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HISTORICAL VOLATILITY FLUCTUATIONS OF BITCOIN: INFLUENCED BY REAL-WORLD EVENTS

(*Sejarah Turun-Naik Kemeruapan Bitcoin: Dipengaruhi oleh Peristiwa Dunia Sebenar*)

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ABSTRACT

Bitcoin market has exhibited substantial volatility over time. Bitcoin returns exhibit high standard deviation. This study employs the GARCH (1,1) model with normal (norm), Student-t (std), and generalized error distributions (ged) to estimate Bitcoin conditional volatility. Bitcoin exhibits fat-tailed returns, volatility clustering, and a remarkably high persistence value. The GARCH (1,1)-ged model showed superior performance compared to other models when evaluated using LL, AIC, and BIC criteria. The indicator saturation (IS) method was employed to concurrently detect historical daily breaks, trend breaks, and outliers in Bitcoin volatility data. The indicator saturation approach revealed that, for the past decade, historical Bitcoin volatility has had 6 outliers, 31 breaks, and 74 trend breaks under the normal distribution, 0 outliers, 26 breaks, and 83 trend breaks under the student-t distribution, and 1 outlier, 29 breaks, and 77 trend breaks under the ged distribution. This shows that assuming a heavy tail led to fewer outliers and breaks, and as the frequency of trend breaks increases, it also shows more volatility clusters represented by GARCH. These discoveries have the potential to comprehend the influence of events on financial markets and guarantee stability in the evaluation of financial risk, management of portfolios, and modeling endeavors.

Keywords: breaks; outliers; indicator saturation; Bitcoin; volatility

ABSTRAK

Pasaran Bitcoin menunjukkan perubahan dan kemeruapan yang ketara sepanjang sejarah. Pulangan Bitcoin dikenali kerana mempunyai sisihan piawai yang tinggi. Kajian ini menggunakan model GARCH (1,1) dengan taburan normal (norma), Student-t (std), dan taburan ralat umum (ged) untuk menganggarkan kemeruapan bersyarat Bitcoin. Bitcoin mempamerkan pulangan berekor tebal, pengelompokan kemeruapan, dan nilai kegigihan yang sangat tinggi. Model GARCH (1,1)-ged menunjukkan prestasi unggul berbanding model lain apabila dinilai menggunakan kriteria LL, AIC, dan BIC. Kaedah penunjuk ketepuan (IS) digunakan untuk secara serentak mengesan sejarah putusan harian, putusan aliran dan data terpencil dalam data kemeruapan Bitcoin. Pendekatan petunjuk ketepuan mendedahkan bahawa, sepanjang dekad yang lalu, sejarah kemeruapan Bitcoin mempunyai 6 data terpencil, 31 putusan dan 74 putusan trend di bawah taburan normal, 0 data terpencil, 26 putusan dan 83 putusan trend di bawah student-t, dan 1 data terpencil, 29 putusan dan 77 putusan trend di bawah taburan ged. Ini menunjukkan bahawa menganggap ekor yang tebal membawa kepada lebih sedikit data terpencil dan putusan, dan apabila kekerapan putusan trend meningkat, ia juga menunjukkan lebih banyak kelompok kemeruapan yang diwakili oleh GARCH. Penemuan ini berpotensi untuk memahami pengaruh peristiwa ke atas pasaran kewangan, dan menjamin kestabilan dalam penilaian risiko kewangan, pengurusan portfolio dan usaha pemodelan.

Kata kunci: putusan; data terpencil; penunjuk ketepuan; Bitcoin; kemeruapan

1. Introduction

The more Bitcoin ages as a financial asset, the more significant its volatility becomes to investors and scholars. Cryptocurrencies are a significant asset category in financial markets due to their high volatility. Recognizing changes in volatility is crucial for efficient risk management, trading strategies, and regulatory compliance. Volatility is a key measure of risk in financial markets, and time series models are often used to describe it. Breaks and outliers in volatility indicate market changes, changing risk perceptions, or the underlying factors causing volatility. Ignoring these can lead to incorrect risk assessments, poor portfolio choices, and ineffective hedging strategies. Changes in volatility can also indicate potential trading opportunities.

Cryptocurrency is a digital currency that uses encryption to protect financial transactions, control unit production, and authenticate asset transfers. It operates on decentralized networks using blockchain technology, unlike traditional government-issued currencies like the dollar or euro. Bitcoin, the first and most renowned cryptocurrency, was created by Satoshi Nakamoto in 2008. Since then, numerous other cryptocurrencies have been developed, each with unique attributes and technologies. Bitcoin's volatility is unstable, with sudden changes and events occurring frequently due to factors like government news, market manipulation, and new technologies. Understanding market dynamics and making better investment decisions requires careful analysis of breaks and outliers. The use of big data and analytics is crucial for informed policy decisions. This study, using high-frequency data, provides insights into past changes since Bitcoin's rise, highlighting global patterns and uncertainties in policy-making processes.

In general, understanding the fluctuation patterns in cryptocurrency data is crucial for making informed investment decisions and formulating effective policies (Aharon 2023). Cryptocurrencies possess many characteristics found in financial data (Kaseke *et al.* 2022). Recent research indicates that the cryptocurrency market has experienced substantial fluctuations and disruptions in its structure (Mandaci & Cagli 2022; Sahoo 2021). The extreme instability of the cryptocurrency market can be attributed to factors such as speculation, inadequate regulation, and negative news (Zhang *et al.* 2018; Katsiampa *et al.* 2019; Hu *et al.* 2019). Additionally, significant macroeconomic events may be linked to interruptions in financial market volatility (Ahmed 2018). Structural breaks are more frequent in all widely recognized cryptocurrencies, and as market capital increases, the shift in structural breaks migrates from smaller to larger cryptocurrencies (Canh *et al.* 2019). In their study, Tan *et al.* (2022) identified the presence of structural changes in the return, price, and squared return of the top ten cryptocurrencies. Bitcoin, the largest cryptocurrency, has experienced significant price volatility due to shifting market conditions and new information.

Volatility is a crucial factor in risk assessment, as it reflects the degree of variation in a variable over time. The GARCH model, specifically the GARCH (1,1) model, is a successful method for modeling volatility in financial time series. This model effectively depicts the fluctuating nature of volatility. Types of volatility include implied, realized, and conditional volatility. This study uses conditional volatility, also known as the conditional standard deviation of daily log returns, which measures a series' variance or standard deviation over time (Brooks 2019). Breaks and outliers in financial data are crucial for understanding past price or return variations. Researchers often focus on these in returns, squared returns, or prices to estimate conditional volatility. Cryptocurrencies have a heavy tail and volatility clustering, indicating periods of excessive volatility. Cryptocurrency volatility persistence influences financial risk analysis and risk management measures (Dutta & Bouri 2022). The GARCH (1,1) model proposed by Bollerslev (1987), commonly used for estimating conditional volatility, can be challenging to accurately capture due to its reliance on Gaussian innovations. High-frequency data and large sample sizes can lead to structural changes that contradict the assumption of normality (Sen & Das 2023). The primary question is whether the estimated conditional volatility data from GARCH (1,1) exhibit any breaks or outliers. This study aims to estimate the conditional volatility of BTC log returns and identify the number of structural breaks, trend breaks, and outliers present in the BTC conditional volatility data.

In addition, previous studies have used separate tests to identify breaks and outliers in returns, squared returns, or prices. However, these tests can sometimes lead to masking effects, which can obscure the presence and quantity of potential breaks (He & Maheu 2010). Rodrigues and Rubia (2011) and Song and Kang (2021) suggest that extreme values can obscure potential breaks, while outliers can negatively affect change point detection. The objective of this study is to estimate the conditional volatility of BTC log returns and to find structural breaks, trend breaks, and outliers in the BTC conditional volatility dataset. To address this, the indicator saturation (IS) approach, developed by Hendry (1999), is used to identify breaks, trend breaks, and outliers simultaneously. This study gives insights into historical volatility shifts by applying the Indicator Saturation (IS) technique to volatility series produced from the GARCH (1,1) model using several error distributions (normal, student's t, and generalized error distribution). So far Mohamed *et al.* (2023) employed the IS technique in cryptocurrency returns to identify breaks, trend breaks, and outliers. This study stands out by analysing the volatility data of BTC using the IS technique, providing valuable insights for investors, portfolio managers, and risk analysts to adapt their strategies to evolving market conditions. IS was chosen because of its capacity to detect structural breaks, outliers, and trend shifts in financial time series without making any assumptions about timing or frequency. Unlike traditional break detection approaches, which need specified breakpoints, IS provides a data-driven approach that is ideal for studying the dynamic and ever-changing character of Bitcoin markets. Given the unpredictable legal, technical, and macroeconomic elements that influence Bitcoin, IS provides a strong technique for capturing underlying structural alterations in volatility, resulting in a more complete knowledge of market dynamics.

In conclusion, utilizing a GARCH model with three error distributions to extract conditional volatility and then detecting historical breaks, trend breaks, and outliers enhances the analysis of Bitcoin's price behavior and offers useful resources for comprehending market dynamics and enhancing decision-making in the constantly changing cryptocurrency investment landscape. Furthermore, this research provides valuable insights for risk management, financial forecasting, and policy-making by enhancing volatility detection, improving predictive models, and informing regulatory decisions in cryptocurrency markets. The following sections of this paper are organized as follows: Section 2 discusses volatility characteristics and methods for finding breaks and outliers. Section 3 describes the methodology used. Section 4 outlines the study's findings, while Section 5 concludes the study.

2. Literature Review

Since the seminal work conducted by Engle (1982) on autoregressive conditionally homoscedastic (ARCH) models, the finance community has widely embraced the use of generalized ARCH (GARCH) models of his student Bollerslev (1987). These models were developed specifically to capture time-varying volatility, which is a common characteristic in financial markets. Volatility clustering, where periods of high volatility follow high volatility and low volatility follows low volatility, is a key feature captured by GARCH models. The digital coin markets have exhibited some common characteristics of volatility, including a fat-tailed distribution, volatility clustering, and volatility persistence (Aharon 2023). While Kaseke *et al.* (2022) confirm that cryptocurrencies share these characteristics with traditional financial assets, other research suggests that developing digital asset markets face abrupt, unexpected volatility fluctuations (Moore 2009). Zhang *et al.* (2018), Katsiampa *et al.* (2019), and Hu *et al.* (2019) have all proven the significant unpredictability of cryptocurrency markets, highlighting the need for more robust volatility modeling methodologies.

Several statistical techniques have been used in previous studies to identify structural breaks and outliers in financial time series data. The Bai and Perron (BP) test (Bai & Perron 1998, 2003) and the iterative cumulative sum of squares (ICSS) test (Inclán & Tiao 1994) are both popular tests. In addition, many outlier identification algorithms have been added into GARCH models, including the methods of Ané *et al.* (2008), Charles and Darné (2005), Doornik and Ooms (2005), and Franses and Ghijsels (1999). However, there are variations in detecting breaks among research, underlining the limitations of current methodologies. For example, Shen *et al.* (2020) used ICSS to discover 35 breaks, but Charles and Darné (2019) found only five. Harb *et al.* (2022) discovered 30 breaks using ICSS, whereas Bouri *et al.* (2019) found just four using BP. Similarly, Abakah *et al.* (2020) discovered two breaks using BP, and Jiang *et al.* (2023) detected a single change point in the mean and three in variance using the Bayesian change point (BCP) approach in conjunction with ICSS. Dutta and Bouri (2022) identified 16 outliers with the Ané *et al.* (2008) approach. Vo and Nguyen (2011) discovered that volatility shifts are significantly lower in the standardized residuals filtered from the GARCH (1,1) model than in the raw return series. These inconsistencies show that typical break detection approaches may not be enough for detecting all fundamental changes in extremely turbulent markets.

BP and ICSS tests are limited in their capacity to detect all structural breaks. The BP test involves trimming, which limits its capacity to detect limited number of breaks, whereas the ICSS test assumes data normality and is susceptible to size distortion. The indicator saturation (IS) technique solves these constraints by concurrently recognizing multiple types of breaks, such as trend breaks and outliers. Castle *et al.* (2012) examined the IIS and BP approaches using actual interest rates in the United States and discovered that the results were identical. Similarly, Ismail and Nasir (2018) discovered that BP and IIS produced equal results when detecting breaks in ASEAN shariah-compliant indices. Mohamed *et al.* (2023) found that the IS approach beats BP by detecting more structural breaks and trend breaks. The IS technique employs several estimators, including impulse indicator saturation (IIS) by Hendry (1999) and Santos *et al.* (2008), step-indicator saturation (SIS) by Castle *et al.* (2015), and trend-indicator saturation (TIS) by Pretis *et al.* (2015). The IS method is unusual in that it saturates the model with a whole set of break indicators before statistically determining which are significant, resulting in a more flexible and thorough approach.

Despite its advantages, IS is still not considered in the study of cryptocurrency volatility. Nasi *et al.* (2022) used IIS and discovered that volatility data usually contain outliers and structural breaks. Mohamed *et al.* (2024) demonstrated the usefulness of IIS, SIS, and TIS in detecting breaks, trend breaks, and outliers in bitcoin datasets. Ismail and Nasir (2020) used modeled GARCH volatility data to demonstrate that SIS is excellent in detecting structural breaks and outliers. Javid and Ahmad (2020) compared event dummy analysis to IIS, stating that IIS is better at catching all instances of breaks during a certain period. Similarly, Nasir and Ismail (2020) identified 47 outliers in the volatility of Malaysia's shariah-compliant index using IIS. In macroeconomic applications, Russell *et al.* (2010) utilized IIS to detect changes in US inflation, while Reade and Volz (2011) used it to examine China's inflation stability. However, the detection of breaks and outliers in conditional volatility data to investigate historical Bitcoin volatility is still unexplored. This study closes the gap by using the IS approach to find breaks and outliers in the extracted conditional volatility series from a fitted GARCH (1,1) model, resulting in a more nuanced understanding of Bitcoin market dynamics.

3. Methodology

3.1. *Data*

The study used BTC daily data from Yahoo Finance, starting on November 22, 2014, and ending on June 30, 2023. The data was based on availability. As of April 2024, BTC's market capitalization was 1.3 trillion dollars, making it the most prominent cryptocurrency globally. The study used logarithmic returns of prices using the formula.

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

whereby P_t is the current lag price at time t, P_{t-1} is the previous lag price at time $t-1$, and r_t stands for returns.

Table 1: Descriptive statistics (log-Returns)

Returns	Mean	Std. Dev	Skewness	Kurtosis	JB	ARCH-LM	ADF test
BTC	0.001419	0.038	-0.7895	14.2458	16883.03*	2.2e-16	Stationary

Table 1 shows that BTC returns have a large standard deviation, indicating dispersion from the mean. They also show significant negative skewness and a high kurtosis value, indicating a left-skewed distribution. An outlier or break is present due to high kurtosis, indicating a heavy tail distribution. The ARCH effect is evident, as indicated by the ARCH-LM test. The Jarque-Bera test results showed a value below the critical threshold, indicating strong evidence against the null hypothesis of normal distribution. The ADF test suggests a stationary distribution, and the augmented Dickey-Fuller test results are less than 0.01. The study used the GARCH (1,1) model to model BTC returns, assuming three error distributions: norm, std, and ged. The estimated conditional volatility series for each distribution was obtained, and descriptive statistics are presented in Table 2.

Table 2: Descriptives of BTC volatility data

	norm Volatility	std Volatility	ged Volatility
Mean	0.037029	0.036678	0.036726
Maximum	0.175709	0.162179	0.171222
Minimum	0.020757	0.013958	0.014269
Std. Dev.	0.014099	0.016039	0.016336
Skewness	2.363709	1.753132	1.843566
Kurtosis	13.95328	8.974680	9.699974
Observations	3142	3142	3142

Table 2 reveals positive skewness in volatility data, with an average volatility value of 0.04 and a leptokurtosis. The standard deviation is lower than returns, and the kurtosis remains high for both returns and volatilities.

3.2. *Volatility model*

To explore volatility persistence, the basic GARCH (1,1) model is employed. The use of GARCH (1,1) is justified by its ability to capture time-varying volatility and persistence in financial and economic time series. The model is commonly used because of its simplicity, which makes it computationally efficient while effectively describing volatility clustering. This structure makes GARCH (1,1) ideal for studying financial returns and macroeconomic data, where volatility persistence is critical. Furthermore, the extracted conditional volatility series from the fitted GARCH (1,1) model serves as the basis for implementing the Indicator Saturation (IS) method. Because the volatility data is produced from a basic GARCH (1,1) process, which normally assumes a normal distribution, its fluctuations naturally mimic the dynamics of the original model. This connection demonstrates conditional volatility as a direct expression of the GARCH (1,1) process, demonstrating its applicability for structural break detection and trend analysis using IS. The GARCH (1,1) model was selected to expand the discussion of its generated volatility series in addition to its well-established function in volatility modeling. This paper seeks to lead research into how the extracted conditional volatility preserves fluctuations and structural breaks, despite the fact that GARCH (1,1) is frequently criticized for its shortcomings. This paper presented a different viewpoint on GARCH (1,1) by using IS to this derived volatility, which sheds light on its behavior outside of the realm of conventional return series analysis.

The conditional mean equation is specified as follows:

$$r_t = \mu + \rho r_{t-1} + \varepsilon_t \tag{2}$$

where ε_t is the error term, defined as:

$$\varepsilon_t = \eta_t \sigma_t, \varepsilon_t \sim N(0, \sigma_t^2), \eta_t \sim i.i.d\, N(0,1) \tag{3}$$

The conditional variance equation is given by:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4}$$

For the model to be valid, it must satisfy the following constraints: $\omega > 0$ and $\alpha, \beta \geq 0, \beta \geq 0$. If $\alpha + \beta$ is less than one, the process is stable. However, if $\alpha + \beta$ is near to one, volatility shocks are more persistent. If $\alpha + \beta = 1$, the model represents an Integrated GARCH (IGARCH) process, showing that shocks have a long-term influence on volatility.
The unconditional variance of ε_t in a stationary GARCH (1,1) process is $\frac{\omega}{1-\alpha-\beta}$. If α and β are both zero, the model becomes conditionally homoscedastic. The model parameters are calculated using the Maximum Likelihood Estimation (MLE) approach.

3.3. *Indicator saturation approach*

The Indicator Saturation (IS) approach is a reliable strategy for detecting structural breaks that employs an extended general-to-specific methodology based on model selection. According to Santos *et al.* (2008), the general unrestricted model (GUM) accurately depicts the occurrence of several structural breaks or level changes.

The IS method systematically estimates underlying models while detecting outliers with Impulse Indicator Saturation (IIS), identifying multiple shifts with Step Indicator Saturation (SIS), and finding trend breaks with Trend Indicator Saturation (TIS). These approaches detect structural changes within a sample without making assumptions about their frequency, length, or timing (Hendry 1999; Johansen & Nielsen 2009).

The mathematical formulations for the IIS, SIS, and TIS models are as follows:

$$IIS\ \sigma_t = \mu + \sum_{j=1}^{n} \delta_j 1_{\{t=j\}} + \varepsilon_t \tag{5}$$

$$\text{SIS}\ \sigma_t = \mu + \sum_{j=2}^{n} \delta_j 1_{\{t\geq j\}} + \varepsilon_t \tag{6}$$

$$TIS\ \sigma_t = \mu + \sum_{j=1}^{n} \delta_j 1_{\{t>j\}}(t-j) + \varepsilon_t \tag{7}$$

where σ_t represents volatility over time, μ is a constant term, δ_j indicates the magnitude of a break or outlier, and ε_t is the error term. The dependent variable, σ_t, is subjected to regression analysis. The IS method allows for the simultaneous identification of breaks, trend breaks, and outliers through SIS, TIS, and IIS estimators, respectively. The sample size (T) is used to determine the significance level for identifying breaks, trend breaks, and outliers, $\alpha = \frac{1}{T}$, resulting in an adaptive threshold. This technique has been demonstrated to successfully detect structural changes while being resilient to overfitting (Pretis *et al.* 2017; Pretis *et al.* 2018). In this study, α is set at 1/T. This decision strikes a compromise between sensitivity and robustness by reducing the likelihood of false positives while allowing for the identification of real volatility changes. A smaller α improves the threshold for identifying breaks, minimizing the risk of overfitting noise as structural changes while potentially missing minor alterations. A bigger α may capture more breaks but also lead to more false detections. The 1/T rule guarantees that the number of recognized breaks remains proportionate to the available data, adjusting dynamically for varying sample sizes. Setting α in relation to the sample size, as noted by Pretis et al. (2015), guarantees that the model does not overfit by using an excessive number of indicators while retaining sensitivity to real breaks. Furthermore, according to Hendry and Doornik (2014), an adaptive significance threshold guarantees that only statistically significant breakpoints, outliers, and trend shifts are kept in big datasets, preventing over-rejection.

To implement the GARCH (1,1) model and IS method, two software tools like R programming language and Eviews 12 were employed. These tools offer powerful functions for estimating GARCH parameters and performing IS analyses respectively. One of the most significant computing issues connected with IS is the saturation approach's high dimensionality, especially when working with huge datasets. The use of many dummy variables for IIS, SIS, and TIS can result in substantial processing cost. To address these problems, the concept of block search for the selection processes and parallel computation whenever possible were considered to improve IS detection performance in large amounts of time series data. Furthermore, the p value for the significance threshold is used to fine-tune the selection of significant indicators while reducing overfitting risk.

4. Results and Discussion

4.1. *Parameter estimations*

The study estimated BTC conditional volatility using different GARCH (1,1) models and then identified breaks, trend breaks, and outliers in the conditional volatility data using IS technique. Estimated models were compared base on the assumed three different error distributions: GARCH (1,1)-norm, GARCH (1,1)-std, and GARCH (1,1)-ged. The estimated parameters were presented in Table 3. Table 3 shows that $\mu, \omega, \alpha_1, \beta_1$, and shape, are statistically significant. The persistence value is close to unity, suggesting an explosive state. The overstated volatility persistence value can be related to uunaccounted structural breaks in the log returns as earlier discussed by Lamoureux and Lastrapes (1990). The ARCH LM test show no leftover ARCH effects are in the residuals of the BTC return series. The GARCH (1,1)-ged model performed better than other models, with smaller AIC and BIC values, indicating the importance of fat tail consideration in the distribution of ged. The three models show good performance and favorable diagnostic results. The study then proceeded to extract the conditional volatility data from each model. The derived conditional volatility data exhibited high fluctuations, with the GED-based volatility data showing greater variation levels. The historical distribution of volatility data from 2014 to 2023 reveals varying spreads, characterized by significant swings and trends.

Table 3: Estimation results of GARCH (1,1) model.

	GARCH (1,1)-NORM	**GARCH (1,1)-STD**	**GARCH (1,1)-GED**
	Panel A: Parameters Estimates		
Constant ($\boldsymbol{\mu}$)	0.0018	0.0014	0.0012
	(0.00)	(0.00)	(0.00)
Omerga ($\boldsymbol{\omega}$)	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Alpha ($\boldsymbol{\alpha_1}$)	0.136	0.116	0.129
	(0.00)	(0.00)	(0.00)
Beta ($\boldsymbol{\beta_1}$)	0.829	0.883	0.869
	(0.00)	(0.00)	(0.00)
Shape	-	3.21	0.881
		(0.00)	(0.00)
Persistence	0.965	0.999	0.999
	Panel B: Model Selection Criteria		
LL	6077.73	6515.83	6518.97
AIC	-3.87	-4.14	-4.15
BIC	-3.86	-4.13	-4.14
	Panel C: Diagnostics		
ARCH LM (7)	2.59	2.03	2.16
	(0.59)	(0.71)	(0.68)
$\boldsymbol{Q^2(9)}$	2.76	2.27	2.39
	(0.79)	(0.87)	(0.85)
Obs.	3142	3142	3142

Figure 1 depicts a time series plot of the three volatilities. Normal volatility (blue line) the baseline volatility, has lower values but dramatic fluctuations during volatile market times. The std-based volatility closely resembles normal-based volatility trends, but peak heights differ, implying that market reactions to price movements vary. Ged-based volatility shows the greatest levels of volatility. Following the volatility fluctuations, there are times that the volatility levels decrease, notably in 2018 and 2020, which may indicate a market adjustment phase. A substantial fall in all three volatilities occur in late 2022 and 2023 indicating that the Bitcoin market is maturing, with lower volatility likely indicating a more stable trading environment. Figure 1 helps identify breaks, trend breaks, and outliers, highlighting the historical distribution of volatility data. Major real-world events are reflected in the figure's key volatility spikes, which include the early 2018 Bitcoin crash after regulatory crackdowns, the mid-2019 surge fueled by Facebook's Libra announcement, the sharp March 2020 drop during the COVID-19 market crash, the early 2021 volatility spike as Bitcoin surpassed $60,000 amid institutional adoption, and the mid-2022 turbulence brought on by the Terra (LUNA) collapse and subsequent market sell-offs.

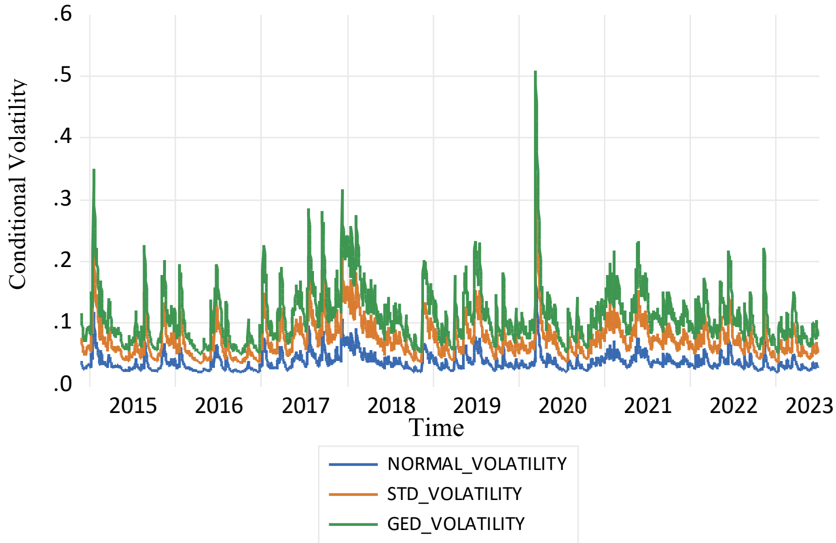

Figure 1: Comparison of conditional volatilities

Since the BTC log returns exhibited a high persistence value of 0.965 under the normal distribution and 0.999 under the STD and GED distributions, the derived conditional volatilities are likely to contain breaks and outliers. This highlights the need to identify the timing and locations of these previously overlooked breaks, trend breaks, and outliers using the IS technique.

4.2. *Volatility breaks, trend breaks, and outliers*

Breaks, trend breaks, and outliers in each conditional volatility dataset were identified using the IS technique. The IS technique generates dummy variables and performs a regression analysis with a constant term. Table 4 shows the total number of dummies generated, as well as the significant dummies.

Table 4: Overall results of IS approach

Volatility	**Sample size**	**All indicators**		**Significant Indicators**			**Direction of Fluctuation**		
		Created	Blocks	IIS	SIS	TIS	Total	Positive	Negative
norm Volatility	3142	9423	105	6	31	74	111	65	46
std Volatility	3142	*9423*	105	0	26	83	109	64	45
ged Volatility	3142	*9423*	105	1	29	77	107	62	45

The IS approach generated a total of 9423 indicators for IIS, SIS, and TIS tests in a sample of 3142 observations. The indicators for each estimator (3142) were divided into 105 blocks, and significant dummies were preserved using a general-to-specific technique. Only 6 dummies for IIS estimator, 31 for SIS, and 74 for TIS were statistically significant, totalling 111 significant dummies for the normal based volatility, with 64 positives and 47 negatives. The std-based volatility showed 0 IIS, 26 SIS, and 83 TIS, resulting in 109 significant dummies with 64 positive and 45 negatives. The ged-volatility showed 1 IIS, 29 SIS, and 77 TIS, resulting in 107 significant dummies with 62 positive and 45 negatives. All these suggest that heavy tails mitigate the presence of fat tails caused by outliers. Generally, volatility data showed a larger number of trend breaks compared to breaks or outliers. Mohamed *et al.* (2024) found 25 IIS, 12 SIS, and 5 TIS in the log return of BTC. Tables 5-7 display the detected breaks, trend breaks, and outliers, along with their corresponding dates, totals, and significance level alphas of each volatility data. Furthermore, Figure 2 graphically shows fluctuations in volatility changes over a 10-year BTC market period, comparing annual counts of breaks, trend breaks, and outliers.

Table 5: IS approach in norm-volatility data

Test	Dates	Total
IIS 0.0003	12/08/2017 (0.030154), 12/09/2017 (0.025471), 12/10/2017 (0.022666), 3/13/2020 (0.037385), 3/14/2020 (0.031120), 3/15/2020 (0.022808)	6
SIS 0.0003	1/04/2015 (0.017321), 8/21/2015 (0.027048), 8/30/2015 (-0.012301), 11/03/2015 (0.026713), 11/18/2015 (-0.016958), 1/27/2016 (-0.019616), 5/29/2016 (0.012790), 1/21/2017 (-0.011806), 3/30/2017 (-0.016860), 7/27/2017 (-0.019951), 9/15/2017 (0.040010), 11/10/2017 (0.009436), 12/08/2017 (0.029899), 2/06/2018 (0.023473), 5/07/2018 (-0.011470), 11/20/2018 (0.023923), 4/01/2019 (0.020257), 5/12/2019 (0.029915), 5/29/2019 (-0.007255), 6/28/2019 (0.035676), 7/25/2019 (-0.014458), 3/13/2020 (0.105544), 6/07/2020 (-0.007063), 7/24/2020 (0.009669), 10/22/2020 (0.006214), 5/20/2021 (0.009217), 7/04/2021 (-0.016290), 3/20/2022 (-0.010443), 6/15/2022 (0.032583), 11/12/2022 (0.029055), 4/01/2023 (-0.012558)	31
TIS 0.0003	1/13/2015 (0.024656), 1/16/2015 (-0.033282), 1/22/2015 (0.007345), 2/13/2015 (0.000976), 3/17/2015 (0.001827), 3/25/2015 (-0.002889), 4/04/2015 (0.001285), 6/21/2015 (0.000276), 8/21/2015 (-0.001288), 9/17/2015 (0.001264), 11/13/2015 (-0.000340), 1/15/2016 (0.029612), 1/16/2016 (-0.029735), 3/16/2016 (0.000319), 6/12/2016 (0.001734), 6/23/2016 (-0.002720), 8/02/2016 (0.018739), 8/03/2016 (-0.018196), 9/12/2016 (0.000571), 11/12/2016 (-0.000406), 12/12/2016 (0.000806), 1/04/2017 (0.010741), 1/07/2017 (-0.012249), 2/08/2017 (0.001219), 3/16/2017 (0.007963), 3/19/2017 (-0.008621), 5/08/2017 (0.006131), 5/11/2017 (-0.005471), 6/13/2017 (-0.000948), 7/14/2017 (0.008667), 7/21/2017 (-0.008730), 9/02/2017 (0.002061), 9/15/2017 (-0.003757), 10/06/2017 (0.002435), 12/08/2017 (-0.000296), 2/06/2018 (-0.001041), 3/07/2018 (0.001374), 7/18/2018 (-0.000168), 11/04/2018 (0.000919), 11/30/2018 (-0.007105), 12/02/2018 (0.005871), 1/31/2019 (0.000644), 2/26/2019 (-0.000541), 9/23/2019 (0.009561), 9/25/2019 (-0.009799), 10/25/2019 (0.027061), 10/26/2019 (-0.027303), 11/21/2019 (0.000862), 3/13/2020 (-0.004111), 4/06/2020 (0.003989), 10/22/2020 (0.000203), 1/01/2021 (0.001150), 1/14/2021 (-0.003108), 1/21/2021 (0.015736), 1/22/2021 (-0.014212), 4/18/2021 (0.001129), 5/22/2021 (-0.001493), 6/19/2021 (0.000782), 9/23/2021 (-0.000276), 11/16/2021 (0.000593), 12/06/2021 (-0.000669), 1/15/2022 (0.000574), 3/02/2022 (-0.000461), 4/15/2022 (0.000721), 5/12/2022 (-0.000778), 6/16/2022 (-0.002045), 7/01/2022 (0.002115), 8/14/2022 (0.000458), 9/15/2022 (-0.001103), 10/13/2022 (0.001478), 11/12/2022 (-0.004841), 11/20/2022 (0.003501), 12/12/2022 (0.000771), 4/11/2023 (-0.000115)	74

Tables 5-7 summarize the detected structural breaks, trend breaks and outliers in BTC volatility, highlighting their timing and magnitude across normal, std, and GED-volatility models, with major disruptions aligning with significant financial events. The magnitude of the identified breaks, trend breaks, and outliers, as indicated in parenthesis, offers useful information on the extent of disruptions in BTC data under various volatility circumstances. As shown in the results, the size varies greatly, with some breaks demonstrating major shifts and others remaining very small. For example, in normal-volatility data, the most significant break in the SIS method happened on March 13, 2020, at a magnitude of 0.105544, indicating a substantial market disruption. Similarly, the highest magnitude in standard deviation volatility data was reported on the same date, at 0.127548. The most significant break in GED-volatility data occurred on March 13, 2020, with a magnitude of 0.135388. These findings indicate that the most significant breaks coincide with known market shocks, emphasizing their impact on BTC price dynamics. The substantial variation between estimating methodologies highlights the need of taking into account both the frequency and intensity of breaks when studying financial time series data.

Table 6: IS approach in std-volatility data

Test	Dates	Total
IIS 0.0003	NA	0
SIS 0.0003	1/04/2015 (0.016758), 2/05/2015 (-0.017897), 2/23/2015 (-0.006790), 7/13/2015 (0.007535), 8/21/2015 (0.029279), 8/31/2015 (-0.027349), 9/20/2015 (-0.013306), 11/03/2015 (0.022756), 1/16/2016 (0.030394), 1/30/2016 (-0.014657), 5/29/2016 (0.017748), 4/05/2017 (-0.016612), 9/15/2017 (0.053215), 12/08/2017 (0.042044), 11/20/2018 (0.024690), 4/01/2019 (0.027740), 5/12/2019 (0.034334), 7/29/2019 (-0.011926), 3/13/2020 (0.127548), 7/24/2020 (0.012953), 10/22/2020 (0.012729), 5/20/2021 (0.014189), 7/04/2021 (-0.015532), 9/17/2021 (0.008003), 6/14/2022 (0.034525), 1/11/2023 (0.014021)	26
TIS 0.0003	1/13/2015 (0.033936), 1/15/2015 (-0.038600), 1/24/2015 (0.004450), 5/25/2015 (0.000228), 10/17/2015 (0.000598), 11/17/2015 (-0.006984), 11/20/2015 (0.006130), 1/16/2016 (-0.000206), 3/16/2016 (0.000476), 6/16/2016 (0.003267), 6/23/2016 (-0.004370), 8/02/2016 (0.028236), 8/03/2016 (-0.028966), 8/15/2016 (0.001651), 10/11/2016 (0.000585), 11/12/2016 (-0.000841), 12/12/2016 (0.001028), 1/03/2017 (0.009544), 1/07/2017 (-0.011520), 2/09/2017 (0.001562), 3/16/2017 (0.008269), 3/19/2017 (-0.008835), 5/10/2017 (0.008646), 5/12/2017 (-0.007857), 6/13/2017 (-0.001227), 7/14/2017 (0.008924), 7/21/2017 (-0.009934), 8/09/2017 (0.001449), 9/15/2017 (-0.001753), 10/12/2017 (0.015134), 10/13/2017 (-0.013360), 11/08/2017 (0.002426), 11/16/2017 (-0.002482), 2/05/2018 (0.023689), 2/06/2018 (-0.024495), 3/07/2018 (0.001002), 6/12/2018 (0.000322), 7/25/2018 (-0.000333), 11/05/2018 (0.001247), 12/01/2018 (-0.010192), 12/02/2018 (0.008618), 2/03/2019 (0.000724), 3/02/2019 (-0.000688), 6/27/2019 (0.039192), 6/28/2019 (-0.039127), 9/24/2019 (0.020561), 9/25/2019 (-0.020753), 10/25/2019 (0.030209), 10/26/2019 (-0.030491), 11/21/2019 (0.000935), 3/13/2020 (-0.005001), 3/28/2020 (0.002479), 4/15/2020 (0.002850), 5/01/2020 (-0.000691), 7/22/2020 (0.000347), 9/21/2020 (-0.000447), 10/22/2020 (0.000612), 1/02/2021 (0.001072), 1/14/2021 (-0.001317), 2/24/2021 (-0.000460), 4/18/2021 (0.005484), 4/20/2021 (-0.004294), 5/22/2021 (-0.001309), 6/19/2021 (0.000651), 9/23/2021 (-0.000270), 11/16/2021 (0.000789), 12/06/2021 (-0.000821), 1/15/2022 (0.000696), 3/02/2022 (-0.000886), 4/15/2022 (0.001234), 5/13/2022 (-0.001089), 6/17/2022 (-0.001420), 7/04/2022 (0.001551), 8/14/2022 (0.000574), 9/15/2022 (-0.001023), 10/13/2022 (-0.010025), 10/14/2022 (0.011767), 11/12/2022 (0.018062), 11/13/2022 (-0.021163), 11/30/2022 (0.001786), 2/10/2023 (0.000699), 3/18/2023 (-0.001149), 4/11/2023 (0.000716)	83

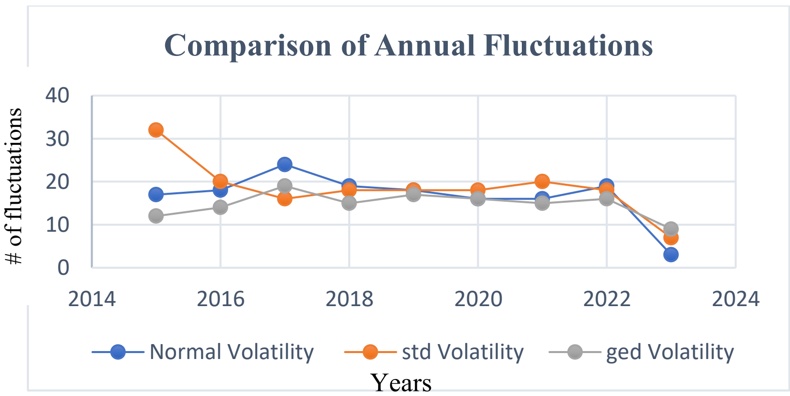

Figure 2: Annual fluctuations of conditional volatilities

Table 7: IS approach in ged-volatility data

Test	Dates	Total
IIS 0.0003	12/08/2017 (0.019549)	1
SIS 0.0003	1/04/2015 (0.018871), 2/05/2015 (-0.019390), 8/21/2015 (0.028831), 8/30/2015 (-0.031802), 9/20/2015 (-0.015117), 11/03/2015 (0.033231), 11/18/2015 (-0.011238), 1/16/2016 (0.035480), 1/28/2016 (-0.020443), 5/29/2016 (0.019203), 1/06/2017 (0.035010), 4/02/2017 (-0.017872), 9/15/2017 (0.055347), 12/08/2017 (0.041867), 2/06/2018 (0.024684), 11/20/2018 (0.025652), 4/01/2019 (0.030504), 5/12/2019 (0.036815), 7/29/2019 (-0.012481), 3/13/2020 (0.135388), 7/24/2020 (0.013850), 10/22/2020 (0.013060), 5/20/2021 (0.011805), 7/07/2021 (-0.016534), 9/17/2021 (0.006956), 3/22/2022 (-0.010165), 6/14/2022 (0.037900), 1/11/2023 (0.009047), 4/02/2023 (-0.012155)	29
TIS 0.0003	1/13/2015 (0.024425), 1/16/2015 (-0.030798), 1/24/2015 (0.006114), 5/25/2015 (0.000403), 11/12/2015 (-0.000497), 3/16/2016 (0.000355), 6/16/2016 (0.003288), 6/23/2016 (-0.004417), 8/02/2016 (0.031014), 8/03/2016 (-0.031841), 8/15/2016 (0.001819), 10/11/2016 (0.000566), 11/12/2016 (-0.000879), 12/12/2016 (0.001257), 1/07/2017 (-0.002239), 2/09/2017 (0.001703), 3/16/2017 (0.008680), 3/19/2017 (-0.009344), 5/10/2017 (0.017400), 5/11/2017 (-0.016587), 6/13/2017 (-0.001250), 7/14/2017 (0.009389), 7/21/2017 (-0.010568), 8/09/2017 (0.001694), 9/15/2017 (-0.002006), 10/12/2017 (0.018164), 10/13/2017 (-0.016172), 11/08/2017 (0.002449), 11/16/2017 (-0.002526), 2/06/2018 (-0.000842), 3/07/2018 (0.001053), 6/12/2018 (0.000344), 7/19/2018 (-0.000351), 11/05/2018 (0.001243), 12/01/2018 (-0.011929), 12/02/2018 (0.010337), 2/02/2019 (0.000764), 3/02/2019 (-0.000786), 6/25/2019 (0.010557), 6/29/2019 (-0.010442), 9/23/2019 (0.010952), 9/25/2019 (-0.011142), 10/25/2019 (0.033529), 10/26/2019 (-0.034106), 11/21/2019 (0.003189), 11/27/2019 (-0.002652), 12/18/2019 (0.011037), 12/19/2019 (-0.010363), 3/13/2020 (-0.005678), 3/28/2020 (0.003249), 4/15/2020 (0.002953), 5/01/2020 (-0.000855), 7/22/2020 (0.000335), 9/21/2020 (-0.000425), 10/22/2020 (0.000610), 1/02/2021 (0.000778), 1/22/2021 (-0.001325), 4/18/2021 (0.001256), 5/22/2021 (-0.001636), 6/19/2021 (0.000788), 9/23/2021 (-0.000316), 11/16/2021 (0.000812), 12/06/2021 (-0.000840), 1/15/2022 (0.000691), 3/02/2022 (-0.000612), 4/15/2022 (0.000922), 5/14/2022 (-0.001102), 6/16/2022 (-0.001463), 7/04/2022 (0.001671), 8/14/2022 (0.000612), 9/15/2022 (-0.001335), 10/14/2022 (0.001832), 11/12/2022 (0.019026), 11/13/2022 (-0.021965), 11/30/2022 (0.001764), 1/11/2023 (0.000440), /14/2023 (-0.000146)	77

From 2014 to 2024, Figure 2 contrasts the yearly fluctuations in the three volatilities, signifying different degrees of mood and market activity. The drop in volatility counts starting in 2021 and continuing through 2022 and 2023 is a noteworthy trend. The Bitcoin market appears to have had a period of relative stability between 2014 and 2016, as seen by the comparatively consistent volatility levels. The sharp rise in Bitcoin's price in 2017 caused volatility to rise. Volatility rose in 2018, signalling a time of increasing uncertainty and correction. Volatility declined between 2019 and 2020, suggesting a period of consolidation. Significant price gains resulted from a resurgence of volatility in 2021 brought on by increased interest and investment in Bitcoin. All volatilities decreased between 2022 and 2023, indicating a period of market maturity or a decrease in speculative trading. The maximum number of breaks/trends breaks is observed in 2015, followed by 2016 and 2021 when std is assumed. For the norm-volatility the greatest number of breaks/trends breaks is observed in 2017, followed by 2018 and 2022, and for the ged-volatility the maximum number of breaks/trends breaks is observed in 2017, followed by 2019 and 2016. This comparative analysis reveals that fluctuations of the norm-volatility is higher in earlier years, but has a more pronounced drop compared to std-volatility in recent years, suggesting potential market shifts or investor sentiment. Ged-volatility remains stable but reflects changes in the market's reaction to extreme events. The yearly counts of detected breaks, trend breaks, and outliers in volatility data reveal the evolving nature of Bitcoin's market dynamics, providing valuable insights into periods of stability and turbulence, aiding in informed investment strategies and risk management.

The findings also show trend breaks are more common than breaks and outliers in Bitcoin market volatility. This shows that long-term structural changes rather than transient shocks influence Bitcoin's price swings. Trend breaks are frequently caused by macroeconomic events, regulatory developments, or movements in investor opinion, implying that volatility clustering is driven by fundamental market changes rather than occasional price increases. This pattern has important implications for market stability since sustained volatility patterns may lead to persistent periods of high risk, making Bitcoin more vulnerable to long-term uncertainty than traditional financial assets. The results also show that assuming GED discovers fewer outliers than assuming normal and Student-t distributions. This is because GED is more flexible in modeling heavy tails, resulting in a smoother characterization of volatility. The student-t distribution, with its larger tails, classifies more severe deviations as outliers, whereas GED incorporates these fluctuations within its distributional structure. For investors, this means that GED-based models may give a more cautious assessment of risk exposure. However, Student-t-based models may highlight dramatic market moves more frequently, which can be advantageous for short-term traders looking to profit from periods of high volatility.

4.3. *Corresponding real events*

Significant shifts in BTC volatility frequently correspond with major financial events, regulatory developments, or macroeconomic shocks. This section investigates how key volatility spikes correlate with significant real-world events, providing insights into the variables that drive Bitcoin's market swings. For example, the first-time oil prices rose was in 2015-2016, when they fell from 106 USD to 45 USD (Ahmed & Bouri 2023). The start of ETH and Bitcoin in 2017 was a good time. The crypto market dropped 80% in 2018 and reached a low point (Harbe *et al.* 2022). The first cryptocurrency hack and initial coin offering (ICO) occurred in New Zealand correspond in 2019 (Ahmed & Bouri 2023). The COVID-19 outbreak from March 11, 2020, to January 11, 2021, led to significant drops in Bitcoin prices in June and November 2022, primarily due to bad news and threats.

On the other hand, the findings are consistent with past research on Bitcoin volatility, notably those that show volatility persisting and long-memory effects on Bitcoin returns (Kaseke *et al.* 2022; Mandaci & Cagli 2022; Sahoo 2021). Previous research has shown that, like other speculative assets, Bitcoin's volatility is driven by external shocks (Mužić & Gržeta 2022; Zhang *et al.* 2018; Katsiampa *et al.* 2019; Hu *et al.* 2019). However, our findings indicate that trend breaks are more important than previously thought, supporting the premise that Bitcoin's volatility dynamics are controlled by market development rather than random shocks. In contrast, some research that focus on short-term trading techniques may underestimate the importance of long-term structural changes, resulting in varying risk assessment interpretations.

The study suggests that identifying changes in volatility and identifying real events can help manage risk in the volatile cryptocurrency market. This study bridges the gap between theory modeling and real-world applications, providing valuable information for both academics and professionals. Finding outliers and structural breaks in the data is essential for identifying changes in market sentiment and behaviour, which may guide trading choices and risk management tactics in the erratic bitcoin market. Understanding trend breaks and volatility persistence is critical to financial risk management. To prevent losses caused by protracted volatility, investors should implement long-term risk assessment techniques and portfolio diversification. Policymakers must create regulatory frameworks to combat prolonged periods of high volatility, such as enforcing capital requirements for cryptocurrency exchanges and increasing market transparency. Furthermore, financial institutions should incorporate these findings into risk models to better prepare for systemic risks in bitcoin markets.

This is important as recent studies have reinforced the importance of accounting for structural breaks when analysing cryptocurrency volatility. Patra and Gupta (2025) emphasize that trading volume alone cannot fully explain volatility but becomes a significant predictor when structural shifts are considered. This aligns with our approach, which consider break detection methods to capture the dynamic nature of Bitcoin's volatility. Similarly, Gorman and Hughen (2024) highlight how Bitcoin's role in investment portfolios has evolved post-COVID-19 due to changing correlation patterns, reinforcing the need to reassess traditional volatility models. Building on this, Alam *et al.* (2024) demonstrate that incorporating structural breaks in monetary policy improves volatility forecasting, a perspective that complements our methodology. Additionally, Teterin and Peresetsky (2024) explore alternative data sources, such as Google Trends, to enhance prediction accuracy. Our study extends this growing body of work by applying a more robust break detection technique to Bitcoin's volatility data, aiming to provide a clearer picture of its structural shifts and market behaviour.

The study reveals that Bitcoin market dynamics are influenced by investor mood and external shocks, supporting major financial theories such as market efficiency, risk management, and volatility modeling. The persistence of volatility aligns with long-memory processes in financial time series, impacting portfolio risk assessment and hedging strategies. These findings are crucial for investors, financial institutions, and governments, as they can improve trading methods by incorporating structural break detection into risk models. The paper provides a comprehensive view of Bitcoin market dynamics and their economic implications.

5. Conclusion

The aging of the Bitcoin market underscores the importance of anticipating the next shock pattern. The study used big data to analyze high-frequency volatility data in the BTC market, which has experienced significant price fluctuations and volatility throughout its history. The GARCH (1,1) model was used to estimate the conditional volatility of BTC log-returns, considering both normal and heavy distributions. The study found that the GARCH (1,1) model with ged performed better than assuming norm and std distributions. The indicator saturation approach was used to identify historical daily breaks, trend breaks, and outliers in each volatility. The findings revealed that heavy tail volatility datasets had fewer outliers and breaks, but more trend breaks. The study demonstrates that the market has fluctuated, leading to sharp price swings, especially in years with strong market activity like 2017 and 2021. However, a trend towards market maturity and less speculative trading is evident in the drop in volatility counts in 2022 and 2023.

The IS approach estimators—IIS (outliers), SIS (structural breaks), and TIS (trend breaks)—behave differently across the three volatility models produced from GARCH-norm, GARCH-std, and GARCH-ged. Overall, IIS detects the most outliers in all models, indicating frequent outliers in Bitcoin returns, although SIS and TIS differ more significantly between models. GARCH-ged consistently detects the greatest number of IIS, SIS, and TIS, indicating a stronger ability to detect market turbulence and regime shifts. GARCH-STD finds a moderate number of breaks, outperforming GARCH-norm but falling short of GARCH-ged, especially when it comes to spotting trend breaks. GARCH-norm, on the other hand, detects the fewest breaks across all categories, demonstrating its limits in detecting structural changes. Furthermore, GARCH-ged gets the highest log-likelihood (LL) and the lowest AIC and BIC values, indicating a superior match. This is consistent with its effectiveness in detecting volatilityinduced breaks, making it the most robust model for capturing outliers, structural shifts, and trend breaks in Bitcoin return dynamics.

By spotting and comparing the historical fluctuations of various conditional volatility datasets, this study emphasizes the necessity of knowing the complexity of Bitcoin volatility. This result provides essential information for investors, researchers, and regulators as they negotiate the complexity of the emerging bitcoin market. understanding volatility patterns and movements can help risk managers improve their strategies and make better decisions in this volatile environment. This analysis is limited to the standard GARCH methodology and focuses solely on BTC, making it an essential tool for financial decision-making and risk assessment. This study relies solely on ten years of daily Bitcoin conditional volatility data, and the dataset excludes external macroeconomic factors. Additionally, the assumptions underlying the GARCH (1,1) model and IS technique may not fully capture nonlinear dependencies or structural shifts in Bitcoin markets.

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