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Risk measurement model on top 10 cryptocurrency market capitalization

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Abstract: This study conducted a large-scale analysis to evaluate the performance of traditional and Markov-Switching GARCH (MS-GARCH) models to estimate the volatility of the top 10 cryptocurrencies by market capitalization. The study compared the performance of the models using goodness-of-fit measures, specifically the Deviance Information Criterion (DIC) and the Bayesian Predictive Information Criterion (BPC). Secondly, we assess the forecasting accuracy for one-day-ahead conditional volatility and Value-at-Risk (VaR). The results obtained show that, in a manner consistent with the findings for the broader cryptocurrency market, the time-varying regime-switching model exhibits superior performance in capturing the complex volatility patterns observed in cryptocurrencies when compared to the traditional GARCH model.

Keywords: *Cryptocurrency, E-GARCH, GARCH, T-GARCH, MSGARCH, Volatility.*

1. Introduction

Blockchain technology that has developed alongside cryptocurrencies, played a crucial role in facilitating technological solutions across various fields [1]. The origin of cryptocurrencies traces back to 2009 when Bitcoin was created by an individual known as Tripathi, et al. [2]. Bitcoin was the pioneer cryptocurrency to function on blockchain, which now underpins all digital currencies. Cryptocurrencies provide a decentralized substitute to the conventional financial system, facilitating peer-to-peer transactions with low fees and enhanced security [3]. The expansion of cryptocurrencies has resulted in significant market growth with the total market capitalization is approximately at $858 billion USD in present time[4, 5].

Cryptocurrencies display varying degrees of volatility compared to traditional fiat currencies. Research by Miglietti, et al. [6] indicates that Litecoin has higher volatility compared to both Euro and Bitcoin. Striking price variations within the cryptocurrency market are instigated by factors such as market speculation, regulations, technology, and investor sentiment. Furthermore, Zhang, et al. [7] demonstrates that regulatory announcements, particularly in China, significantly heighten price volatility, liquidity, and returns, with a more pronounced effect observed during the COVID-19 pandemic.

In recent years, the cryptocurrency market has encountered significant pressure due to global events, including the COVID-19 epidemic, the Russia-Ukraine conflict, monetary policy changes, and the decline of speculative markets. As a result, cryptocurrencies offer great profit opportunities but also carry significant risks, with volatility being a major challenge in risk measurement. Therefore, robust analytical models are required to effectively capture the nature of volatility [8].

This research aims to analyze and forecast cryptocurrency volatility by examining the top 10 cryptocurrencies by market capitalization over the past decade using data obtained from CoinMarketCap. The selected cryptocurrencies include Bitcoin, Ethereum, Tether, Binance Coin, Solana, XRP, USD Coin, Cardano, Dogecoin, and Avalanche.

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Recent advancements in financial risk modeling and predictive analytics, such as machine learning approaches for financial distress prediction Foroutan and Lahmiri [9] and deep learning models for Bitcoin price forecasting Kristanti, et al. [10] and By assessing the volatility of cryptocurrencies through Value at Risk, as noted by Jonathan, et al. [11] the most efficient approach for estimating VaR in cryptocurrencies is emphasized, showcasing its importance in enhancing financial literacy and crafting strong trading strategies. The author will utilize GARCH and its derivatives, including SGARCH, EGARCH, TGARCH, and MSGARCH, for measurement.

2. Literature Review

2.1. GARCH Model and Its Variants in Cryptocurrency Volatility

The classic GARCH model has limitations in capturing complex volatility patterns, so its extended versions such as EGARCH, TGARCH, and MSGARCH are more commonly used. EGARCH and CGARCH have proven to be more accurate in estimating volatility for short term. They are able to capture asymmetries in price fluctuations that often occur in cryptocurrencies [12]. EGARCH (1,1) also performs well in predicting volatility during crisis periods, supporting its use for emerging markets that are prone to economic instability [13]. For fiat currencies, research found that TGARCH is more suitable for currencies such as yen and ringgit, while GARCH is more suitable for yuan and US dollar [14]. This suggests that selecting the GARCH model should be tailored to the financial assets being analyzed.

The TV-MSGARCH model utilizing student-t distribution yields the most effective predictions regarding Bitcoin volatility [15]. This model is designed to handle fluctuations in volatility over time. In addition, various studies indicate that MSGARCH surpasses single-regime models in forecasting Value-at-Risk (VaR) [16]. Further investigations reveal that PGARCH is better suited for student-t distributions, which tend to provide more precise representations of market movements [17]. Moreover, the GARCH (1,1) model with the student-t distribution is recognized for its robustness against changes in volatility, making it a great choice for cryptocurrency markets [18]. Simpler models can perform as well as more complex ones, provided they are able to capture return distributions with fat tail characteristics [19]. Regarding GARCH (1,1), it is the best prior for modeling volatility when combined with EGARCH to capture asymmetric effects [20].

2.2. Effectivity of EGARCH, EGARCH, TGARCH, and MSGARCH Model in Analyzing Volatility

Several studies compared EGARCH, TGARCH, and MSGARCH models to find the best approach to capture crypto market volatility. EGARCH shown to be more accurate in measuring volatility [21]. This model can capture the greater impact of bad news than good news on market volatility. However, in some cases GARCH and TGARCH provide better results [22].

MSGARCH shown more accurate VaR and Expected Shortfall (ES) estimates than single-regime models, suggesting cryptocurrency volatility is better explained by models with regime changes [23]. While TGARCH (1,1) was found more effective in capturing asymmetric shocks in the crypto market [24]. Moreover, complex GARCH models are better at explaining cryptocurrency volatility fluctuations than simpler models [25]. Lastly, the EGARCH-M model is employed to study the connection between returns and trading volume, indicating that volatility has a variable relationship with market activity [9].

2.3. Impact of External Factors on Cryptocurrency Volatility

External elements affect the volatility of cryptocurrencies. Although the volatility decreased during the COVID-19 pandemic, the correlation among cryptocurrencies has risen [26]. Regulatory actions by the Chinese government have notably influenced the price volatility and liquidity of cryptocurrencies, especially during uncertainty [7]. Events such as the COVID-19 pandemic, the Russia-Ukraine conflict, and global monetary policies exert tremendous pressure on cryptocurrency markets, creating difficulties in measuring and predicting volatility [27]. Among different cryptocurrencies, Ethereum (ETH) displays the greatest volatility, demonstrating higher sensitivity to market fluctuations [28].

2.4. Effectiveness of GARCH Model in Market Analysis and Risk Management

ARMA-GARCH-VaR models shown to be efficient in assessing risk within the cryptocurrency market [29]. The GARCH model effectively estimates Bitcoin's volatility, revealing clustering patterns and an inverted leverage effect through the GJR-GARCH (1,1) model, suggesting potential rise in volatility even in response to positive news [30]. The GARCH (1,1) model demonstrates volatility clustering in the crypto sector, whereas the GJR-GARCH (1,1) version identifies significant leverage effects in cryptocurrency returns [31]. However, GARCH is less effective in modeling a few cryptocurrencies, indicating that some digital assets might need different modeling approaches [32].

3. Methods

This study employs a quantitative methodology utilizing a 5-year time series data analysis to assess Value-at-Risk (VaR) for 10 different cryptos. The analytical models applied include GARCH, Exponential GARCH (EGARCH), Threshold GARCH (TGARCH), and Markov-Switching GARCH (MSGARCH). These models facilitate the examination of shifts in price volatility among crypto assets crucial for evaluating risks in unstable markets.

The dataset utilized in this research comprises daily historical pricing for 10 cryptocurrencies gathered from CoinMarketCap. This study spans a decade to effectively capture the various market dynamics that unfold over time. By utilizing a wide range of historical data, this research aims to uncover significant and pertinent volatility trends that are essential for assessing the risk of crypto assets. The analysis in this study used statistical software such as R or Python, which offer specialized packages for GARCH, EGARCH, TGARCH, and MSGARCH models.

The analysis method applied in this study begins with the estimation of volatility models using the GARCH Bollerslev [33] EGARCH Nelson [34] TGARCH Zakoian [35] and MSGARCH [36]. With each model as below.

GARCH Bollerslev [33] $h_{k,t} = \alpha_{0,k} + \alpha_{1,k}\gamma_{t-1} + \beta_k h_{k,t-1}$ (1)

EGARCH Nelson [34] $logh_{k,t} = \alpha_{0,k} + \alpha_{1,k}\left(\left|\eta_{k,t-1}\right| - E\left[\left|\eta_{k,t-1}\right|\right]\right) + \alpha_{2,k}\eta_{k,t-1} + \beta_k logh_{k,t-1},$ (2)

TGARCH Zakoian [35] $h_{k,t}^{1/2} = \alpha_{0,k} + \alpha_{1,k}I\left(\gamma_{t-1} \geq 0\right)\gamma_{t-1} + \alpha_{2,k}I\left(\gamma_{t-1} < 0\right)\gamma_{t-1} + \beta_k h_{k,t-1}^{1/2}$ (3)

MSGARCH Ardia, et al. [36] $h_{k,t} = h\left(y_{t-1}, h_{k,t-1}, \theta_k\right)$ (4)

Optimal model selection depends on information criteria like the Deviance Information Criterion (DIC) and the Bayesian Predictive Information Criterion (BPIC), which assess the model's efficacy in capturing the volatility of cryptocurrency asset values. Model selection is essential for statistical inference, especially in hierarchical Bayesian models and empirical Bayes models. Conventional metrics such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are inapplicable to Bayesian models since they depend on maximum likelihood estimation. Instead, DIC Spiegelhalter, et al. [37] and BPIC Ando [38] were created to assess model fit and complexity by taking into account the Bayesian posterior distribution.

General Framework for Bayesian Model Selection:

Let $y = (y, \ldots, y_n)$ be the observed data generated from the true unknown distribution $G(y)$ with density $g(y)$, and let $(f\{y \mid \theta); \theta \in \Theta \subset R^p\}$ be the model to estimate $G(y)$

In Bayesian modeling, a prior distribution is specified for the parameters. The posterior distribution is given by:

$$\pi(\theta \mid y) = \frac{L(y|\theta)\pi(\theta)}{\int L(y|\theta)\pi(\theta)d\theta} \quad (5)$$

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Whereas $L(y|\theta)$ is the likelihood function. The prediction distribution for future observation z is as follow.

$$q(z \mid y) = \int f(z \mid \theta)\pi(\theta \mid y)d\theta \quad (6)$$

With the aim of evaluating how well the predictive model approximates the true g(z) using BPIC Ando [38] and DIC [37].

DIC is defined as follow:

$$DIC = -2E_{\theta|y}[logL(y \mid \theta] + P_D \quad (7)$$

BPIC is defined as follow:

$$BPIC = -2E_{\theta|y}[logL(y \mid \theta)] + 2nb_y \quad (8)$$

Furthermore, model evaluation is performed by forecasting volatility one step ahead, we use the first half of our yt data for initial model estimation and then evaluate the forecast accuracy over the remaining half (out-of-sample period). The rolling window approach is used for estimation, where the model parameters are re-estimated every 10 observations. Since the actual volatility cannot be observed, we use proxies to assess the prediction performance. We compare the predictions of GARCH models using two metrics: Mean Squared Error (MSE) and Mean Absolute Error (MAE).

Table 1.
Descriptive Statistics.

Symbol	Mean	Median	Std Dev	Kurtosis
ADA	0.0008	-0.0006	0.0467	7.0332
BNB	0.0032	0.0012	0.0467	33.7472
BTC	0.002	0.0008	0.0338	12.8558
DOGE	0.005	-0.0003	0.1002	731.0627
ETH	0.0023	0.0009	0.043	11.1073
SOL	0.0054	0.0002	0.0676	8.444
TRX	0.0023	0.0023	0.0489	70.0946
USDC	-1.592E-06	9.97E-05	0.0032	51.165
USDT	-5.481E-06	-1E-04	0.003	108.1218
XRP	0.0022	0.0002	0.0544	32.6233

Note: This table presents summary information for cryptocurrencies with differing levels of market capitalization.

Table 2.
Price Descriptive Statistics.

Symbol	MeanP	StdDevP	SkewnesP	KurtosisP
ADA	0.7519	0.5824	1.5795	4.8398
BNB	259.0137	208.5721	0.3033	1.9370
BTC	31501.4309	22114.3	0.7671	2.9922
DOGE	0.0909	0.10039	1.7147	6.6997
ETH	1682.4769	1244.145	0.2865	1.9842
SOL	68.6085	67.9654	0.8726	2.4722
TRX	0.0689	0.04879	1.5191	7.4769
USDC	1.0010	0.0043	3.1376	24.640
USDT	1.0008	0.0036	3.3654	30.1581
XRP	0.5332	0.3488	2.6165	12.6457

Note: This table presents summary information for cryptocurrencies with differing levels of market capitalization. P for Price.

Table 3.
Return Descriptive Statistics.

Symbol	Mean R	Std Dev R	Skewnes R	Kurtosis R
ADA	0.0008	0.0466	0.4932	7.0539
BNB	0.0032	0.0467	1.5818	33.8246
BTC	0.0020	0.0338	-0.3107	12.8558
DOGE	0.0050	0.0999	21.4868	735.0901
ETH	0.0023	0.0429	-0.2793	11.1223
SOL	0.0054	0.0675	0.5421	8.4644
TRX	0.0022	0.0488	3.2195	70.5145
USDC	-1.33e-06	0.0029	1.1750	61.3864
USDT	-4.67e-06	0.0028	0.9565	127.0100
XRP	0.0021	0.0543	2.3467	32.7287

Note: R for Return

In financial risk modeling, the accuracy of Value-at-Risk (VaR) estimates is critical for risk management and regulatory compliance. Two statistical tests used to evaluate the performance of VaR models are Conditional Coverage (CC) and Dynamic Quantile (DQ) Test. The CC Test Christoffersen [39] tests whether VaR exceptions (violations) occur independently over time, ensuring correct conditional coverage. This test combines two hypotheses: Unconditional Coverage (UC), which ensures that the observed violation rate corresponds to the expected rate, and independence (IND), which ensures that violations occur independently over time. By defining the hit function as:

$$I_t = \{1, if\ y_t < VaR_t\ (VaR\ violation)\ 0, otherwise$$

The UC hypothesis states that the observed frequency of VaR violations should match the expected probability as p:

$$\hat{p} = \frac{1}{T}\sum_{t=1}^{T} \quad I_t \approx p \quad (9)$$

Likelihood Ratio (LR) is used to evaluate this hypothesis.

UC Test using:

$$LR_{UC} = -2[logL(\hat{p}) - logL(p)] \sim \chi^2 \quad (10)$$

IND Test using:

$$LR_{IND} = -2[logL(\pi_0, \pi_1) - logL(\hat{p})] \sim \chi^2 \quad (11)$$

If it is statistically significant, then the VaR model fails to provide correct conditional coverage, meaning the violations are not independent and indicate volatility that is not captured by the model.

Meanwhile, the DQ Test Engle and Manganelli [40] extends the CC Test by testing whether VaR violations depend on historical information, ensuring the quantile model is dynamic. The hit deviation function is defined as:

$$Hit_t = I_t - p$$

then regression is performed as follows:

$$Hit_t = \beta_0 + \sum_{j=1}^{m} \beta_j\, Hit_{t-j} + \sum_{k=1}^{n} \gamma_k\, X_{t-k} + \varepsilon_t \quad (12)$$

where are additional explanatory variables such as past volatility and market conditions, measures serial dependence in the offense (should be zero in the correct model specification), and measures dependence on market conditions. The null hypothesis of the correct model is defined as:

$$H_0\colon \beta_1 = \beta_2 = \cdots = \beta_m = \gamma_1 = \cdots = \gamma_n = 0 \quad (13)$$

Testing is conducted using Likelihood Ratio:

$$DQ = TR^2 \sim \chi^2(m+n) \quad (14)$$

where DQ is the coefficient of determination of the regression. If the DQ test result is significant, then VaR violations are influenced by historical factors and market conditions, which means that the VaR model is not appropriate. The DQ Test is more robust in evaluating dynamic risk models because it considers external factors that affect VaR violations.

4. Result

4.1. Top 10 Crypto Returns

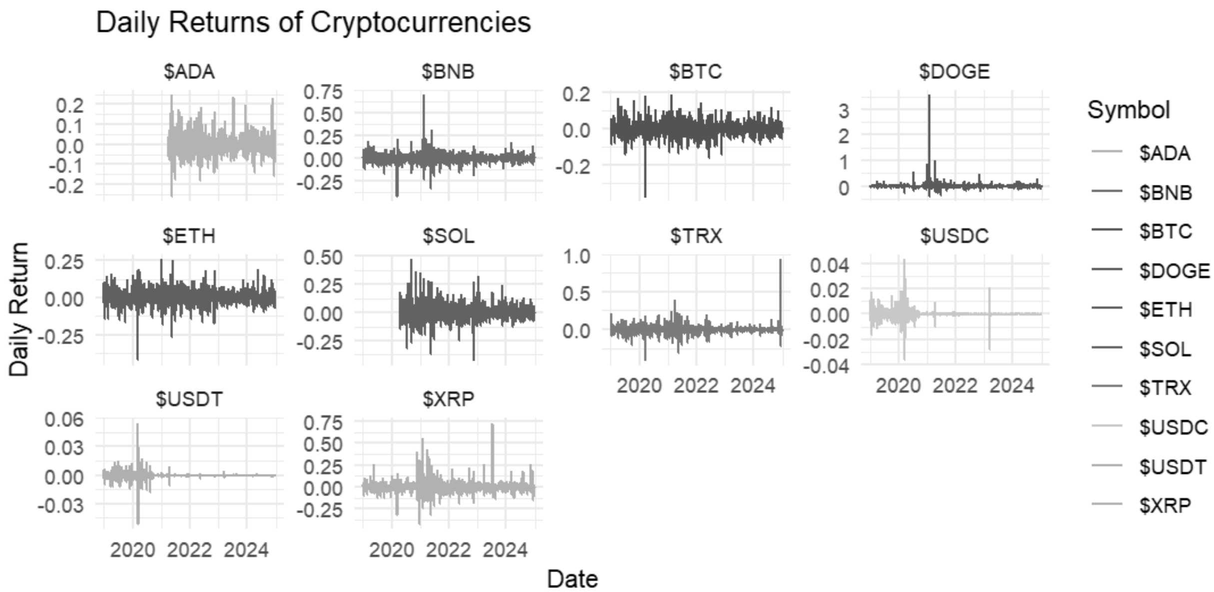

Figure 1.
Return Cryptocurrency.

Table 4.
Model selection based on DIC and BPIC.

Symbol	DIC	BPIC	Both Agree
ADA	TGARCH-T-(3)	SGARCH-T (3)	-
BNB	SGARCH-T-(2)	EGARCH-T-(3)	-
BTC	SGARCH-G-(2)	TGARCH-G-(3)	-
DOGE	SGARCH-T-(3)	TGARCH-T-(3)	-
ETH	TGARCH-T-(3)	EGARCH-T-(3)	-
SOL	TGARCH-T-(2)	SGARCH-T-(3)	-
TRX	SGARCH-T-(3)	EGARCH-T-(3)	-
USDC	EGARCH-G-(2)	EGARCH-G-(2)	EGARCH-G (2)
USDT	EGARCH-G-(2)	TGARCH-G-(3)	-
XRP	TGARCH-T-(1)	TGARCH-T-(3)	-

Note: Total number of cryptocurrencies is 10. Values indicate the number of time series that fit the selected model through DIC (panel A), BPIC (panel B) and both criteria (panel C). N, S and G are Normal, Student's-t and GED distributions, respectively. K refers to the number of regimes in the model.

Table 5.
Effect of Inverse Leverage.

Regimes	Distribution	EGARCH	TGARCH
K=1	N	0	5
0	Std	0	7
0	Ged	0	3
K=2	N	0	6
0	Std	0	8
0	Ged	0	3
K=3	N	0	6
0	Std	0	8
0	Ged	0	3

Note: Total number of cryptocurrencies is 10. Values indicate the number of time series of each model.

4.2. B. Out of Sample Analysis

Table 6.
Model selection based on VaR forecasts.

Symbol	CC	DQ
$ADA	SGARCH-G-(2)	SGARCH-T-(2)
$BNB	TGARCH-T-(2)	SGARCH-T-(1)
$BTC	EGARCH-T-(1)	EGARCH-T-(1)
$DOGE	SGARCH-T-(1)	SGARCH-T-(2)
$ETH	SGARCH-N-(2)	SGARCH-T-(1)
$SOL	SGARCH-N-(2)	SGARCH-N-(2)
$TRX	SGARCH-T-(1)	EGARCH-T-(1)
$USDC	EGARCH-T-(1)	SGARCH-T-(1)
$USDT	EGARCH-T-(3)	SGARCH-T-(1)
$XRP	EGARCH-G-(3)	SGARCH-N-(2)

Note: Total number of cryptocurrencies is 10. Values indicate the number of time series corresponding to the model that minimizes CC (panel A), DQ (panel B) and both criteria (panel C). N, Std and GED denote the Normal, Student's-t and GED distributions, respectively. K refers to the number of regimes in the model.

5. Discussion

Examining the ten leading cryptocurrencies, we find that generally both performance metrics (MSE and MAE) align with the most effective model. Specifically, for BTC and USDT, the two-regime TGARCH model with Student's t-distribution offers the best fit. In contrast, ETH is most accurately captured by a three-regime GARCH model with a generalized distribution. Despite detecting shifts in volatility regimes in some cryptocurrencies, the criteria of MSE and MAE occasionally indicated varying optimal models. Furthermore, DIC and BPIC sometimes presented differing opinions regarding the optimal number of regimes for a specific cryptocurrency.

Table 5 indicates a reversal of the leverage effect in at least one environment. N, Std, and GED denote the Normal, Student's t, and Generalized Error Distribution, respectively. K denotes the quantity of regimes within the model. For most of these cryptocurrencies (BTC, ETH, ADA, SOL, BNB, XRP), our model shows a positive asymmetry in volatility. In particular, BTC and ETH show a clear pattern of positive asymmetry, reacting more to positive price changes. ADA and SOL also show this characteristic, but weaker.

In this set of ten, only USDT shows a consistent inverse leverage effect across all model specifications. Implying positive past returns have a greater impact on volatility than negative past returns, which is an unusual finding. For DOGE and TRX, while the EGARCH model suggests that negative returns affect volatility more strongly than positive returns, the TGARCH model, at least in one of its specifications, indicates a reverse leverage effect. This suggests that the relationship between returns and volatility for these two cryptocurrencies may be more nuanced and dependent on the specific model used. USDC shows no clear evidence of positive asymmetry or inverse leverage.

SOL showed the highest volatility among the ten coins, consistently across all models. ETH showed moderate volatility, while USDT and USDC showed relatively lower volatility. TRX, ADA, BNB, and XRP were somewhere in between, showing moderate levels of volatility but XRP at the end of the quarter showed its volatility. DOGE showed more fluctuating volatility, indicating greater sensitivity to market changes.

Based on the behavior of the average and standard deviation across models, these cryptocurrencies could be split into some categories. BTC and ETH fall into a group that has relatively consistent averages and standard deviations across different model specifications. USDT and USDC also show stability. TRX, SOL, ADA, BNB, and XRP show some variation in mean and standard deviation depending on the model used. Generally, these ten cryptocurrencies have higher mean than the standard deviation, indicating positive average return. However, we observed instances where the standard deviation was higher than the mean for DOGE indicating periods of significant price fluctuations and potentially negative average returns over the observed period.

For Out-of-Sample we examine the one-day forward conditional volatility and (VaR) estimates. By using MSE and MAE for volatility forecasts, we find that single-regime models generally outperform two- and three-regime models. Particularly for BTC and BNB, the TGARCH model with Student's t-distribution provides the most accurate volatility forecasts. ADA and SOL are best modeled with a two-regime GARCH model with the Common Error Distribution. DOGE, and ETH performed better with the EGARCH model, while USDT best fit the one-regime SGARCH.

For forecasting VaR, Christoffersen's CC test indicates that the two-regime TGARCH model with a normal distribution is the most efficient for BNB and ADA. In contrast, SOL and ETH are best represented by a two-regime GARCH model. TRX and DOGE fit best with a single-regime GARCH model, while USDT and USDC demonstrated the highest VaR forecasting accuracy using the EGARCH model. XRP is ideally modeled with a three-regime GARCH using a General Error distribution. The DQ test yielded somewhat different results, often favoring models with fewer regimes, yet it generally aligned with the best performing model type for each cryptocurrency.

Overall, while MSGARCH models tend to perform better than single-regime models, no model can be said to be the best across all ten cryptos. Asymmetric models were often preferred, especially for more volatile cryptos. Optimal models for volatility and VaR forecasting varied widely, highlighting the importance of considering individual cryptocurrency characteristics. In our Value-at-Risk (VaR) forecasting, the traditional GARCH model proved to be the best fit for ETH and USDT. However, for most other leading cryptocurrencies, the asymmetric TGARCH model is preferred (see Table 7 for a summary of in- and out-of-sample findings across the ten major cryptocurrencies).

6. Conclusions

Overall, this research shows that there is no model that can universally capture the volatility patterns of all cryptos. Each asset has unique characteristics, affecting the selection. GARCH-based models, especially TGARCH and EGARCH, are often superior in capturing the complex nature of volatility, especially for cryptocurrencies with high price fluctuations such as BTC, ETH, and SOL. In addition, asymmetry effects in volatility were found for most cryptocurrencies, with some exhibiting positive asymmetry, where volatility is more responsive to price increases than price decreases. However, USDT showed an inverse leverage effect, meaning its volatility was more affected by positive than negative returns which is an unusual finding in financial assets.

In the context of Value-at-Risk (VaR) forecasting, TGARCH and EGARCH models are often superior to the standard GARCH model, especially in capturing short-term volatility risk. However, the MSGARCH model with a multi regime approach shows great potential in adjusting to changes in market structure, although the optimal results still depend on the specifics of the cryptocurrencies analyzed. This study confirms that the selection of volatility models cannot be generalized for all cryptocurrencies. Instead, a more flexible approach tailored to the specific characteristics of each digital asset is required, taking into account factors such as asymmetry effects, volatility regime changes, and the corresponding return distribution.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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