurrencies, including Bitcoin, Ripple, and Ethereum and found a distinctive risk-return trade-off compared to stocks, currencies, and precious metals. Cryptocurrencies showed limited susceptibility to traditional stock market and macroeconomic influences, as well as the returns of currencies and commodities. Instead, cryptocurrency returns were observed to be influenced by factors unique to cryptocurrency markets, including a strong time-series momentum effect

and the forecasting power of proxies for investor attention. Jinan and Apostolos (2019) focused on estimating volatility in the cryptocurrency market using GARCH-in-mean models. Their analysis aimed to examine the correlation between volatility and returns in prominent cryptocurrencies, explore spillovers within the cryptocurrency market, and evaluate the transmission of spillover effects from the cryptocurrency market to other financial markets. The results indicated statistically significant transmission of shocks and volatilities among major cryptocurrencies. Furthermore, the study unveiled notable spillover effects from the cryptocurrency market to financial markets in the United States, Germany, the United Kingdom, and Japan.

In a study by Soqiq and Oluwasegun (2020), the investigation focused on the exchange rate, stock market prices, and the most traded cryptocurrencies in Nigeria. Using monthly data from August 2015 to December 2019, the study applied GARCH (1,1), EGARCH (1,1), and Granger causality techniques. The research sought to gauge the response of exchange rates and stock market prices' volatility to shifts in cryptocurrency prices. Findings revealed that the volatility of Bitcoin and Ethereum prices had a greater influence on stock market prices compared to exchange rates in Nigeria. Furthermore, evidence suggested a unidirectional causality from Bitcoin and Ethereum to the all-share index. In the work by Malhotra and Gupta (2019), the focus was on volatility spillovers among five Asian stock indices and four cryptocurrencies from November 2014 to December 2018. The study

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100 \quad (1)$$

where r_t represents the daily return on cryptocurrencies at time t , P_t signifies the closing price at time t , and P_{t-1} denotes the

examined the leverage effect, volatility spillovers, and time-varying correlation utilizing EGARCH, Diagonal BEKK, and DCC tests, respectively. Results indicated the absence of a leverage effect in cryptocurrency returns, with Bitcoin's past innovations exerting the most significant influence on future volatility of equity market returns. Additionally, the DCC model unveiled evidence of time-varying correlation between the markets and Bitcoin.

From the reviewed literature, it is glaring to know that most of the researches were conducted on Bitcoin cryptocurrency volatility while neglecting majority of other cryptocurrencies that also dominate the digital coin market. The current study therefore extends the existing literature by incorporating more cryptocurrencies based on market capitalization and performance. The best twelve performing cryptocurrencies at the time of conducting this study were selected for this study.

3. MATERIALS AND METHODS

3.1 Source of Data

The study utilizes secondary data from coinmarketcap.com, covering the period from January 14th, 2014, to July 16th, 2021. The best twelve performing cryptocurrencies at the time of conducting this study were selected for study. The twelve cryptocurrencies, include Bitcoin, Ethereum, XRP, Litecoin, Dogecoin, Cardano, Stellar, Bitcoin Cash, Monero, Tether, and Binance. The analysis involves examining the time series closing prices of these cryptocurrencies. The return series for each cryptocurrency is computed by taking the natural logarithm of the first difference of daily closing prices, expressed as follows:

corresponding price in the preceding period at time $t - 1$.

Summary statistics such as the daily mean, maximum and minimum, standard deviation as

well as normality measures such as skewness, kurtosis and Jarque-Bera statistic were employed to aid the understanding of descriptive and distributional characteristics of the cryptocurrency returns.

$$r_t = \theta_1 r_{t-1} + \theta_2 r_{t-2} + \dots + \theta_p r_{t-p} + \varepsilon_t \quad (2)$$

If $H_0: \hat{\theta} = 0$, against the alternative $H_1: \hat{\theta} < 0$, then r_t includes a unit root. To examine the null hypothesis, the ADF test is applied, utilizing the t – statistics:

$$t_{\hat{\theta}} = \frac{\hat{\theta}}{SE(\hat{\theta})} \quad (3)$$

where $\hat{\theta}$ denotes the estimated value of θ , and $SE(\hat{\theta})$ represents the standard error of the coefficient.

Heteroskedasticity test

The study employs the Lagrange Multiplier (LM) test, introduced by Engle (1982), to test for heteroskedasticity or ARCH effect in the residuals of cryptocurrency returns. The testing procedure entails deriving residuals (e_t) from an ordinary least squares regression of the

$$r_t = \phi_1 r_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} \quad (4)$$

where r_t is the return series, ϕ_1 and θ_1 are the coefficients of the AR and MA terms while ε_t is the random error term. The residuals (e_t) so obtained are squared and regressed on a constant and q lags as follows:

$$e_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + \alpha_3 e_{t-3}^2 + \dots + \alpha_q e_{t-q}^2 + v_t \quad (5)$$

The null hypothesis that there is no ARCH effect up to lag q is expressed as follows:

$H_0: \alpha_1 = \alpha_2 = \alpha_3 = \dots = \alpha_q$ versus the alternative $H_1: \alpha_i > 0$ for at least one $i = 1, 2, 3, \dots, q$.

The study employs two test statistics, the F-statistic and nR^2 , to evaluate the combined significance of squared residuals up to lag q . The F-statistic gauges the overall impact of these residuals on the model. The specific formula for the F-statistic is given as:

$$F = \frac{SSR_0 - SSR_1/q}{SSR_1(n - 2q - 1)} \quad (6)$$

$$\text{where } SSR_1 = \sum_{t=q+1}^T e_t^2, SSR_0 = \sum_{t=q+1}^T (r_t^2 - \bar{r})^2 \text{ and } \bar{r} = \frac{1}{n} \sum_{t=1}^T r_t^2$$

The residual \hat{e}_t is derived from the least squares linear regression, with, \bar{r} representing the sample mean of r_t^2 . The nR^2 is assessed against a $\chi^2(q)$ distribution with q degrees of freedom under the null hypothesis H_0 .

Augmented-Dickey Fuller unit root test

To assess stationarity, the study utilizes the Augmented Dickey Fuller (ADF) unit root test, introduced by Dickey and Fuller (1979). The ADF test includes a parametric adjustment for higher-order correlation, presuming the series adheres to an autoregressive AR(p) process outlined as:

conditional mean equation, which might be an autoregressive (AR), moving average (MA), or autoregressive moving average (ARMA) model tailored to suit the dataset. Emphasis is placed on an ARMA (1,1) model, with the conditional mean equation outlined as:

Model Specification

The ARCH model of Engle (1982) was extended by Bollerslev (1986) to the Generalized Autoregressive Conditional Heteroskedasticity

$$r_t = \mu_t + \varepsilon_t \quad (7)$$

$$\varepsilon_t = \sigma_t e_t; \quad e_t \sim N(0, 1) \quad (8)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (9)$$

The model specifies that ε_t represents the innovation or shock at day t , following a heteroskedastic error process, σ_t^2 denotes the volatility at day t , or the conditional variance, ε_{t-1}^2 is the squared innovation at day $t - 1$, ω is a constant term, μ_t represents the conditional mean, p, q denote the autoregressive order (GARCH term) and the moving average order (ARCH term). The requirements for stationarity in GARCH (1,1) model are that $\alpha_1 + \beta_1 < 1$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\omega > 0$.

(GARCH) model. The definition of the GARCH (1,1) model as a specific mathematical formulation is:

a constant term, μ_t represents the conditional mean, p, q denote the autoregressive order (GARCH term) and the moving average order (ARCH term).

Modeling Mean Reversion

Given that the enduring level of variance ε_t in a stationary GARCH (1,1) model is

$$\bar{\sigma}^2 = \frac{\omega}{(1 - \sigma_1 - \beta_1)} \quad (10)$$

In this scenario, volatility consistently gravitates towards its long-term level through the revision of the ARMA representation.

$$\varepsilon_t^2 = \omega + (\alpha_1 + \beta_1)\varepsilon_{t-1}^2 + \mu_t - \beta_1\mu_{t-1} \quad (11)$$

as follows

$$\left(\varepsilon_t^2 - \frac{\omega}{1 - \sigma_1 - \beta_1} \right) = (\sigma_1 + \beta_1) \left(\varepsilon_{t-1}^2 - \frac{\omega}{1 - \sigma_1 - \beta_1} \right) + \mu_t - \beta_1\mu_{t-1} \quad (12)$$

By iterating the equation above k times, it can be demonstrated that

$$\left(\varepsilon_{t+k}^2 - \frac{\omega}{1 - \sigma_1 - \beta_1} \right) = (\alpha_1 + \beta_1)^k \left(\varepsilon_t^2 - \frac{\omega}{1 - \sigma_1 - \beta_1} \right) + \eta_{t+k} \quad (13)$$

here η_t represents the moving average process, given that $(\alpha_1 + \beta_1) < 1$ for a stationary GARCH (1,1) model,

$(\alpha_1 + \beta_1)^k \rightarrow 0$ as $k \rightarrow \infty$. Despite potentially significant deviations between ε_t^2 and the long-run variance at time t , $\varepsilon_{t+1}^2 = \omega/(1 - \sigma_1 - \beta_1)$ will tend towards zero on average as k increases significantly. This implies that volatility reverts to its long-run level of $\omega/(1 - \sigma_1 - \beta_1)$. Conversely, if $\omega/(1 - \sigma_1 - \beta_1) > 1$ and the GARCH model is non-stationary, volatility will ultimately escalate towards infinity as k approaches infinity. Comparable arguments can be readily formulated for a GARCH (p,q) model.

Half-Life of Volatility

The half-life of volatility denotes the duration it takes for the volatility shock to regress halfway back to its mean volatility following a deviation

$$(\varepsilon_t^2 - \bar{\sigma}^2) = (\alpha_1 + \beta_1)(\varepsilon_{t-1}^2 - \bar{\sigma}^2) + \mu_t - \beta_1\sigma_{t-1}^2 \quad (14)$$

where $\bar{\sigma}^2 = \omega/(1 - \alpha_1 - \beta_1)$ is unconditional long-run level of volatility and $\mu_t = (\varepsilon_t^2 - \bar{\sigma}^2)$ the rate of mean-reversion ($\alpha_1 + \beta_1$) indicated by most fitted models typically approaches 1 closely. The value of

from it. In a stationary GARCH (1,1) model expressed as $\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$, the mean-reverting form of the basic GARCH (1,1) model is provided by

$(\alpha_1 + \beta_1)$ governs the pace of mean reversion. The formula for the half-life of a stock's volatility is expressed as follows:

$$L_{Half} = 1 - \left\{ \frac{\ln(2)}{\ln(\alpha_1 + \beta_1)} \right\} \quad (15)$$

The half-life signifies the typical duration for $|\varepsilon_t^2 - \bar{\sigma}^2|$ to diminish by half. The nearer $(\alpha_1 + \beta_1)$ is to unity, the greater the half-life of a stock's volatility. If $(\alpha_1 + \beta_1) > 1$, the GARCH (1,1) model is non-stationary, and $H_0 = (\alpha_1 + \beta_1) > 1$ (that is, the return series is not-stationary) versus $H_1 = (\alpha_1 + \beta_1) < 1$ (i.e., the return series is mean reverting).

Model Order and Error Distribution Selection

Choosing the order of a GARCH model and the distribution of errors entails selecting a model order that minimizes one or more information

$$SIC(P) = -2 \ln(L) + P \ln(T) \quad (16)$$

where P represents the count of free parameters to be estimated within the model, T stands for the number of observations, and L denotes the maximum likelihood function for the estimated model, as defined by:

$$L = \prod_{t=0}^n \left(\frac{1}{2\pi\sigma_t^2} \right)^{1/2} \exp \left[- \sum_{t=1}^n \frac{(y_i - \mu)^2}{2\sigma_t^2} \right] \quad (17)$$

$$\ln(L) = \ln \left[\prod_{t=1}^n \left(\frac{1}{2\pi\sigma_t^2} \right)^{1/2} \right] - \frac{1}{2} \sum_{t=1}^n \frac{(y_i - \mu)^2}{\sigma_t^2} \quad (18)$$

Therefore, when presented with a collection of estimated GARCH models based on a particular dataset, the preferred model is the one characterized by the lowest information criterion and the highest log-likelihood value.

Distribution assumption of the error (ε_t)

In order to estimate the fluctuating volatility within cryptocurrency returns and accommodate the excess kurtosis and fat-tailed nature evident

1. *Normal (Gaussian) Distribution:* The normal distribution is given by:

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}, -\infty < z < \infty \quad (19)$$

The normal distribution to the log likelihood for observation t is given as:

$$l_t = \frac{-\frac{1}{2} \log(2\pi) - \frac{1}{2} \log \sigma_t^2 - \frac{1}{2} (y_t - X_t' \theta)^2}{\sigma_t^2} \quad (20)$$

(ii) *Student's-t Distribution (STD):* The student's-t distribution is given as:

$$f(z) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\Gamma\left(\frac{v}{2}\right)} \left(1 + \frac{z^2}{v}\right)^{-\left(\frac{v+1}{2}\right)}, -\infty < z < \infty \quad (21)$$

volatility surges toward infinity. To examine the mean-reverting characteristics of the return series, assuming a GARCH (1,1) model, we assess the following set of hypotheses.

criteria assessed across a spectrum of model orders. In this work, we employed Schwarz information Criterion (SIC) due to (Schwarz, 1978). The criterion is given as:

in the return series residuals, we incorporate various distributions for modeling the error term within GARCH models. These distributions include the normal (Gaussian) distribution, Student's-t distribution, and Generalized Error Distribution (GED), each suitable for capturing the excess kurtosis and skewness observed in the return series residuals.

For student's t – distribution, the log-likelihood contributions are of the form:

$$l_t = \frac{1}{2} \log \left[\frac{\pi(v-2)\Gamma(v/2)^2}{\Gamma((v+1)/2)} \right] - \frac{1}{2} \log \sigma_t^2 - \frac{(v+1)}{2} \log \left[1 + \frac{(y_t - X_t' \theta)^2}{\sigma_t^2(v-2)} \right] \quad (22)$$

The gamma function $\Gamma(\cdot)$ is employed here. This distribution consistently features fat tails and typically offers a superior fit compared to the normal distribution for the majority of financial return series. The degree of freedom, denoted as v and exceeding 2, dictates the tail characteristics. This distribution is only valid when $v > 2$ since the variance of a Student's t -distribution with $v \leq 2$ is infinite. Essentially, the t -distribution converges towards the normal distribution as v approaches infinity.

(iii) *The Generalized Error Distribution (GED)*: The Generalized Error Distribution (GED) is given as:

$$f(z; \mu, \sigma, v) = \frac{\sigma^{-1} v e^{(-0.5 |(\frac{z-\mu}{\sigma})/\lambda|^v)}}{\lambda 2^{(1+(1/v))} \Gamma(\frac{1}{v})}, \quad 1 < z < \infty \quad (23)$$

where $v > 0$ is the degree of freedom or tail-thickness parameter and

$$\lambda = \sqrt{2^{(-2/v)} \Gamma(\frac{1}{v}) / \Gamma(\frac{3}{v})}$$

When v equals 2, the GED results in a normal distribution. For v less than 2, the density function exhibits thicker or fatter tails compared to the normal density function, while for v greater than 2, it has thinner tails. To use this distribution for estimating GARCH parameters, it is essential that v is greater than or equal to 1 since the variance becomes infinite when v is less than 1.

RESULTS AND DISCUSSION

Preliminary Test Results

Summary statistics and normality measures are crucial for understanding the characteristics of the data, especially in the context of financial analysis. They help researchers and analysts make inferences about the central tendency, variability, and shape of the distribution of cryptocurrency returns. The summary statistics and normality measures are reported in Table 1.

Table 1: Summary Statistics and Normality Measures of Cryptocurrency Returns

	Mean	Range	SD	Skewness	Kurtosis	JB	P-value
BTC	0.1451	232.30	5.5494	5.7403	221.87	5648377	0.0000
ETH	0.2765	84.823	5.7997	-0.6154	11.317	5957.91	0.0000
ADA	0.0847	88.567	6.3994	-0.1426	8.9971	2045.64	0.0000
DOGE	0.2696	829.77	17.082	0.4647	448.32	12997330	0.0000
BNB	0.3716	111.17	6.5494	0.2504	17.315	12088.12	0.0000
LTC	0.0023	0.0001	2.83E-05	0.0296	1.8010	111.5499	0.0000
XRP	0.1693	202.45	9.4709	0.7699	29.6228	72181.52	0.0000
XLM	0.2934	116.88	8.0426	1.6024	17.7387	15887	0.0000
BCH	0.0298	103.32	7.4368	0.0946	13.3866	6807.713	0.0000
LINK	0.2878	111.26	7.4728	-0.3061	10.1427	2850.168	0.0000
XMR	0.2741	249.33	12.3902	-0.0128	37.7097	136444.7	0.0000
USDT	0.0007	10.276	0.50763	0.03864	28.8216	45117.45	0.0000

From the results presented in Table 1, the averages of the entire cryptocurrency returns are positive. This implies that the cryptocurrencies experienced gains during the trading period under review. The daily standard deviations of

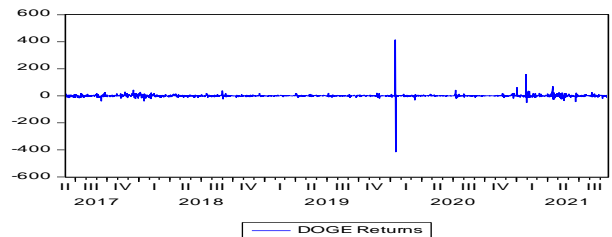
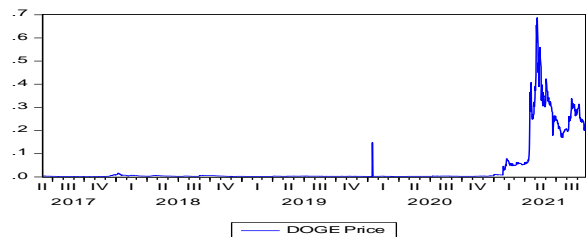
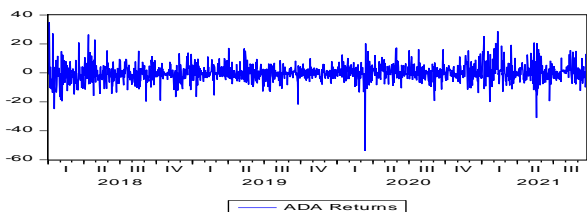
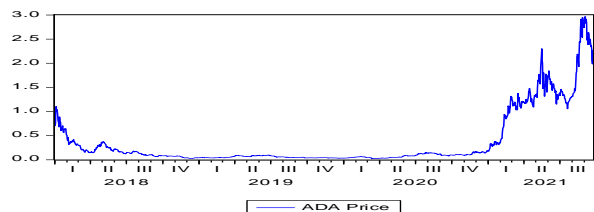
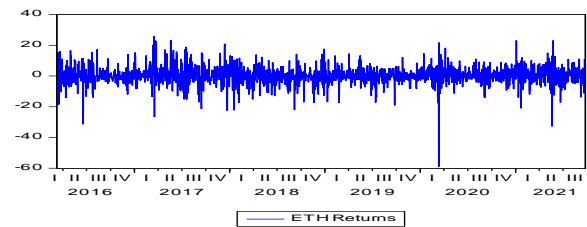
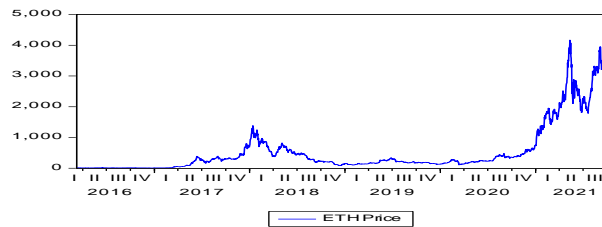
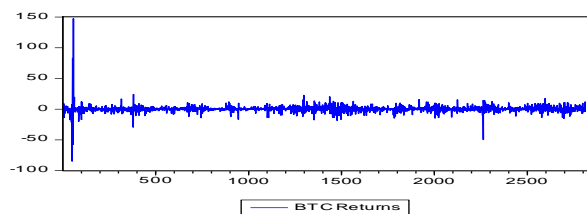
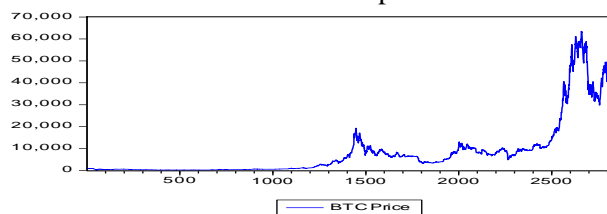
the returns are high compared to the means, indicating a high level of dispersion from the average daily returns. This suggests significant volatility in the cryptocurrency market over the analyzed period, except for litecoin. The high

ranges of the log returns provide evidence of the high variability of price changes in the digital market, with litecoin being an exception.

In terms of skewness, Ethereum (ETH), Cardano (ADA), Chainlink (LINK), and Monero (XMR) displayed negative skewness, indicating that the distribution of returns for the cryptocurrencies has a longer left tail. Other cryptocurrencies exhibited positive skewness. All cryptocurrency returns, except for litecoin (LTC), exhibit excess kurtosis. Excess kurtosis implies that the distribution has fatter tails compared to a normal

distribution. The Jarque-Bera test rejects the null hypothesis of normality for all returns with statistically significant p-values ($p < 0.05$). This suggests that cryptocurrency returns are non-Gaussian and do not conform to normal distributions.

The original series (daily cryptocurrency prices) and the transformed series (daily cryptocurrency log returns) are graphed over time to observe their graphical properties. These plots are shown in Figures 1 and 2.



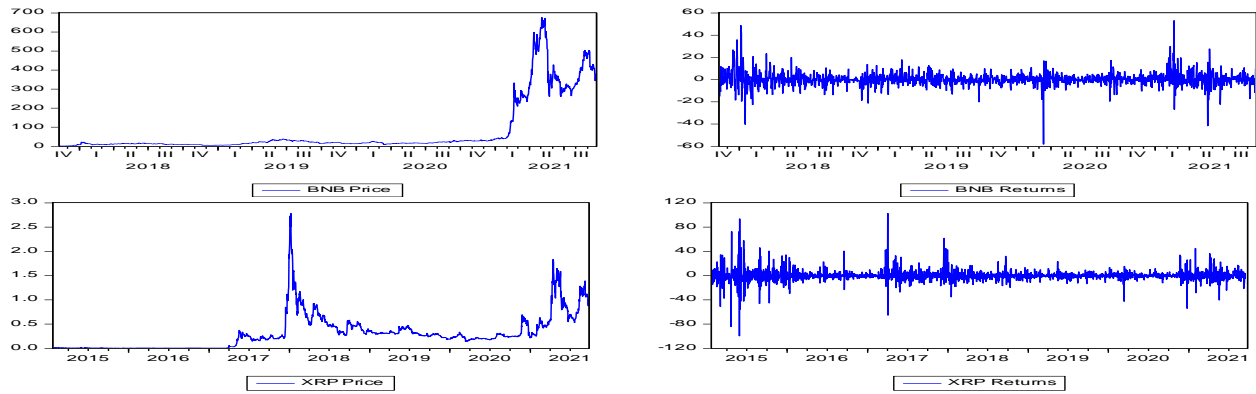
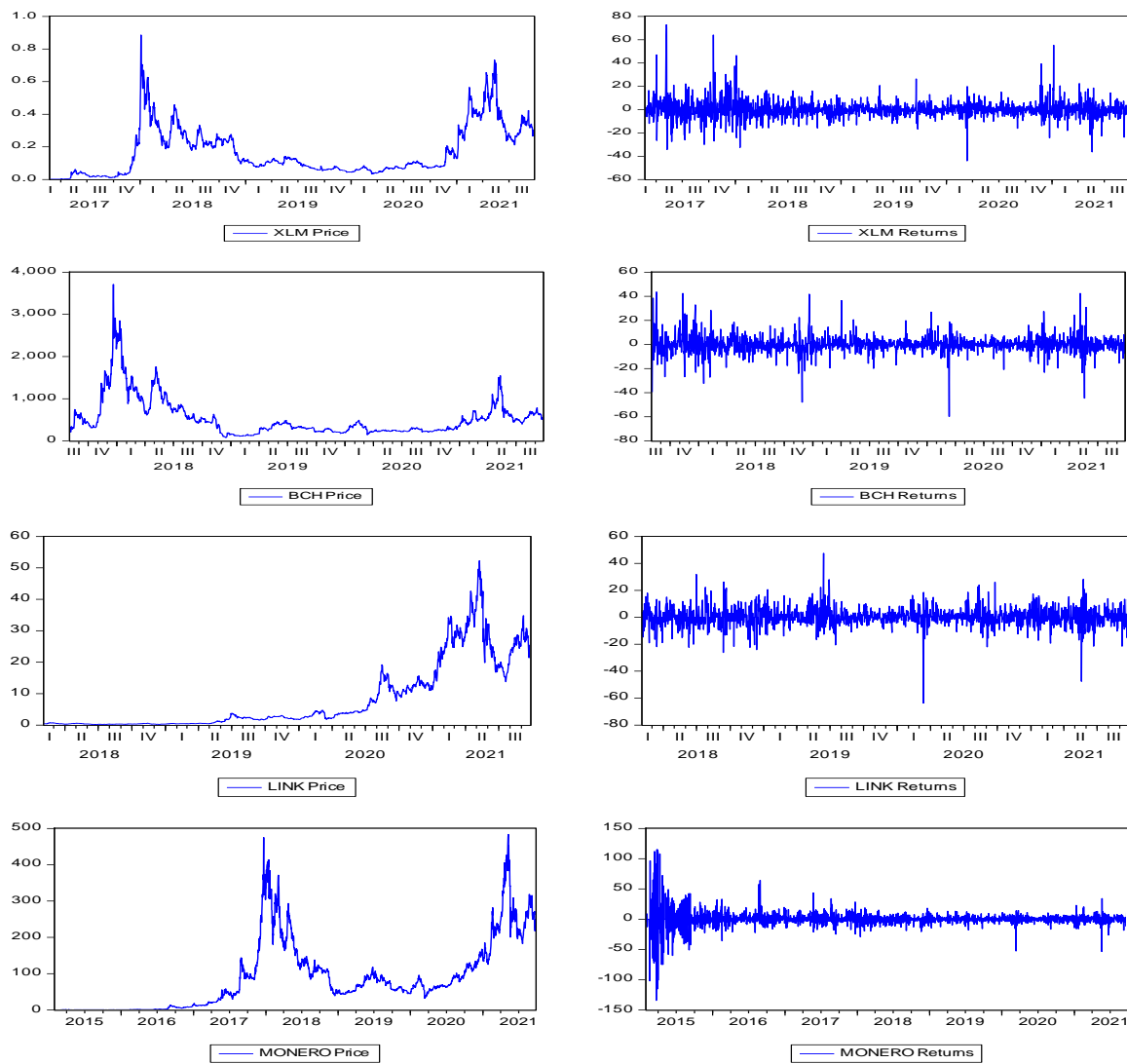


Figure 1: Time Plots of BTC, ETH, ADA, DOGE, BNB and XRP Cryptocurrency Prices and Returns



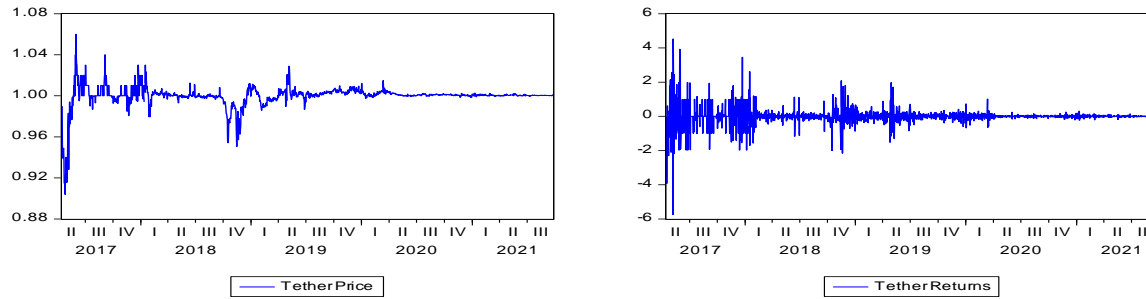


Figure 2: Time Plots of XLM, BCH, LINK, XMR and USDT Cryptocurrency Prices and Returns

Figures 1 and 2 (left) show time plots of daily cryptocurrency prices. The plots indicate that the series exhibit changing means and variances over time, suggesting the presence of a trend. These series are considered non-covariance stationary, implying that statistical characteristics such as mean and variance fluctuate over time. Figures 1 and 2 (right) display time plots of the daily cryptocurrency log return series. These plots suggest that the log return series have constant means and variances, indicating covariance stationarity. The absence of trend in the log return series implies stability in statistical properties over time. The time plots of cryptocurrency log returns reveal a phenomenon known as volatility

clustering which was first noticed in studies conducted independently by Mandelbrot (1963), Fama (1965) as well as Black (1976). Volatility clustering is characterized by periods of clustered large changes followed by similar patterns with small changes. Many researchers including Emenike (2010) and Ezzat (2012) have in recent times documented evidence in literature proving that financial time series normally exhibit volatility clustering and leptokurtosis. Ethereum (ETH), Cardano (ADA), Binance (BNB), Ripple (XRP), Stellar (XLM), Bitcoin Cash (BCH), and Chainlink (LINK) exhibit more noticeable volatility clustering in their returns.

Table 4: ADF Unit Root Test Results of Cryptocurrency Prices and Returns

Variable	Option	ADF Test Statistic	P-value	5% Critical Value
Cryptocurrency Prices				
BCT	Intercept & trend	-1.0854	0.9299	-3.4114
ETH	Intercept & trend	-0.2269	0.9925	-3.4120
ADA	Intercept & trend	-1.7489	0.7288	-3.4131
DOGE	Intercept & trend	-3.1775	0.0893	-3.4127
BNB	Intercept & trend	-2.1259	0.5303	-3.4130
LTC	Intercept & trend	-2.9294	0.1533	-3.4122
XRP	Intercept & trend	-1.5933	0.1768	-3.4117
XLM	Intercept & trend	-2.6972	0.2379	-3.4125
BCH	Intercept & trend	-3.1088	0.1045	-3.4128
LINK	Intercept & trend	-2.6908	0.2406	-3.4132
XMR	Intercept & trend	-2.9392	0.1502	-3.4117
USDT	Intercept & trend	-1.4019	0.1609	-3.4126
Cryptocurrency Returns				

BCT	Intercept & trend	-20.3607	0.0000	-3.4114
ETH	Intercept & trend	-47.2424	0.0000	-3.4120
ADA	Intercept & trend	-39.6876	0.0000	-3.4131
DOGE	Intercept & trend	-39.2865	0.0000	-3.4127
BNB	Intercept & trend	-24.6261	0.0000	-3.4130
LTC	Intercept & trend	-19.2491	0.0000	-3.4123
XRP	Intercept & trend	-36.1978	0.0000	-3.4117
XLM	Intercept & trend	-38.6508	0.0000	-3.4125
BCH	Intercept & trend	-38.7244	0.0000	-3.4128
LINK	Intercept & trend	-40.4913	0.0000	-3.4132
XMR	Intercept & trend	-12.7601	0.0000	-3.4117
USDT	Intercept & trend	-6.2659	0.0000	-3.4126

The result of ADF unit root tests for cryptocurrency prices and returns, as reported in Table 4, reveal important findings about the stationarity of the data. All daily cryptocurrency prices examined in the study are found to be non-stationary in levels as indicated by the test statistics exceeding the corresponding critical values at the 5% significance level. Non-stationarity is further supported by the insignificant p-values associated with the test statistics. The ADF unit root tests conducted on the log returns (series after the first differencing), as presented in the lower panel of Table 4, show that the log returns are stationary. Stationarity is confirmed when the test statistics are below the corresponding critical values at the 5% significance level, accompanied by statistically significant p-values.

The existence of a unit root in the levels of cryptocurrency prices implies a lack of stability and persistence in their patterns over time, while the stationarity of log returns suggests a more stable and predictable behaviour after differencing. This insight is crucial for modeling

and analyzing the time series dynamics of cryptocurrency data. The finding that cryptocurrency prices are non-stationary while log returns are stationary suggests the need for specialized modeling techniques that account for non-stationarity and volatility dynamics. By focusing on modeling log returns and employing appropriate forecasting methods, investors can potentially make more accurate predictions and better manage risk in cryptocurrency markets.

This study employs the Engle's Lagrange Multiplier (LM) test for the ARCH effect to investigate heteroskedasticity in the individual return series and the results are presented in Table 5. The choice of Engle's LM test for ARCH effects in the paper reflects its effectiveness and relevance in the field of time series analysis, particularly in the context of financial data analysis. However, researchers should carefully consider alternative methodologies for detecting ARCH effects such as the Ljung-Box test and the Breusch-Godfrey test based on their specific research objectives and the characteristics of the data under analysis.

Table 5: Heteroskedasticity Test Results for ARCH Effects

Variable	F-statistic	P-value	nR ²	P-value
BTC	8.159589	0.0043	8.141805	0.0043
ETH	43.18527	0.0000	42.32279	0.0000
ADA	11.77495	0.0006	11.69092	0.0006
DOGE	146.5410	0.0000	134.1943	0.0000
BNB	89.69158	0.0000	84.44704	0.0000
LTC	356564.8	0.0000	1846.399	0.0000
XRP	187.4755	0.0000	174.2010	0.0000
XLM	323.9915	0.0000	271.7255	0.0000
BCH	37.56892	0.0000	36.70545	0.0000
LINK	14.26547	0.0039	14.25821	0.0039
XMR	321.2049	0.0000	383.8832	0.0000
USDT	177.8314	0.0000	160.4391	0.0000

The results from the LM test by Engle for ARCH effects, as reported in Table 5, provide insights into the presence of heteroskedasticity in the cryptocurrency log returns: The p-values associated with the F-statistics and nR² in the Engle's LM test results all show statistical significance at the 1% marginal level of significance ($p < 0.01$). This statistical significance indicates that there is evidence of heteroskedasticity in the cryptocurrency log returns. This finding highlights the importance of using models that can capture time-varying conditional variance, such as ARCH or GARCH models, for a more accurate representation of the dynamics of volatility in the cryptocurrency market.

In this study, the use of Schwarz Information Criterion (SIC) assists in identifying the most

suitable model order and error distribution for each cryptocurrency log return series. The approach takes into account both model complexity and goodness of fit, helping to balance the trade-off between accurate representation of the data and model simplicity. The choice of Schwarz Information Criterion for model selection in this study reflects its effectiveness and relevance in the field of time series analysis, particularly in the context of financial data analysis. However, researchers should carefully consider alternative methodologies such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) based on their specific research objectives and the characteristics of the data under analysis. The results in Table 6 provide insights into the chosen models for individual cryptocurrencies based on this criterion.

Table 6: Error Distribution Selection for Fitting Volatility Model using SIC

Variable	ND	STD	GED
BTC	5.5070	5.2047	5.2040
ETH	6.2294	6.0697	6.0616
ADA	6.4742	6.3433	6.3501
DOGE	7.1931	6.8263	6.8729
BNB	6.2961	6.1057	6.1122
LTC	6.4806	6.3975	6.3769
XRP	6.7543	6.3099	6.3347
XLM	6.6714	6.4832	6.3347
BCH	6.6557	6.3625	6.3739
LINK	6.7907	6.6638	6.6806
XMR	6.9520	6.5897	6.5943
USDT	-0.3727	-0.6309	-0.6391

The results from the model order and error distribution selection, as reported in Table 6, provide insights into the modeling choices for each cryptocurrency return series: Three different error distributions were considered for modeling: Gaussian (normal) distribution (ND), student's-t distribution (STD), and the generalized error distribution (GED). For the symmetric GARCH (1,1) model, student's-t distribution (STD) was selected for modeling the log return series of ADA, DOGE, BNB, XRP, BCH, LINK, and XMR cryptocurrencies. Generalized error distribution (GED) was selected for modeling the return series of BTC, ETH, LTC, XLM, and USDT. The choice of error distribution for each cryptocurrency return

series implies that the digital currency returns exhibit heavy or fat tails. Fat-tailed distributions exhibit a heightened likelihood of extreme events in contrast to a normal distribution. The heavy/fat-tailed nature indicates a higher propensity for extreme events, emphasizing the importance of accurate modeling for risk management and forecasting in the volatile cryptocurrency market.

Estimation of Symmetric GARCH Models

To examine the symmetric attributes of cryptocurrency returns, we estimate symmetric lower GARCH model for all the twelve cryptocurrency log returns under review, results are presented in Table 7.

Table 7: Parameter Estimates of Symmetric GARCH (1,1) Volatility Models

	Variable	Coefficient	Std. Error	z-Statistic	P-value	$\alpha_1 + \beta_1$
BTC	μ	0.147213	0.030791	4.781028	0.0000	0.9995
	ω	0.341902	0.067017	5.101735	0.0000	
	α_1	0.172449	0.020356	8.471655	0.0000	
	β_1	0.827074	0.014201	58.31084	0.0000	
	v	0.855367	0.023789	35.95573	0.0000	
ETH	μ	0.078472	0.077927	1.007000	0.3139	0.9455
	ω	2.110937	0.550094	3.837411	0.0001	
	α_1	0.147423	0.026081	5.652532	0.0000	
	β_1	0.798080	0.031861	25.04855	0.0000	
	v	0.989654	0.034740	28.48739	0.0000	
ADA	μ	-0.028973	0.133547	-0.216952	0.8282	0.9468
	ω	3.005088	0.991832	3.029835	0.0024	
	α_1	0.138405	0.036197	3.823706	0.0001	
	β_1	0.808363	0.040303	20.05735	0.0000	
	v	3.809938	0.469219	8.119747	0.0000	
DOGE	μ	0.012445	0.339266	0.036681	0.9707	0.5974
	ω	4.632048	1.539405	3.008986	0.0027	
	α_1	0.088018	0.036437	2.415620	0.0157	
	β_1	0.509346	0.024052	21.17687	0.0000	
	v	3.651898	0.306319	11.92186	0.0000	
BNB	μ	0.192836	0.108413	1.778727	0.0753	0.9795
	ω	1.548066	0.454784	3.403956	0.0007	
	α_1	0.142574	0.030786	4.631137	0.0000	
	β_1	0.836953	0.025665	32.61107	0.0000	
	v	3.483653	0.356715	9.765937	0.0000	
LTC	μ	0.002296	4.61E-07	4977.094	0.0000	0.8277
	ω	4.114376	0.921542	4.464665	0.0000	
	α_1	0.150135	0.039858	3.766747	0.0007	
	β_1	0.677551	0.013755	49.25852	0.0000	
	v	0.986514	0.133876	7.368864	0.0000	
XRP	μ	-0.173614	0.074166	-2.340883	0.0192	0.9092
	ω	5.795894	1.652971	3.506350	0.0005	
	α_1	0.286881	0.021170	13.55129	0.0000	
	β_1	0.622347	0.026138	23.80991	0.0000	
	v	2.434097	0.147854	16.46285	0.0000	
XLM	μ	-0.115694	0.117673	-0.983184	0.3255	0.9989
	ω	3.038285	0.769969	3.945984	0.0001	
	α_1	0.217403	0.041326	5.260643	0.0000	
	β_1	0.781485	0.027675	28.23752	0.0000	

	v	3.285743	0.318927	10.30249	0.0000	
BCH	μ	-0.120113	0.090342	-1.329536	0.1837	0.9677
	ω	1.523281	0.458746	3.320534	0.0009	
	α_1	0.088403	0.019499	4.533770	0.0000	
	β_1	0.879301	0.022140	39.71468	0.0000	
	v	0.890856	0.034324	25.95460	0.0000	
LINK	μ	0.250793	0.161330	1.554534	0.1201	0.9707
	ω	1.839372	0.659856	2.787535	0.0053	
	α_1	0.092096	0.021626	4.258584	0.0000	
	β_1	0.878642	0.025053	35.07134	0.0000	
	v	4.869707	0.577784	8.428241	0.0000	
XMR	μ	0.181971	0.092914	1.958497	0.0502	0.9259
	ω	2.191496	0.478115	4.583617	0.0000	
	α_1	0.219842	0.037219	5.906744	0.0000	
	β_1	0.706074	0.019015	37.13247	0.0000	
	v	3.117170	0.220250	14.15290	0.0000	
USDT	μ	5.94E-07	0.000822	0.000722	0.9994	0.9957
	ω	0.000142	6.74E-05	2.101027	0.0356	
	α_1	0.346217	0.043235	8.007728	0.0000	
	β_1	0.649529	0.017689	36.71937	0.0000	
	v	0.868352	0.027120	32.01902	0.0000	

The results from the estimates of basic GARCH (1,1) models, as reported in Table 7, offer valuable insights into the features of the cryptocurrency log return series: All coefficients in the conditional variance equations for the twelve cryptocurrency log returns are statistically significant. The significance and satisfaction of non-negativity constraints indicate the reliability of the parameter estimates. Positive and significant coefficients of the ARCH terms (α_1) and GARCH terms (β_1) indicate that previous volatilities possess explanatory power over current volatilities. This supports the presence of volatility clustering, where past volatility shocks influence current volatility in the digital coin market.

The models show evidence of volatility clustering, leptokurtosis (fat-tails), and persistent volatility shocks in the cryptocurrency log return series. The sums of ARCH and GARCH terms being less than unity ($\alpha_1 + \beta_1 < 1$) suggest that conditional variances are stationary, stable, mean-reverting, and volatility is quite persistent. Volatility shock persistence varies among cryptocurrencies. DOGE, LTC, XRP, and XMR log returns exhibit less volatility shock persistence, indicating faster reactions to market changes. BTC, XLM, and USDT log returns, on the other hand, show higher volatility shock persistence, indicating delayed reactions to market changes. The parameter estimates provide comprehensive insights into the

volatility characteristics of cryptocurrency log return series, including the influence of past volatilities, volatility clustering, and the heavy-tailed nature of the distributions. The variation in volatility shock persistence among cryptocurrencies is also noteworthy, indicating differences in how these digital assets respond differently to market changes.

The findings of volatility clustering and shock persistence in cryptocurrency returns observed in the symmetric GARCH (1,1) models are consistent with the broader literature on cryptocurrency volatility dynamics and align with the previous works of Katsiampa (2017), Jinan and Apostolos (2019) as well as Ngunyi *et al.* (2019) among others. They underscore the non-random nature of cryptocurrency price movements and highlight the importance of understanding and modeling volatility dynamics for effective risk management and investment decision-making in cryptocurrency markets.

For all GARCH models estimated using STD, the shape parameter (v) is greater than 2. For all GARCH models estimated with GED, the shape parameter (v) is less than 2. This implies that the cryptocurrency log return series are leptokurtic or fat-tailed.

Models Diagnostic Checks

The post-estimation heteroskedasticity test due to Engle (1982) for ARCH effects in the residuals of the estimated GARCH (1,1) models

for the twelve cryptocurrencies is presented in Table 8.

Table 8: Heteroskedasticity Test for the Estimated GARCH (1,1) Models

Variable	F-statistic	P-value	nR ²	P-value
BTC	0.028950	0.8649	0.028970	0.8648
ETH	0.155442	0.6934	0.155583	0.6933
ADA	0.189320	0.6636	0.189572	0.6633
DOGE	0.118709	0.7305	0.118851	0.7303
BNB	0.099588	0.7524	0.099722	0.7522
LTC	0.897525	0.4739	0.896512	0.4741
XRP	0.040694	0.8401	0.040727	0.8401
XLM	0.950722	0.3297	0.951318	0.3294
BCH	0.063849	0.8005	0.063930	0.8005
LINK	0.035124	0.8514	0.035176	0.8512
XMR	0.031499	0.8591	0.031524	0.8591
USDT	0.053891	0.8165	0.053956	0.8163

The result of the heteroskedasticity test of ARCH effects, as reported in Table 8, provide a positive assessment of the estimated symmetric GARCH (1,1) models for the cryptocurrency log return series: The heteroskedasticity test is conducted to assess whether the estimated models effectively account for all the ARCH effects present in the residuals of the cryptocurrency log return series. The p-values associated with the F-statistics and nR² ARCH LM test statistics are reported as statistically insignificant. The insignificance of these p-values suggests that the ARCH effects in the residuals are well-captured by the estimated symmetric GARCH (1,1) models indicating that

the estimated symmetric GARCH models are effective in describing the volatility patterns in the digital coin market. The results further suggest that the estimated models are robust and meet the assumptions of capturing conditional heteroskedasticity adequately. This validation is crucial for the reliability of the models in capturing and explaining the complex and dynamic nature of cryptocurrency price movements.

RESULTS OF VOLATILITY HALF-LIFE

The volatility means reversion half-life for the twelve cryptocurrency log returns are computed and presented in Table 9.

Table 9: Volatility Mean Reversion and Half-Life in the Cryptocurrency Indices

	α_1	β_1	λ	$\ln(\lambda)$	$\ln(2)$	$1 - \frac{\ln(2)}{\ln(\lambda)}$
BTC	0.172449	0.827074	0.999523	-0.00048	0.693147	1453.792
ETH	0.147423	0.798080	0.945503	-0.05604	0.693147	13.36919
ADA	0.138405	0.808363	0.946768	-0.0547	0.693147	13.67152
DOGE	0.088018	0.509346	0.597364	-0.51523	0.693147	2.34532
BNB	0.142574	0.836953	0.979527	-0.02069	0.693147	34.50888
LTC	0.150135	0.677551	0.827686	-0.18912	0.693147	4.665091
XRP	0.286881	0.622347	0.909228	-0.09516	0.693147	8.284065
XLM	0.217403	0.781485	0.998888	-0.00111	0.693147	623.9872
BCH	0.088403	0.879301	0.967704	-0.03283	0.693147	22.11385
LINK	0.092096	0.878642	0.970738	-0.0297	0.693147	24.33933
XMR	0.219842	0.706074	0.925916	-0.07697	0.693147	10.00521
USDT	0.346217	0.649529	0.995746	-0.00426	0.693147	163.5933

Note: $\lambda = \alpha_1 + \beta_1$ (volatility shock persistence)

The results from Table 9 provide insights into the volatility mean reversion and half-life of

twelve cryptocurrencies, offering implications for trading and investment strategies: The sums

of ARCH and GARCH terms are less than unity ($\alpha_1 + \beta_1 < 1$) for all twelve cryptocurrency log returns, suggesting mean reversion. Cryptocurrency prices can revert back to their historical values after a certain period. The elevated totals of ARCH and GARCH coefficients ($\alpha_1 + \beta_1$) are associated with higher volatility. The rate of mean reversion is slower with higher volatility, indicating a more persistent process. Bitcoin (BTC) exhibits the

slowest mean reversion process with the highest volatility among the cryptocurrencies under study. It takes about 1453.79 days for Bitcoin's volatility to revert to half of its mean. Dogecoin (DOGE) demonstrates the swiftest mean reversion and least volatility among cryptocurrencies. It takes only 2.35 days for the volatility of Dogecoin to revert to half of its mean.

Table 10: Speeds and Volatility Rankings of Mean Reversion with Choice of Investment

	Half-life	Rank	Investment Decision		
			Open (days)	Close (days)	Choice of investment
BTC	1454	12	0	2908	Long-term
ETH	13	5	0	26	Short-term
ADA	14	6	0	28	Short-term
DOGE	2	1	0	4	Short-term
BNB	35	9	0	70	Short-term
LTC	5	2	0	10	Short-term
XRP	8	3	0	16	Short-term
XLM	624	11	0	1248	Long-term
BCH	22	7	0	44	Short-term
LINK	24	8	0	48	Short-term
XMR	10	4	0	20	Short-term
USDT	164	10	0	328	Middle-term

Table 10 ranks the cryptocurrencies based on the speed of mean reversion and provides actionable insights for short-term trading. Dogecoin (DOGE), Litecoin (LTC), Ripple (XRP), and Monero (XMR) are identified as suitable choices for short-term trading due to their short volatility half-lives. Bitcoin (BTC) and Stellar (XLM) are identified as better choices for long-term trading and investment. Bitcoin has the slowest mean reversion, taking about 1453.79 days to revert to half of its mean, while Stellar takes about 623.99 days. Bitcoin and Stellar provide maximum leverage for investors due to their longer mean reversion periods. Dogecoin, Litecoin, Ripple, Monero, etc., provide smaller time periods for investors to operate freely, making them suitable for short-term trading.

The analysis suggests that investors should consider the volatility mean reversion and half-life characteristics when choosing

cryptocurrencies for trading and investment. Investors looking to apply the volatility mean reversion characteristics of cryptocurrencies in their investment decisions should first grasp the concept, analyzing historical data to identify cryptocurrencies exhibiting pronounced patterns. They should then evaluate risk-adjusted returns, diversify portfolios across assets with varying volatility behaviours, and stay vigilant about market conditions that influence volatility dynamics. Implementing risk management strategies and seeking professional advice can help navigate the complexities of cryptocurrency markets, enabling investors to make informed decisions aimed at maximizing returns while managing risk effectively. Short-term traders may find opportunities in Dogecoin, Litecoin, Ripple, and Monero, while Bitcoin and Stellar are highlighted as potential choices for long-

term strategies due to their slower mean reversion processes.

CONCLUSION AND RECOMMENDATIONS

This study evaluates the suitability of various cryptocurrencies for both short-term and long-term investments through the application of volatility mean reversion and half-life models. The analysis covers twelve cryptocurrencies, including Bitcoin, Ethereum, Cardano, Dogecoin, Litecoin, Binance, Ripple, Bitcoin Cash, Stellar, Chainlink, Monero, and Tether, spanning from January 14, 2014, to July 16, 2021. The methodology involves statistical techniques like Augmented Dickey-Fuller unit root test, Engle's LM heteroskedasticity test and symmetric GARCH (1,1) models. Results revealed non-Gaussian and leptokurtic log returns. While cryptocurrency prices were found to be non-stationary, the log returns were covariance or weakly stationary, with detected ARCH effects in the residuals.

Results demonstrate volatility clustering and high shock persistence across cryptocurrency returns, indicating stable, mean-reverting, and predictable log returns. The study found that all cryptocurrencies exhibit mean reversion to their historical mean values after specific periods. Dogecoin, Litecoin, Ripple, Monero, Ethereum, Cardano, Bitcoin Cash, Chainlink, and Binance show faster mean reversion, providing traders

and investors with short-term trading and investment opportunities based on historical data. Tether is suggested for middle-term trading and investment, while Bitcoin and Stellar are deemed suitable for long-term trading and investment due to their slower mean reversion rates and larger volatility half-lives.

The study's empirical findings lead to the following recommendations:

1. It is recommended to use heavy or fat-tailed distributions as alternative error distributions when estimating volatility in the cryptocurrency market.
2. Adopting an excessive and more aggressive trading strategy for cryptocurrencies to increase market depth and consequently reduce the volatile nature of the digital coin market is recommended.
3. Cryptocurrencies with the fastest mean reversion and the smallest volatility half-lives such as Dogecoin, Litecoin, Ripple, Monero, Ethereum, Cardano, Bitcoin Cash, Chainlink, and Binance are recommended for short-term trading and investment opportunities.
4. Bitcoin and Stellar cryptocurrencies exhibit the slowest mean reversion and the largest volatility half-lives and are therefore recommended for long-term trading and investment opportunities.

REFERENCES

- Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, 64, 74-81.
- Baur, D. G. and Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, 45(2), 217-229.
- Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017a). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, 20, 192-198.
- Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017b). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, 23, 87-95.
- Ciaian, P., Rajcaniova, M., & Kancs, D. A. (2016). The economics of BitCoin price formation. *Applied Economics*, 48(19), 1799-1815.
- Cheah, E. T., Mishra, T., & Parhi, M. (2019). The drivers of Bitcoin demand: A short- and long-run analysis. *International*

- Review of Financial Analysis, 63, 273-281.
- Conlon, T., McGee, R. J., & Murphy, A. (2018). Cryptocurrency–Modelling the opportunities and risks posed by cryptocurrencies: How do cryptocurrency exchanges react to variations in the cryptocurrency index? *Research in International Business and Finance*, 46, 385-396.
- Dwyer, G. P. (2015). The economics of Bitcoin and similar private digital currencies. *Journal of Financial Stability*, 17, 81-91.
- Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar–A GARCH volatility analysis. *Finance Research Letters*, 16, 85-92.
- Foley, S., Karlsen, J. R., & Putniņš, T. J. (2019). Sex, drugs, and Bitcoin: How much illegal activity is financed through cryptocurrencies? *Review of Financial Studies*, 32(5), 1798-1853.
- Gronwald, M. (2014). The Economics of Bitcoins Market Characteristics and Price Jumps *International Journal of Social and Management Sciences*, 7: 112-121.
- Jinan, L., and Apostolos, S. (2019). Volatility in the Cryptocurrency Market. *International Conference on Applied Economics*, 4(3):1-41.
- Katsiampa P (2017) Volatility Estimation for Bitcoin: A Comparison of Garch Models. *Econometric Letter*, 158: 3–6.
- Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PloS One*, 10(4), e0123923.
- Liu, Y. and Tsyvinski, A. (2018). Risks and Returns of Cryptocurrency. NBER Working Papers, National Bureau of Economic Research, Inc. No. 24877.
- Malhotra, N. and Gupta, S. (2019). Volatility Spillovers and Correlation between Cryptocurrencies and Asian Equity Market. *International Journal of Economics and Financial Issues*, 9(6):208-215.
- Menger, C. (2007). Principles of Economics. Ludwig von Mises Institute. For information on the origins of money.
- Naimy, V. Y., and Hayek, M. R. (2018). Modelling and predicting the Bitcoin Volatility using GARCH Models. *International Journal of Mathematical Modelling and Numerical Optimization (IJMMNO)*, 8(3): 24-38.
- Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. Bitcoin whitepaper.
- Narayanan, A., Bonneau, J., Felten, E., Miller, A., and Goldfeder, S. (2016). Bitcoin and Cryptocurrency Technologies: A Comprehensive Introduction. Princeton University Press.
- Ngunyi, A., Mundia, S., and Omari, C. (2019). Modelling Volatility Dynamics of Cryptocurrencies Using GARCH Models. *Journal of Mathematical Finance*, 9: 591-615.
- O’Sullivan, M., Sheffrin, S. M., and Ziti, C. (2003). Economics: Principles in Action. Pearson/Prentice Hall, 2003.
- Sodiq, O. J. and Oluwasegun, O. B. (2020). The Effect of Cryptocurrency Returns Volatility on Stock Prices and Exchange Rate Returns Volatility in Nigeria. *Acta Universitatis Danubius*, 16(3), 200-213.
- Weatherford, J. (1997). The History of Money. Crown Business, 1997.
- Yelowitz, A., & Wilson, M. (2015). Characteristics of Bitcoin users: An analysis of Google search data. *Applied Economics Letters*, 22(13), 1030-1036.