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Evaluating Cryptocurrency Market Risk on the Blockchain: An Empirical Study Using the ARMA-GARCH-VaR Model

YONGRONG HUANG [1], HUIQING WANG [1], ZHIDE CHEN [1], CHEN FENG [2], KEXIN ZHU [3], XU YANG [4], AND WENCHENG YANG [5]

[1] School of Computer and Cyberspace Security, Fujian Normal University, Fuzhou 350117, China
[2] Department of Information Engineering, Fuzhou Polytechnic, Fuzhou 350108, China
[3] Department of Computer Science and Engineering, National Sun Yat-sen University, Kaohsiung 80424, Taiwan
[4] College of Computer and Data Science, Minjiang University, Fuzhou 350108, China
[5] School of Mathematics, Physics and Computing, University of Southern Queensland, Toowoomba, QLD 4350, Australia

CORRESPONDING AUTHOR: XU YANG (e-mail: xu.yang@mju.edu.cn).

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ABSTRACT Cryptocurrency, a novel digital asset within the blockchain technology ecosystem, has recently garnered significant attention in the investment world. Despite its growing popularity, the inherent volatility and instability of cryptocurrency investments necessitate a thorough risk evaluation. This study utilizes the Autoregressive Moving Average (ARMA) model combined with the Generalized Autoregressive Conditionally Heteroscedastic (GARCH) model to analyze the volatility of three major cryptocurrencies—Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB)—over a period from January 1, 2017, to October 29, 2022. The dataset comprises daily closing prices, offering a comprehensive view of the market's fluctuations. Our analysis revealed that the value-at-risk (VaR) curves for these cryptocurrencies demonstrate significant volatility, encompassing a broad spectrum of returns. The overall risk profile is relatively high, with ETH exhibiting the highest risk, followed by BTC and BNB. The ARMA-GARCH-VaR model has proven effective in quantifying and assessing the market risks associated with cryptocurrencies, providing valuable insights for investors and policymakers in navigating the complex landscape of digital assets.

INDEX TERMS GARCH, VaR, market risk, cryptocurrency, and data analysis.

I. INTRODUCTION

Cryptocurrencies, defined as electronic assets designed for secure transactions and controlled creation of additional units, have made a significant impact on the global financial landscape. BTC, the pioneering cryptocurrency, has achieved a trillion-dollar market capitalization in under a decade, inspiring the creation of over 10,000 subsequent cryptocurrencies. Their ubiquity is not only increasing worldwide adoption but also influencing global currency transactions. This is evidenced by initiatives such as the People's Bank of China's active promotion of cryptocurrency business [1] and the Bank of Japan's 2021 cryptocurrency trial. Despite their convenience and practicality, cryptocurrencies cannot supplant traditional currencies due to their inherent instability and high volatility [2].

Making its way into the financial sector and gaining mainstream acceptance, cryptocurrencies have become popular investment assets [3]. By 2021, the industry's market value peaked at 3 trillion, delivering substantial wealth to early adopters. However, the industry's inherent volatility was underscored when rising inflation led to a sharp market value contraction from its 3 trillion peak to less than 1 trillion in June 2022. Such drastic fluctuations are not uncommon in the cryptocurrency market, underscoring the importance of rigorous investment risk assessment in this volatile sector.

Compared to traditional financial markets, cryptocurrency has unique attributes, such as transaction fees and miner extractible value, which can significantly impact price dynamics. For example, Liu et al. [4] and Zhang and Zhang [5] discussed the role of transaction fees in influencing cryptocurrency prices and wait times. Besides, the unregulated practice of front-running in decentralized exchanges, highlighted by Fu et al. [6], is nonexistent in traditional markets. Furthermore, centralized and decentralized exchanges, with differing levels of decentralization, may exhibit different trading and risk profiles.

These unique attributes present both opportunities and challenges. On the one hand, they enable innovations like automated market makers, flash loans, and novel incentive designs. On the other hand, issues like front-running and discrimination can emerge. Therefore, while these features showcase the versatility of blockchain-based finance, addressing their downsides through prudent governance is pivotal. Ultimately, the cryptocurrency market, though bearing similarities with traditional finance, remains distinct in many aspects. Recognizing these nuances is critical to understanding the landscape's risks and matching suitable models. A balanced approach that prudently leverages the market's uniqueness while drawing on proven financial theories would be instrumental in advancing the cryptocurrency finance frontier.

In the financial field, VaR has emerged as an efficient and precise tool for measuring investment risk, garnering international attention and acceptance. The generalized autoregressive conditionally heteroscedastic model (GARCH) is a prevalent choice for risk assessment in the financial investment market. For instance, Hu and Qian [7] employed the realized GARCH model to analyze five-minute high-frequency interest rate fluctuations of the CSI 300 stock index. Xiong and Che [8] constructed the ARIMA-GARCH-M model for short-term stock price predictions, although it posed challenges for long-term forecasts. Xu et al. [9] applied the VAR model to empirical research based on quarterly data from 2008 to 2021. Zhou et al. [10] suggested a price chain reaction between cryptocurrencies and the stock market, indicating that cryptocurrencies could predict stock market returns and that cryptocurrency market risk influences the stock market. Hence, it is feasible to apply the stock risk assessment model to cryptocurrency evaluation.

Exploring the intricacies of the cryptocurrency market and its impact on other financial domains, several studies have utilized different models and techniques. Liu and Serletis [11] utilized the GARCH-in-mean model to investigate the spillover effects within the cryptocurrency market and those from the cryptocurrency market to other financial spheres. They observed significant shock and volatility transmissions between major cryptocurrencies and from the cryptocurrency market to other financial markets. Bhatti [12] and his team compared five traditional econometric techniques - ordinary least squares (OLS) regression, fixed effects model (FEM), random effects model (REM), panel vector error correction model (VECM), and GARCH - for modeling cryptocurrency prices, returns, and volatility. They found GARCH superior in terms of explanatory and predictive power. Almasri et al. [13] predicted future cryptocurrency prices using the GARCH model with different error distributions, finding that GARCH models with student T-distribution skewness offered the best accuracy and reliability. As cryptocurrencies mature, their price predictability becomes increasingly challenging [14].

Recent research has also explored the risks associated with blockchain and cryptocurrency markets, as well as the use of cryptocurrencies in the financial sector. For example, Likitratcharoen et al. [15] assessed the efficiency of various VaR models in measuring risk under extreme market stress. Fang et al. [16] focuses on predicting systemic risk in the cryptocurrency market, helping to understand the overall market risk associated with blockchain-based assets. Jana et al. [17] examined the role of cryptocurrencies in hedging stock market risk, providing insights into their potential applications in the broader financial sector. In addition, Jana et al. [18] also examined the application of cryptocurrencies in the Indian stock market as a potential hedging and diversification tool, providing practical insights for financial risk management. Finally, Jana et al. [19] explore the interrelationship between cryptocurrencies and the Indian stock market, assessing their role as diversified assets and safe havens, which is related to their financial applications.These studies contribute to the existing body of knowledge by providing insights on risk measurement, systemic risk forecasting, hedging potential, and the benefits of diversification of cryptocurrencies in the financial sector. The unique properties of cryptocurrencies, as well as the inherent risks, highlight the need to conduct careful risk assessments and develop appropriate models and strategies to address the needs of this dynamic market.

The appeal of cryptocurrencies continues to attract more investors, even though the associated risks are becoming increasingly evident. Risk assessment and management in cryptocurrency investments [20] are therefore crucial. This paper introduces a pioneering approach by employing the ARMA-GARCH-VaR model, uniquely adapted to the distinct dynamics of the cryptocurrency market, to examine and analyze the market risk of three major cryptocurrencies: BTC, ETH, and BNB. Diverging from previous studies, this research integrates ARMA and GARCH models with VaR analysis in a novel manner, providing a comprehensive and detailed understanding of cryptocurrency volatility and market risk. The primary contributions of this paper are as follows:

1) It demonstrates the effectiveness of the ARMA-GARCH-VaR model in capturing the complex volatility dynamics of cryptocurrencies, marking a significant advancement over traditional risk assessment models.
2) It introduces an innovative method for determining the optimal GARCH model parameters, specifically tailored to the cryptocurrency return series, thereby

enhancing the model's precision and relevance to cryptocurrency markets.
3) It conducts an extensive analysis of the VaR for BTC, ETH, and BNB, revealing significant fluctuations and a wide range in the VaR curves. This analysis includes the application of the Kupiec regression test, further validating the model's robustness and applicability in the context of cryptocurrency risk assessment.
4) This study provides a quantitative risk assessment tool that helps portfolio managers understand and manage the volatility and risk exposure of cryptocurrencies in their portfolios, especially during times of extreme market volatility and is critical for developing risk mitigation measures and mitigating potential losses. important.

The insights gained from this study offer invaluable guidance for investors and policymakers in managing and comprehending the complexities and risks associated with cryptocurrency investments.

II. RELATED WORK

A. BLOCKCHAIN

Blockchain technology, a type of distributed ledger technology, is characterized by its growing chain structure that links transaction records in blocks. Each block encapsulates a batch of transaction data and a unique identifier associated with the preceding block [21], thereby enhancing data integrity and security. Notable features of blockchain technology include decentralization, security, transparency, immutability, scalability, and the implementation of smart contracts.

Decentralization, the core of blockchain technology [22], ensures that data and transaction records are collaboratively maintained and verified by multiple network nodes, mitigating the risk of undue control or manipulation by a single entity. As a result, blockchain technology bypasses the intermediaries inherent to traditional financial institutions, facilitating direct peer-to-peer transactions while minimizing transaction costs and risks. Owing to the immutability and transparency of the blockchain, financial data and transaction records achieve a higher level of security and trustworthiness. Furthermore, the advent of blockchain technology has opened new avenues for innovation in the financial sector, including smart contracts, digital assets, and decentralized financial services, thereby adding a layer of versatility to the financial system.

B. CRYPTOCURRENCY

Cryptocurrency, a digital asset, leverages cryptography and distributed ledger technology. It employs cryptographic algorithms [23] to safeguard the security, anonymity, and verifiability of transactions while being independent of centralized authorities for issuance and management. Unlike conventional currencies, cryptocurrencies are not tethered to any specific country or central bank. They utilize public key cryptography to facilitate secure peer-to-peer transactions without the need for third-party involvement. Each transaction is recorded on the blockchain, which is collectively maintained and authenticated by several network nodes to ensure transaction security and transparency. Fig. 1 presents detailed information regarding three significant cryptocurrencies: BTC, ETH, and BNB.

Cryptocurrencies, unlike traditional stocks representing company ownership and subject to government and financial authority regulations, operate in a decentralized and unregulated environment. The cryptocurrency markets are open round the clock, enabling continuous trading, unlike traditional exchanges which adhere to specific trading hours. The lack of a comprehensive regulatory framework makes the cryptocurrency market more susceptible to volatility and manipulation. Conversely, traditional stocks, regulated and often providing investors with dividend income and voting rights, offer a different investment experience. In the current landscape, Fig. 2 depicts the market share distribution among various cryptocurrencies. This chart provides a snapshot of the dominance of different cryptocurrencies in the market, offering a clear understanding of their relative significance and impact.

III. METHODOLOGY

A. GARCH

The GARCH is a statistical modeling technique [24] that is extensively utilized to forecast the volatility of financial asset returns. This model is adept at handling time-series data where the variance of the error term exhibits serial auto-correlation following an autoregressive moving average process. Financial institutions frequently employ GARCH models to estimate the return volatility of assets, including stocks, bonds, and market indices. This is especially prevalent when dealing with assets that exhibit periods of clustered return volatility and heteroscedasticity in the variance of the error term. Therefore, GARCH provide a robust framework for evaluating risk and expected return under such conditions.

Heteroscedasticity refers to the irregular variation patterns in the error terms or variables within a statistical model. Unlike heteroscedasticity, where errors distribute evenly, heteroscedastic observations do not follow a consistent linear pattern but tend to cluster. In the context of the GARCH model, the error term exhibits conditional heteroscedasticity as it follows an autoregressive moving average pattern and is a function of the average of its preceding values.

The general expression for the GARCH(m, s) model [25] can be denoted as follows:

$$\alpha_t = \sigma_t \in_t \tag{1}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i \alpha_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \tag{2}$$

Among them, m and s represent the order of the GARCH model. The model ensures that the conditional variance is non-negative due to the independent and identically distributed random variable sequence, which has a mean value of 0 and a

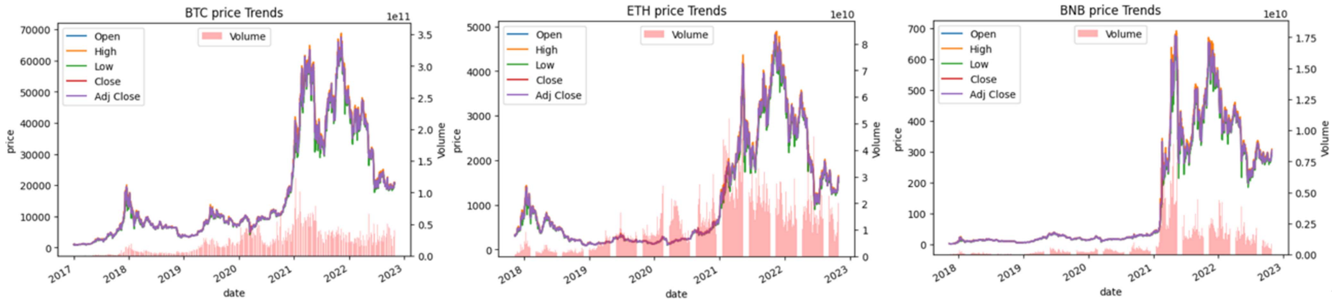

FIGURE 1. BTC ETH and BNB currency information.

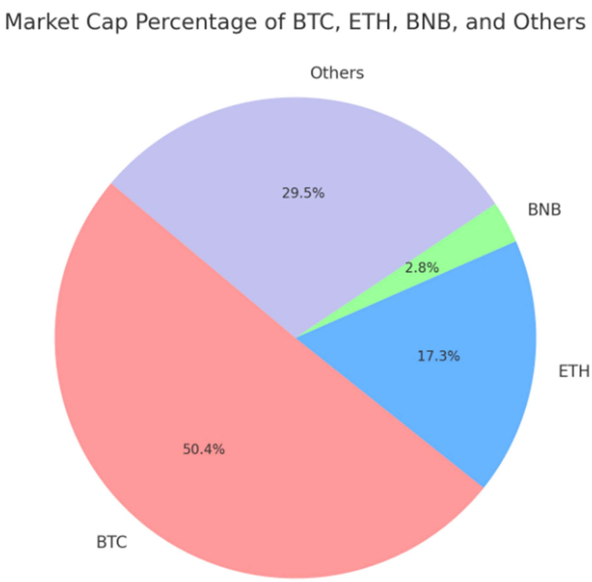

FIGURE 2. Cryptocurrency market share chart.

variance of 1. Furthermore, this restriction guarantees that the unconditional variance remains finite.

B. VAR

VaR is a statistical measure [26] that quantifies the level of financial risk within a firm or portfolio over a specific time frame. It provides an estimate of the potential loss that a financial asset may face within a certain future period, given a specified confidence level.

There are three main methods of calculating VaR:

1) The Historical Method: This method involves the process of ranking past returns from worst losses to the largest gains.
2) The Variance-Covariance Method: This approach operates under the assumption that gains and losses follow a normal distribution. It does not rely on the premise that past events influence the future. Potential losses are therefore calculated using standard deviation events from the mean.
3) Monte Carlo Simulation [27]: This method employs computational algorithms to simulate the expected returns over hundreds or thousands of possible iterations.

In this study, the Variance-Covariance method [28] was employed to calculate VaR. It was assumed that the cryptocurrency return sequences in this paper follow a normal distribution, leading to the following VaR calculation formula:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left\{-\frac{1}{2\sigma^2}(x-\mu)^2\right\} \tag{3}$$

$$VaR = P_{t-1} Z_\alpha \sigma_t \tag{4}$$

Among them, $f(x)$ is the probability density function of the cryptocurrency return rate, VaR represents the risk value on day failure days, μ is the mean, σ is the variance, Z_α is the z-score corresponding to the confidence level α, and P_{t-1} is the rate of return on day $t-1$.

C. ARMA-GARCH MODEL

The ARMA-GARCH model is a hybrid approach that combines the ARMA model with the GARCH model. This composite model is particularly suited for analyzing and forecasting time-series data, providing a more comprehensive understanding of data patterns.

The ARMA-GARCH model is devised to concurrently capture two critical characteristics of time-series data: the linear dynamic dependencies through the ARMA component, and the volatility clustering via the GARCH component.

The ARMA component is a linear model that represents the current observation as a linear combination of past observations (the autoregressive part, AR) and past error terms (the moving average part, MA). While ARMA models can effectively capture the short-term dependence structure in time-series data, they struggle to effectively handle volatility clustering.

The GARCH component, on the other hand, is a volatility model that defines the conditional variance at the current time as a linear combination of past conditional variances and past squared error terms. GARCH models are proficient at capturing volatility clustering, a common phenomenon where large price changes tend to follow large price changes, and similarly, small price changes tend to follow small price changes.

By integrating the ARMA model with the GARCH model, the ARMA-GARCH model can simultaneously capture both the linear dynamic dependence and volatility clustering phenomenon inherent in time-series data, offering a more nuanced and accurate analysis.

IV. CASE ANALYSIS

This study utilizes BTC, ETH, and BNB as representative examples within the cryptocurrency market, employing the variance-covariance method to calculate their respective VaR figures and used daily data for 3 cryptocurrencies (BTC, ETH, and BNB) from 2017 to 2022. Fully meet the needs of complex models such as GARCH and avoid overfitting due to insufficient data.

A. DATA COLLECTION

The data source of this article is the real-time daily market data of the cryptocurrency market given by CoinMarketCap (https://coinmarketcap.com/). This website shows the market conditions of cryptocurrency more comprehensively, showing that there are 27,622 cryptocurrencies with a total market value of US $1.55 trillion. The total market value of the three selected cryptocurrencies reaches 1.09308 trillion US dollars, accounting for 70.52% of the market share, as depicted in Fig. 2. The research results of these three cryptocurrencies can represent the overall fluctuation trend of the cryptocurrency market. The selected analysis period is the daily data from January 1, 2017, to October 29, 2022. Fig. 1 illustrates the data samples from the past five years, providing a comprehensive analysis of cryptocurrency fluctuations.

B. DATA PROCESSING

After assessing various popular cryptocurrencies, BTC, ETH, and BNB were chosen as the focus of this research. This study focuses on BTC, ETH, and BNB because of their significant impact on the cryptocurrency market [29].As the first and most widely recognized cryptocurrency, BTC leads the market trend [30]. ETH, thanks to its smart contract capabilities, represents the second-largest market capitalization and introduces different market dynamics compared to BTC. As a relatively new currency, BNB provides insight into the ever-changing nature of the market. The selected time frame is from January 1, 2017, to October 29, 2022, covering various market cycles, including periods of rapid growth, market correction periods, and major events like the COVID-19 pandemic global events [31]. Have a profound impact on the cryptocurrency market. This time frame allows us to fully understand how the market reacts to different conditions.

Furthermore, BTC and ETH, as early entrants in the cryptocurrency market, have demonstrated their stability. Although BNB is relatively newer, it has secured its position in the market as the native token of the BNB exchange. The maturity and stability of these three currencies lend credibility to the empirical analysis of market risk.

The data obtained for BTC, ETH, and BNB include five price-related attributes: opening price, highest price, lowest price, closing price, and adjusted closing price. Financial time-series data often exhibit characteristics such as spikes, heavy tails, and skewness, which deviate from the properties of a normal distribution. Therefore, it is crucial to handle missing values in the dataset and extract necessary sequences. The volatility of a cryptocurrency market index refers to the fluctuations in its returns. To measure the volatility or stability of a market, the rate of return or squared return is sometimes chosen. In this study, the size of returns is chosen as the measure of volatility. Return is a measure of a market index's gains (positive returns) or losses (negative returns), while volatility (the size of returns) is a measure of the index's stability. The subsequent formulas calculate the arithmetic rate of return and volatility of the cryptocurrencies:

$$Return(t) = \frac{Price(t) - Price(t-1)}{Price(t-1)} * 100 \tag{5}$$

$$Volatility(t) = |Return(t)| \tag{6}$$

C. STATISTICAL FEATURE ANALYSIS

1) NORMALITY TEST

The normality test judges whether the continuous variable obeys or approximately obeys the normal distribution. Most of the standard statistical testing methods require the data to be normally distributed, and the statistical conclusions may be invalid if the data does not obey the normal distribution. Therefore, this article draws a histogram of the cryptocurrency data to describe the change law of cryptocurrency return and volatility, as shown in Fig. 3.

As depicted in Fig. 3, the histograms of the returns of BTC, ETH, and BNB display a bell-shaped curve (low at both ends, high in the middle, and symmetrical), indicative of a normal distribution. Consequently, the returns of these three cryptocurrencies can be utilized for subsequent research and analysis.

Conversely, the histograms of the volatility for BTC, ETH, and BNB lean towards the left, deviating from the normal distribution. This observation underscores the necessity of employing the GARCH model for a more detailed fitting.

2) STATIONARITY TEST

For the establishment of the GARCH model, stationarity of the time series is a prerequisite. The Augmented Dickey-Fuller (ADF) test serves as the primary method for verifying if a time series exhibits stationarity. If the series proves to be stationary, it indicates the absence of a unit root; however, the presence of a unit root suggests otherwise. The null hypothesis $H0$ for the ADF test posits that a unit root is present. If the obtained test statistic is significant and falls below the three confidence levels (10%, 5%, and 1%), it gives corresponding confidence to reject the null hypothesis. The results of the ADF test that calculates the returns of BTC, ETH, and BNB are displayed in Tables 1 –3.

From the test results, the statistical values failure days for BTC, ETH, and BNB returns all fall below the 1% critical value of −3.443. Therefore, the null hypothesis is rejected at the 99% confidence level, i.e., there is no unit root. This

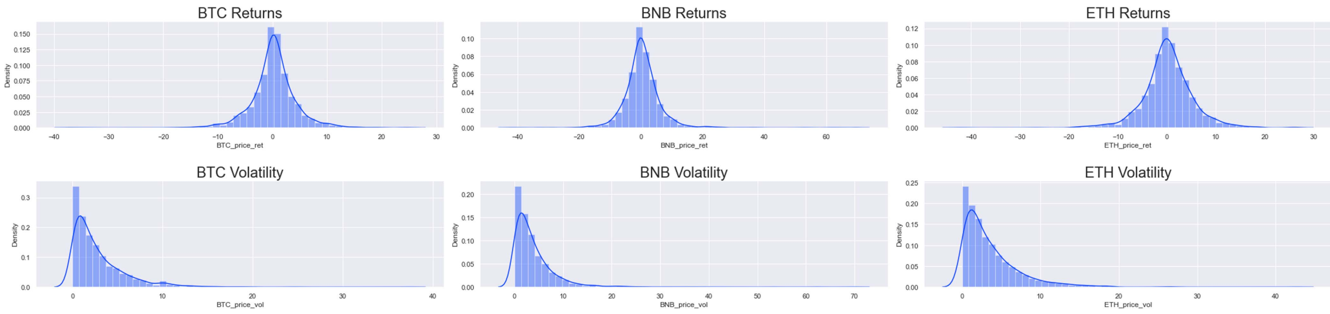

FIGURE 3. **Three cryptocurrencies sequence histogram.**

TABLE 1. **BTC ADF Inspection Form**

T Value	p Value	Delay	Test Number	ADF Value
-31.29	0.0	1	2035	1%: -3.443
				5%: -2.862
				10%: -2.567

TABLE 2. **ETH ADF Inspection Form**

T Value	p Value	Delay	Test Number	ADF Value
-12.24	1.01e-22	9	1715	1%: -3.443
				5%: -2.862
				10%: -2.567

TABLE 3. **BNB ADF Inspection Form**

T Value	p Value	Delay	Test Number	ADF Value
-8.84	1.67e-14	12	1712	1%: -3.443
				5%: -2.862
				10%: -2.567

confirms that the sequence data are stable and meet the prerequisites for establishing a GARCH model.

3) AUTOCORRELATION TEST

Autocorrelation is a characteristic commonly exhibited in time series data, such as cryptocurrency returns. This property, along with heteroscedasticity and volatility clustering, forms the basis for the application of the GARCH model. An autocorrelation test, which examines the linear dependence of different values within the series, can help determine the suitability of using the GARCH model.

The autocorrelation coefficient (ACF) and partial autocorrelation coefficient (PACF) graphs for the first 40 lags of BTC, ETH, and BNB returns are shown in Fig. 4. The ACF graph illustrates the correlation between a data point and its preceding data points, while the PACF graph depicts the correlation with the data point from one lag period prior, accounting for the influence of intervening data points.

Fig. 4 shows the magnitude of the ACF and PACF at each order of BTC returns. The height of each bar corresponds to the ACF value at each order. The blue region represents the 95% confidence interval; when a bar representing the ACF crosses these boundaries, it suggests a significant departure from 0. The ACF at the 10th order, for instance, falls outside the 95% confidence interval, suggesting probable autocorrelation at this order.

From Fig. 4, the ACF and PACF for BTC returns are truncated at the 10th order, suggesting $p = 10$ and $q = 10$ for the GARCH model. For ETH returns, the ACF and PACF are truncated at the 2nd and 1st orders, respectively, indicating $p = 2$ and $q = 1$ for the GARCH model. For BNB returns, both ACF and PACF are truncated at the 2nd order, suggesting $p = 2$ and $q = 2$ for the GARCH model. This analysis aids in determining the optimal parameters for the GARCH model for each cryptocurrency.

4) ARCH EFFECT TEST

The presence of the ARCH effect is a prerequisite for utilizing the GARCH model. This effect is assessed by determining whether there is serial autocorrelation present in the squared residuals of the mean equation, indicative of heteroskedasticity in the time series data. This can be evaluated using the Ljung-Box statistic, where the null hypothesis posits that the ACF values of the first m intervals of the residual squared sequence are all zero. In other words, the null hypothesis states that there is no autocorrelation in the residual sequence and, by extension, no ARCH effect. The p-value is then used to decide whether to reject or accept the null hypothesis.

This study used the ARCH LM method to detect the ARCH effect on the time series data of three cryptocurrencies. The results are shown in Table 4. The p-value (1) column shows the observed calculation if the null hypothesis of no ARCH effect is true. statistics or the probability of a more extreme situation occurring by chance. The LM statistics column represents the Lagrange multiplier statistic used to test for the presence of autocorrelation at lag order m. The p-value (2) column shows the probability of observing the LM statistic if the null hypothesis of no autocorrelation is true, or if one of the more extreme cases would occur by chance. The results show that all p-values are significantly smaller than the traditional threshold of 0.05, indicating strong evidence against the null hypothesis and indicating the presence of ARCH effects in return series volatility for all three cryptocurrencies. This supports the use of GARCH models to capture and model volatility clustering observed in cryptocurrency return data.

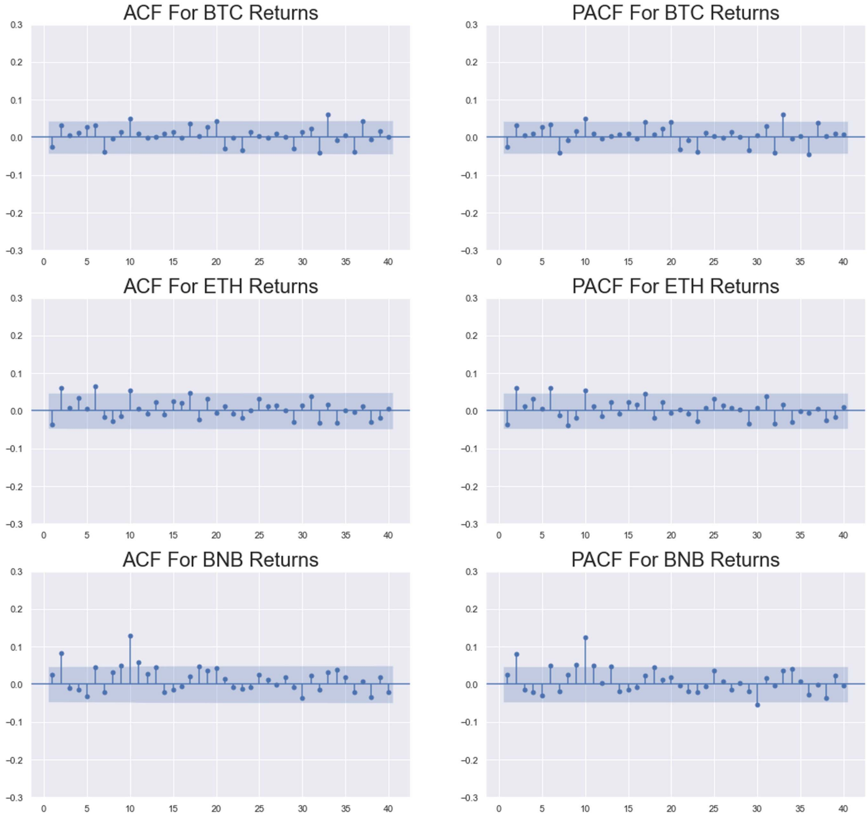

FIGURE 4. Three cryptocurrencies autocorrelation test diagram.

TABLE 4. ARCH LM Test Result

Cryptocurrency Type	Test Statistic	p-value (1)	LM Statistic	p-value (2)
BTC	79.66	5.86e-13	8.23	3.31e-13
ETH	75.89	3.19e-12	33.87	1.75e-12
BNB	286.64	1.03e-55	33.87	7.62e-61

V. MODEL BUILDING

A. MODEL OPTIMIZATION FRAMEWORK

The GARCH model adeptly models conditional variance (volatility) in time series data by exploiting volatility clustering, where current volatility depends on that of recent periods. A key advantage of GARCH is its ability to reduce the effects of high-order moving averages on fitting accuracy.

To achieve an excellent fitting effect, multiple fittings on parameter values are performed prior to establishing the model. This is evaluated using the Akaike Information Criterion (AIC) where a lower value of AIC signifies a better fitting effect. To supplement the AIC, which can be affected by the size of the data, this paper also uses the Bayesian Information Criterion (BIC). The model with the smallest average AIC and BIC values is considered to have the best fitting effect.

The GARCH model was applied to three cryptocurrencies: BTC, ETH, and BNB. Specifically, GARCH (10, 10), GARCH (2, 1), and GARCH (2, 2) were calculated for BTC, ETH, and BNB respectively. The BTC series modeled with GARCH (10,10) showed significant volatility clustering. The model results are presented in Table 5.

The results in Table 5 demonstrate that GARCH (10,10) for BTC, GARCH (1,1) for ETH, and GARCH (2,1) for BNB provide the best fit for each cryptocurrency. With a 95% confidence level, the Root Mean Square Error under the GARCH model was 2.658 for BTC, 3.858 for ETH, and 2.389 for BNB.

In summary, the GARCH model accurately assessed risk for the three cryptocurrencies, with model selection based on information criteria that showed optimal fits of GARCH (10,10) for BTC, GARCH (1,1) for ETH, and GARCH (2,1) for BNB.

B. MODEL SELECTION METHODOLOGY

Model selection not only considers the goodness of fit but also balances model complexity. This study adopted the AIC and BIC criteria, both of which penalize models that are too complex. Forecasting volatility is critical in finance, and the GARCH model is widely accepted for this task. The traditional GARCH has advantages including straightforward

TABLE 5. Model Selection Result

Cryptocurrency Type	Model	AIC	BIC	Average of AIC Value and BIC Value
BTC	GARCH(10,10)	11376.6	11348.5	11362.6
ETH	GARCH(1,1)	10416.6	10438.4	10427.5
BNB	GARCH(2,1)	10561.2	10588.4	10574.8

TABLE 6. VaR Comparison for Different Cryptocurrencies Using Various Methods

Cryptocurrency Type	Historical Simulation VaR (95%)	Monte Carlo Simulation VaR (95%)	Parametric VaR (95%)
BTC	-0.062554	-0.096856	-0.066846
ETH	-0.076715	-0.080753	-0.083572
BNB	-0.076531	-0.095678	-0.096636

interpretation and estimation, adeptly capturing volatility clustering in financial data, computational efficiency, and flexibility across markets like cryptocurrencies.

However, GARCH may not suit all situations. Variants like EGARCH and TGARCH better capture asymmetry and non-linearity but are more complex. Model selection depends on balancing performance versus complexity, data characteristics, and computational needs.

Though sometimes less accurate, GARCH's efficiency and interpretability often make it the best choice. More complex variants like EGARCH are preferred when data exhibits specific features like asymmetry. Overall, the model should match the data characteristics and balance performance with complexity and computational constraints. For many financial applications, GARCH provides a satisfactory and efficient volatility forecast.

To gain an in-depth understanding of the effectiveness of the ARMA-GARCH-VaR model, this study compared it with two other commonly used risk assessment models: historical simulation method (Value-at-Risk, Historical VaR) and Monte Carlo simulation method (Monte Carlo Simulation VaR). These models were chosen for comparison because of their theoretical and applied differences from the ARMA-GARCH-VaR model, which allows us to look at the problem of risk assessment from different perspectives. Each model was used to predict VaR for different retention periods and compared at a 95% confidence level.The results are shown in Table 6.

The historical simulation method gave the lowest VaR value, which may mean that it assessed the risk more conservatively. Monte Carlo simulations and parametric VaR give higher VaR values, which may reflect a higher estimate of the market's underlying volatility. Experimental results show that parametric VaR can provide a similar or higher degree of risk sensitivity than other methods, especially in capturing potential tail risks. In addition, compared with the historical simulation method and the computationally intensive Monte Carlo simulation method based on a large amount of historical data, parametric VaR is more concise and efficient in actual operation, and can quickly respond to market changes and conduct risk assessment. These characteristics make parametric VaR an ideal choice for analyzing dynamic and complex financial markets such as the cryptocurrency market, which can not only ensure the accuracy of assessment but also meet the convenience of actual operation.

VI. CALCULATION AND ANALYSIS OF MODEL VALUE AT RISK VAR

A. VAR CALCULATION

Employing the ARMA-GARCH model, we can ascertain the predicted value of variance. Given that the financial series of the three cryptocurrencies—BTC, ETH, and BNB—adhere to a normal distribution, we can apply the VaR formula under normal distribution for calculation. This paper utilizes the covariance-variance method of the GARCH model to compute the VaR value. The computation is carried out as follows:

$$VaR = P_{t-1} Z_\alpha \sigma_t \tag{7}$$

where P_{t-1} is the return on day $t-1$, Z_α is the quantile at the 95% confidence level (calculated to be 1.64464), and σ is the standard deviation of the return. The respective VaR for the three cryptocurrencies is illustrated in Fig. 5. At a 95% confidence level, the predicted VaR values for BTC, ETH, and BNB are compared with the actual return prices.

The VaR fluctuation for BTC at the 95% confidence level is the smallest, whereas ETH exhibits the largest fluctuation among the three cryptocurrencies. This suggests that, in the investment market, the risk associated with investing in ETH is the highest due to its substantial price changes.

Furthermore, for the three cryptocurrencies in October 2022, the VaR fluctuations remained relatively stable, indicating low risk. However, the daily returns of the three cryptocurrencies exhibit a scattered distribution, suggesting unstable market sentiment and high volatility, particularly for BNB, making it a risky investment.

As seen in Fig. 5, the VaR curves for the three cryptocurrencies exhibit substantial fluctuation and encompass a wide range of returns, indicating a relatively high prediction risk.

FIGURE 5. BTC ETH and BNB VaR value map.

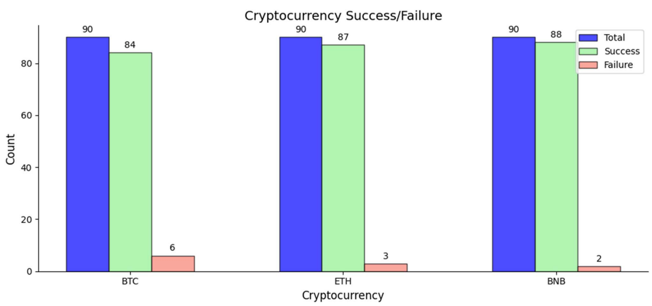

FIGURE 6. Number of days cryptocurrency loss exceeds VaR.

B. ROBUSTNESS ANALYSIS OF THE MODEL

Following the calculations, we proceed to conduct a robustness test on the VaR computed via the ARMA-GARCH model for the three cryptocurrencies. The number of days when losses exceed the VaR is considered as the failure days. We use MATLAB to compute the failure rate over a total of 90 days. The three cryptocurrencies respectively recorded six, three, and two failure days, resulting in failure rates of 6.67%, 3.33%, and 2.22%. These rates are closely aligned with the significance level. The experimental results are illustrated in Fig. 6.

This Fig. 6 represents the number of days when the loss in each of the three cryptocurrencies exceeds the VaR, reflecting the number of failure days. The relatively low failure rates suggest that the ARMA-GARCH model provides a robust measure of VaR, aligning closely with the actual loss experience of the cryptocurrencies. This robustness analysis underscores the model's reliability and its utility in risk assessment for cryptocurrency investments.

C. KUPIEC TEST OF VAR

Following the computation of VaR using the GARCH model, it is crucial to test the accuracy of the risk forecast. This study employs the Kupiec test—a simple yet effective method for failure rate testing. First, we compare VaR with the corresponding loss value. If the actual loss exceeds the estimated VaR, the event is recorded as a failure. The actual loss calculation proceeds as follows:

1) Given the significance level α, the actual number of inspection days is N.
2) The number of failure days is denoted as x.
3) The failure rate is calculated as $\mathrm{p} = \mathrm{x}/\mathrm{N}$.
4) The expected failure probability is $1-\alpha$.

Under the condition of the null hypothesis, the following LR statistics are introduced.

$$LR = -2 * \ln((1-\alpha)^{N-x} * \alpha^{x}) + 2 * \ln((1-p)^{N-x} * p^{x})^{\omega} \tag{8}$$

If the null hypothesis is true, $LR \sim \chi^2(1)$. Here, $\chi^2(1)$ denotes a chi-square distribution with one degree of freedom at the significance level $\alpha = 0.05$.

Given the robustness test results above, we can test the VaR calculated by the ARMA-GARCH model. The actual test days are $N = 90$. The three cryptocurrencies—BTC, ETH,

TABLE 7. Kupiec Test Results for ARMA-GARCH Model at 95% Confidence Level

Type	Failure Days	Failure Rate	LR Inspection Amount	Acceptable
BTC	6	6.6%	0.4786	Accept
ETH	3	3.3%	0.5933	Accept
BNB	2	2.2%	1.8286	Accept

and BNB—record failure days of $x_1 = 6$, $x_2 = 3$, and $x_3 = 2$, respectively. We calculate the *LR* value and compare to measure. The results are presented in Table 7.

1) If the *LR* value falls within the confidence interval, it indicates the model's prediction accuracy.
2) If the *LR* value is to the left of the confidence interval, it suggests an overestimation of the actual loss.
3) If the *LR* value is to the right of the confidence interval, it indicates an underestimation of the actual loss.

At the 95% confidence level, the critical value of the chi-square distribution with one degree of freedom is 3.841. Using the Kupiec back-test method to calculate the *LR* value at the 95% confidence level, the three cryptocurrencies' *LR* values—0.479, 0.593, and 1.829—are all less than 3.841, implying that the null hypothesis $H0$ cannot be rejected. The actual failure rate closely aligns with the expected failure rate.

Consequently, the VaR method proves effective in measuring the maximum potential loss of these three assets during the holding period.

D. ANALYSIS OF RESULTS

This study uses ARMA-GARCH modeling and VaR analysis to assess cryptocurrency volatility and risk. The ARMA-GARCH model effectively simulates volatility dynamics, while VaR provides loss value estimates. These methods quantify the volatility buildup and downside risk of cryptocurrencies. Portfolio managers can use the results to optimize strategies and mitigate losses during extreme market volatility. At the same time, investors can better understand market volatility and make informed decisions through these analyses.

In addition, when comparing existing studies, we found higher volatility than traditional markets consistent with Fang's study [23]. However, compared with Naimy's study, they used the same GARCH model version. The results of this article show Higher frequency spikes and thick tails appear [32]. This may be because this study employed a newer dataset and a more diverse sample of cryptocurrencies. More recent market changes are covered, and the sample cryptocurrencies for this study are more diverse. At the same time, the ARMA-GARCH-VaR model of this study performs well in capturing the high volatility of the cryptocurrency market. However, we acknowledge that there are limitations to the model, especially when considering the rapid development of the crypto market and emerging market drivers such as the rise of DeFi applications and regulatory changes. Future research could explore more complex models to include more risk factors, such as the impact of cybersecurity incidents and legal changes on crypto market risks.

The ARMA-GARCH-VaR model has its limitations when applied to high-volatility markets like cryptocurrencies. It may not fully capture the extreme volatility and irregular patterns of these markets, affecting the accuracy of risk assessments. In addition, model reliance on historical data can lead to underestimation or overestimation of risk, especially when market conditions change rapidly. Sensitivity to parameter selection can also affect model performance, so parameter determination and validation must be carefully considered to ensure the robustness and validity of research results.

VII. CONCLUSION

This study uses the ARMA-GARCH-VaR model to assess the market risks of BTC, ETH, and BNB, providing a new perspective on cryptocurrency risk assessment. The results show that these cryptocurrencies are riskier, especially ETH, and reveal the important role of speculative demand and pricing bubbles. We recommend that policymakers monitor the market to protect consumers and promote a healthy crypto ecosystem. This work lays the foundation for future risk management research and in-depth analysis of cryptocurrency market characteristics.

In summary, while the ARMA-GARCH-VaR model lays the foundation for risk assessment, reflecting the unique attributes of the cryptocurrency market remains challenging. This article only analyzes the three major cryptocurrencies, which does not fully represent the diversity and complexity of the entire market. Since there are multiple cryptocurrencies on the market, each with its unique market behavior and risk characteristics, future research should be expanded to more diverse cryptocurrencies to gain a more comprehensive understanding of market volatility and risks.

Additionally, we recognize the limitations of our study in fully addressing the impact of external factors such as regulatory changes, technological advances, and macroeconomic conditions. These factors play a crucial role in shaping the dynamics of the cryptocurrency market and can significantly impact its volatility and investment viability. Future research could explore the impact of global regulatory policies on cryptocurrency prices, the impact of blockchain and digital financial technology innovations on market stability, and the impact of macroeconomic trends on cryptocurrency investment patterns. Such research would provide a more comprehensive understanding of the cryptocurrency market, provide valuable insights into its multifaceted nature, and inform effective risk management and regulatory strategies. By addressing these areas, future research can further elucidate the complex interplay between internal market mechanisms and external influences, thereby enhancing our understanding of the evolving landscape of digital assets.

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YONGRONG HUANG is currently working toward the graduation degree majoring in network and information security with the College of Computer and Cybersecurity, Fujian Normal University, Fuzhou, China. His research interests include across the fascinating domains of cryptocurrency, large language models, and deep learning.

HUIQING WANG is currently working toward the graduation degree majoring in network and information security with the the College of Computer and Cybersecurity, Fujian Normal University, Fuzhou, China. Her research interests include across the fascinating domains of cryptocurrency, large language models, and deep learning.

ZHIDE CHEN received the doctor's degree from the Department of Computer Science and Engineering, Fudan University, Shanghai, China. He is currently a Professor with the College of Computer and Cybersecurity, Fujian Normal University, Fuzhou, China. His main research interests include cybersecurity, blockchain, Internet of Things, Big Data and cloud computing.

CHEN FENG received the graduation degree from the School of Computer and Cyberspace Security, Fujian Normal University, Fuzhou, China. He is currently a Lecturer with Fuzhou Polytechnic, Fuzhou, China. His research interests include artificial intelligence and computer vision.

KEXIN ZHU received the graduation degree from the Information Engineering Department, Sun Yat-Sen University, Taiwan. He is currently working toward the undergraduation degree from Fujian Normal University, Fuzhou, China. His research interests include statistics and analysis, computer vision, and artificial intelligence.

XU YANG received the Ph.D. degree from the School of Science, RMIT University, Melbourne, VIC, Australia, in collaboration with Data61, CSIRO, Canberra, ACT, Australia, in 2021. He was a Postdoctoral Researcher with the School of Mathematics and Statistics, Fujian Normal University, Fuzhou, China. He is currently an Associate Professor with the College of Computer and Big Data, Minjiang University, Fuzhou, China. His research interests include cryptography and information security.

WENCHENG YANG received the Ph.D. degree in computer science from the University of New South Wales, Sydney, NSW, Australia. He is currently a Senior Lecturer with the School of Mathematics, Physics and Computing, University of Southern Queensland, Toowoomba, NSW, Australia. He has authored more than 60 peer-reviewed conference and journal publications, including a number of papers published in high-ranking journals, IEEE Transactions on Information Forensics and Security, IEEE Transactions on Industrial Informatics, and Pattern Recognition in his research field include biometric security, biometric recognition, and AI security and privacy.