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Analyzing Cryptocurrency Volatility Data for Breaks, Trend Breaks, and Outliers using the Indicator Saturation Method

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ABSTRACT

Blockchain technology sank a volatile market. Extracting volatility insights from real-time cryptocurrency price data using advanced methods is a problem that needs to be addressed. The cryptocurrency market is volatile and subject to enormous swings in value. Thus, this study examines the daily volatility of five cryptocurrency markets, including Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Tether (USDT), and Ripple (XRP), for the last ten years. The volatility data obtained from the GARCH (1,1) model was used to identify daily breaks, trend breaks, and outliers using the indicator saturation (IS) method. The IS method identified a total of 24 outliers, 91 structural breaks, and 305 trend breaks across the cryptocurrency volatility data over the last decade. Of which BTC had 111 daily breaks, trend breaks, and outliers, compared to LTC's 101, ETH's 74, XRP's 71, and USDT's 63. Fluctuations occurred each year, mostly in 2017, 2018, 2020, and 2021, due to legal uncertainty, security issues, and initial coin offers (ICOs). The COVID-19 pandemic in 2020 also caused economic uncertainty and increased volatility. These findings can aid in improving volatility models by comprehending how various events affect financial markets. Authorities and decision-makers may also ensure financial stability. This study sheds light on how future money and virtual currencies may affect financial technology. Our analysis shows that the market has been risky for a decade.

1. Introduction

Volatility is an important consideration when assessing risk. Investors need to understand how asset variations change over time to estimate risk. Volatility is used, for instance, to price securities and calculate market risk. Hence, it is beneficial to analyze the history of volatility variations. Brooks [1] defined volatility as the degree to which a series is highly inconsistent over time, as evaluated by its standard deviation or variance. In financial applications, volatility is typically classified into three categories based on the data sources used: implied volatility, realized volatility, and conditional volatility [2]. This study uses conditional volatility, known as the conditional standard deviation of

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daily returns. Models like the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) of Bollerslev [3] are frequently utilized to estimate conditional volatility.

Financial datasets, such as cryptocurrencies, are known for extreme price fluctuations and high volatility that persist. When focusing solely on cryptocurrency returns, the trends might not be as apparent. So, focusing on cryptocurrency volatility directly enables a more detailed risk assessment. In this study, the standard GARCH (1,1) model, which assumes normal errors, serves as a tool to estimate the volatility of the cryptocurrency market. So, spotting breaks, trend breaks, and outliers in the volatility data of such a highly volatile market is interesting. However, because financial markets are dynamic, there are underlying factors that determine whether volatility can shift over time. Significant events, such as financial crises, abrupt changes in market regimes, or investor sentiment, are examples of structural changes that represent abrupt changes in the properties of financial time series data [4]. Significant macroeconomic changes can link to shifts in financial market volatility [5-6]. These interruptions can significantly impact the reliability of risk assessments and volatility forecasts. In addition, an outlier is a data point that considerably deviates from the other observations in a data sample, while a trend break is a form of break counted as a trend.

Cryptocurrency is a digital or virtual version of money that uses cryptography to safeguard financial transactions, regulate the creation of new units, and verify the transfer of assets. Cryptocurrencies run on decentralized networks based on blockchain technology, unlike conventional currencies issued by governments (such as dollars or euros). Bitcoin, the first and most well-known cryptocurrency, was developed by Satoshi Nakamoto in 2008 [7]. Since the creation of Bitcoin, tens of thousands of additional cryptocurrencies have been created, each with its unique traits, objectives, and underlying technologies. Ethereum, Litecoin, Ripple, and Tether are other well-known examples. Kaseke et al. [8] found that cryptocurrencies have the most characteristics of financial data, including fat tails, volatility clustering, asymmetry, and persistency.

According to Asmawi et al. [41], cryptocurrencies are a prime example of how cutting-edge technologies like blockchain may be used to facilitate safe transactions in the ever-changing cryptocurrency markets. This demonstrates how blockchain is revolutionizing a number of sectors, including finance. Additionally, in highly turbulent markets, risk management strategies can be improved by examining volatility patterns using advanced approaches like GARCH models and detecting historical volatility shifts through the IS approach. Cryptocurrencies are extremely volatile, and GARCH models are frequently applied in these situations [42]. When assessing volatility from their technical values, blockchain technologies must have a thorough understanding of volatility variations in order to evaluate risks and changes appropriately. According to Nakamoto [7], there would be no security breaches on blockchain networks. However, because the blockchain network relies on trust, numerous experts and observers noted that cyberattacks will probably undermine it in several ways [43]. In contrast, algorithmic trading techniques frequently employ volatility models to maximize buy and sell decisions. Blockchain protocols can be modified with the use of volatility insights to reduce the risks brought on by extreme price swings.

Recent studies have revealed that the cryptocurrency market has seen significant volatility and structural break [9-11]. According to Zhang et al. [12], Katsiampa et al. [13]), and Hu et al. [14]), the severe volatility of the cryptocurrency market can be linked to numerous variables, including speculation, a lack of regulation, and unfavorable news. They all continue to emphasise the highly volatile character of the cryptocurrency market. This attracted the application of different statistical techniques that have been considered in the literature to detect breaks and outliers in such volatile data. For example, break tests used include Bai and Perron [15-16], known as the BP test, the Iterative cumulative sum of squares of Iclan and Tiao [17], known as ICSS, and Kokoszka and Leipus [18] approach, known as KL. Consequently, the most common tests that consider outliers within the GARCH framework include approaches by the following authors [19-22].

The earlier research raised several concerns: Firstly, they focused on identifying only one feature—a break or an outlier in the returns or prices. Second, to identify breaks and outliers they used different tests that were subject to limitations based on the results they provided. Third, there is a possibility of masking breaks and outliers. Durdag et al. [23] state that outliers in time series can have smearing and masking effects. The former refers to the possibility that some outliers could skew diagnostics. The latter is linked to the existence of significant outliers that obscure the presence of others. Rodrigues and Rubia [24] demonstrated how additive outliers may mask the existence and number of prospective breaks, causing outliers to cause massive size distortions in break detection methods. Fourth, most of the studies did not consider the volatility data generated from the GARCH model. Thus, the issue that this work aims to solve is the detection and dating of structural breaks, trend breaks, and outliers in the conditional volatility data of cryptocurrencies.

This study analyses high-frequency daily cryptocurrency volatility data to reveal market dynamics during the dramatic volatility shifts across major digital assets from 2014 to June 2023. So, this study aims to detect breaks, trend breaks, and outliers in the daily volatility data of the five cryptocurrencies over a long period by applying the indicator saturation (IS) approach. Detecting breaks, trend breaks, and outliers in volatility data is challenging due to noise in financial data and the need to differentiate between real and random fluctuations, especially in cryptocurrencies with high volatility persistence. Considering cryptocurrency data and applying the IS approach will make this study different from others. The indicator saturation approach of Hendry [25], known as the IS approach, is used to detect breaks, outliers, and trend breaks concurrently.

The IS approach's ability to simultaneously identify breaks and outliers addressed a limitation in previous tests. For example, in a BP test, it cannot detect breaks and outliers together and requires trimming, which leads to a minimum break length. Testing breaks also require knowing the break date for cumulative sum (CUSUM) tests. For both leptokurtic and platykurtic innovations, the ICSS algorithm exhibits significant size distortion. The IS method does not require a break, a trend break, or an outlier to be known in advance; it does not restrict a segment; hence, it detects breaks, trend breaks, and outliers at any location in the data.

In the literature, the IS method has been considered. This method combines different estimators to detect different nonstationary aspects. In their study, Pretis et al. [30] evaluated the IIS and SIS methodologies by analysing a time series of Northern Hemisphere mean temperature data over a period of approximately 1200 years. Ghouse et al. [36] utilised IIS as a tool to detect disruptions caused by COVID-19 in the returns and volatility patterns of Islamic banks in Pakistan, with the aim of forecasting the volatility series. The results indicate that all the events due to COVID-19 are significant. Che Rose et al. [37] used IIS to identify outliers in the Financial Times Stock Exchange (FTSE) of the United States of America (USA) shariah index. Interestingly, the findings aligned with the financial crisis that occurred during 2008–2009. Nasir and Ismail [38] utilised IIS in the Malaysian Shariah-compliant index. The analysis identified 47 outliers, attributed to significant global events such as the global financial crisis of 2008 and 2009, the stock market decline in 2011, the United States debt-ceiling crisis in 2013, and the decline in international crude oil prices in 2014.

By tackling this issue, this study contributes the comprehensive detection of the volatitliy dynamics in cryptocurrency markets. It offers valuable resources for investors, portfolio managers, and risk analysts to modify their strategies in response to shifting market circumstances. According to Aharon et al. [26], knowing the dynamics of the volatility of cryptocurrency values is essential for investing in the financial markets and determining policy.

Currently, the GARCH model is one of the most advanced systems for extracting conditional volatility series from financial markets, successfully capturing time-varying volatility patterns. The use of GARCH models to examine the volatility of the cryptocurrency market highlights important insights for the field of applied science and technology journals. It illustrates how cutting-edge statistical techniques and cutting-edge technologies like blockchain may coexist. In terms of detecting structural breaks, trend breaks, and outliers, previous researchers used single-type tests such as the Chow, BP, and ICSS tests, among others. One limitation of such tests is that they separately detect structural breaks and outliers. In contrast, we propose the IS approach, an advanced technique that can detect three different types of changes simultaneously, such as breaks, trend breaks, and outliers. Furthermore, identifying different change points from such advanced technologies in volatility series provides more insight into market dynamics. The remaining parts of the paper are organized as follows: Section 2 covers the methods and methodology, Section 3 discusses the study's results, and Section 4 concludes the study.

2. Methodology

2.1 Datasets

The dataset employed is the daily closing prices of five different cryptocurrencies: Tether (USDT), Litecoin (LTC), Ripple (XRP), Ethereum (ETH), and Bitcoin (BTC). The data were retrieved from the Yahoo financial website, https://finance.yahoo.com/. The total number of observations for BTC starting on November 22, 2014, LTC starting on September 22, 2014, and XRP, ETH, and USDT starting on November 13, 2017, are 3143, 3204, and 2056, respectively, and all prices are through June 30, 2023. The data start date was chosen based on data availability, and these coins were chosen based on the dates of their releases. BTC has the largest market capitalization, at $540 billion. ETH is the second most valuable cryptocurrency behind Bitcoin, with a market worth of $198 billion. With a market cap of $83 billion, USDT ranks third among all cryptocurrencies. While XRP is ranked fifth with $28 billion, and LTC is ranked fifteenth with $4.7 billion. All market capitalization values are from the market capital website accessed on October 5, 2023. The study used log-returns of prices by the formula:

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

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.

2.2 Volatility Model

A typical GARCH (1,1) model for returns is used to assess the data's most significant stylized facts and investigate the volatility persistence of the five cryptocurrencies under study. The GARCH (1,1) model has shown satisfactory performance in forecasting time series data in recent years [27-29]. The conditional mean can be illustrated as:

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

where $\varepsilon_t = \eta_t \sigma_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$ and $\eta_t \sim \mathrm{i.i.d}\ N(0,1)$. Moreover, the conditional variance of ε_t is given by

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (3)$$

To guarantee that the conditional variance is positive and the existence of the GARCH process, the parameters must meet at least $\omega > 0$ and $\alpha, \beta \geq 0$. If $\alpha + \beta < 1$, the process is stationary; nevertheless, if their sum is near to 1 it shows the presence of a shock likely to be highly persistent. The Integrated GARCH (IGARCH) process, in which shocks have a lasting impact on volatility, is indicated if their sum is exactly 1. The unconditional variance of ε_t for a stationary GARCH (1,1) is given by $\frac{\omega}{1-\alpha-\beta}$. The series exhibits conditional homoscedasticity when $\alpha = 0$ and β is set to 0. Maximum likelihood estimators (MLE) are used to estimate the parameters.

2.3 Indicator Saturation Approach

Indicator saturation (IS) offers an alternate strategy to other break detection approaches, which employs an extended general-to-specific methodology based on model selection. Without specifying a minimum break duration, maximum break number, or forced co-breaking, structural breaks can be recognized by starting with a full set of step indicators and leaving only the most significant ones [30]. Hendry et al. [31] recommend the General Unrestricted Model (GUM) methodology to capture the occurrence of many structural breaks or level changes.

The indicator saturation approach that Hendry [25] developed is thus used in this work to identify breaks, trend breaks, and outliers in the cryptocurrency volatility data. The impulse indicator saturation (IIS) technique was first created by Soren et al. [32] to identify outliers with uncertain numbers, magnitudes, and timing in the sample and the start and end of observations. A unique dummy variable is created for each observation, yielding one dummy variable per observation. The sample data is divided into two or more sections to make the number of observations exceed the number of parameters. Only the crucial dummies have been discovered. The step indicator saturation (SIS) method, however, is a modified version of IIS techniques for multiple breaks.

The IS approach has different estimators for specific feature detection. The IS technique is a border term that concurrently estimates the underlying modeling and finds outliers (via IIS), multiple break shifts (by SIS), and trend breaks (by trend indicator saturation, or TIS). IIS, SIS, and TIS are general estimators for any location in the sample of an unknown quantity of structural changes happening at an unknown time, with an unknown duration and amplitude [33]. Pretis et al. [34] formulated general unrestricted model (GUM) mean model y_t for IIS, SIS, and TIS. But we reframe it using sigma (σ_t):

$$\text{IIS } \sigma_t = \mu + \sum_{j=1}^{n} \delta_j 1_{\{t=j\}} + \varepsilon_t \quad (4)$$
$$\text{SIS } \sigma_t = \mu + \sum_{j=2}^{n} \delta_j 1_{\{t\geq j\}} + \varepsilon_t \quad (5)$$
$$\text{TIS } \sigma_t = \mu + \sum_{j=1}^{n} \delta_j 1_{\{t>j\}}(t-j) + \varepsilon_t \quad (6)$$

Whereby σ_t stands for volatility data over time, μ for constant term, δ for the magnitude of either break, trend break, or outlier, and ε for errors. So, in this study, starting with the GARCH (1,1) model with a normal distribution, we model the returns of each cryptocurrency. We derived the volatility data from this model, neglecting breaks and outliers in the return series. The retrieved sigma values from this model, σ_t, were treated as a dependent variable and regressed with the constant μ to apply the IS estimators. In addition, we run the three equations simultaneously in a method known as the ultra-saturation indicator, with an alpha value based on the sample size i.e., $\alpha = \frac{1}{T}$.

3. Results and Discussion

A GARCH (1,1) model with normal distribution was employed to model each cryptocurrency return. Then, the daily volatility data obtained from the estimated GARCH (1,1) equations of each cryptocurrency was used as volatility data. The descriptive statistics for the returns series and volatility data are shown in Tables 1 and 2, respectively. Table 3 shows the parameter estimates for the fitted returns of five different cryptocurrencies based on GARCH (1,1).

Table 1
Descriptive Statistics (Returns)

Returns	Mean	Std. Dev	Skewness	Kurtosis	JB	ARCH-LM	ADF test
BTCDR	0.001419	0.038	-0.7895	14.2458	16883*	0.00	0.00
LTCDR	0.001011	0.055	0.103561	15.851	22044*	0.00	0.00
ETHDR	0.000880	0.0497	-0.923868	13.145	9104*	0.00	0.00
USDTDR	-0.0000045	0.004	0.745575	53.31	216890*	0.00	0.00
XRPDR	0.000412	0.062	0.850	20.35	26032*	0.00	0.00

* Significant at 1% with d.f of 2

As in Table 1, the cryptocurrency returns show the typical characteristics of financial data, such as the dominance of a large standard deviation over a small mean. It gauges how widely apart the data points are from one another around the mean. An indicator of greater volatility or variability is a higher standard deviation. The most volatile series are LTC and XRP, while the least volatile series is USDT. Returns are also strongly negatively skewed and have large kurtosis, which is extremely unusual. In a right-skewed distribution, the tail on the right side is longer or fatter than the tail on the left, and the skewness value is positive (higher than 0). A distribution is left-skewed if the skewness value is negative (smaller than 0). There is an outlier, according to kurtosis, which spans from 13.145 for ETH to 53.31 for USDT. Unlike a normal distribution, a distribution with a high kurtosis value has heavy tails or more extreme values in the tails. Based on the ARCH-LM test results, it is evident that the ARCH effect is present in all series, with all p-values indicating a significant impact. Each return was subjected to the Jarque-Bera test, and all the data fell below the threshold of 0.01, providing strong evidence that the null hypothesis of normalcy is false. Strong evidence is found by the ADF test to rule out the occurrence of a unit root, suggesting that the returns are most likely stationary. The augmented Dickey-Fuller test's p-values are all under 0.01.

Table 2
Descriptive Statistics (Volatility Data)

Volatility Data	Mean	Std. Dev	Skewness	Kurtosis
BTC	0.04	0.013	2.36	13.95
LTC	0.05	0.016	2.46	11.50
ETH	0.05	0.013	2.69	16.69
USDT	0.003	0.003	3.06	17.20
XRP	0.06	0.05	3.06	15.79

Table 2 presents a variety of statistical measurements pertaining to the volatility data of the five cryptocurrencies. The volatility data entails the attributes of the return data. The volatility data exhibits positive skewness, which is corroborated by Figure 1 in alignment with Table 2. Moreover, the distribution of the volatility data is leptokurtic, with a mean volatility value of 0.04 for BTC. However, the Jarque-Bera test indicates that the null hypothesis of a normal distribution is rejected. These statistical findings are valuable in discerning the characteristics of the volatility distribution for each coin and can be effectively employed in risk assessment, portfolio management, and financial modeling endeavors.

The parameter estimates for the fitted returns of five different cryptocurrencies are shown in Table 3. These estimates include the coefficients, which are essential for describing the behavior of cryptocurrency. The constant term stands for the long-term or unconditional variance of the returns on the cryptocurrency. All the estimated values in this situation are 0.000, indicating that none of these coins have a constant term in the GARCH model. This indicates that the model considers the GARCH and ARCH terms to be the only factors affecting the long-term variance. This is the calculated coefficient for the ARCH term. It shows how volatility shocks in the past have affected volatility in the present. For instance, the coin BTC shows that historical squared returns have a moderate influence on current volatility. The value is the estimated coefficient for the GARCH term. It shows how historical conditional variances have affected the current level of volatility. For instance, the BTC indicates that conditional variations from the past have an enormous influence on current volatility. So, an increase in this summation value of α and β estimates denotes increased persistence, which suggests that previous volatility shocks had a longer-lasting effect on the coin's present volatility. However, knowing that cryptocurrencies show high persistence, some studies related to the existence of breaks and outliers to these highly persistent estimates. This result is consistent with the research done by Lamoureux and Lastrapes in 1990 [35].

Table 3
MLE for GARCH (1,1)

Crypto	$\hat{\omega}$	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha}+\hat{\beta}$
BTC	0.000	0.136	0.829	0.965
ETH	0.000	0.092	0.869	0.961
LTC	0.000	0.082	0.869	0.951
USDT	0.000	0.146	0.848	0.994
XRP	0.000	0.277	0.722	0.999

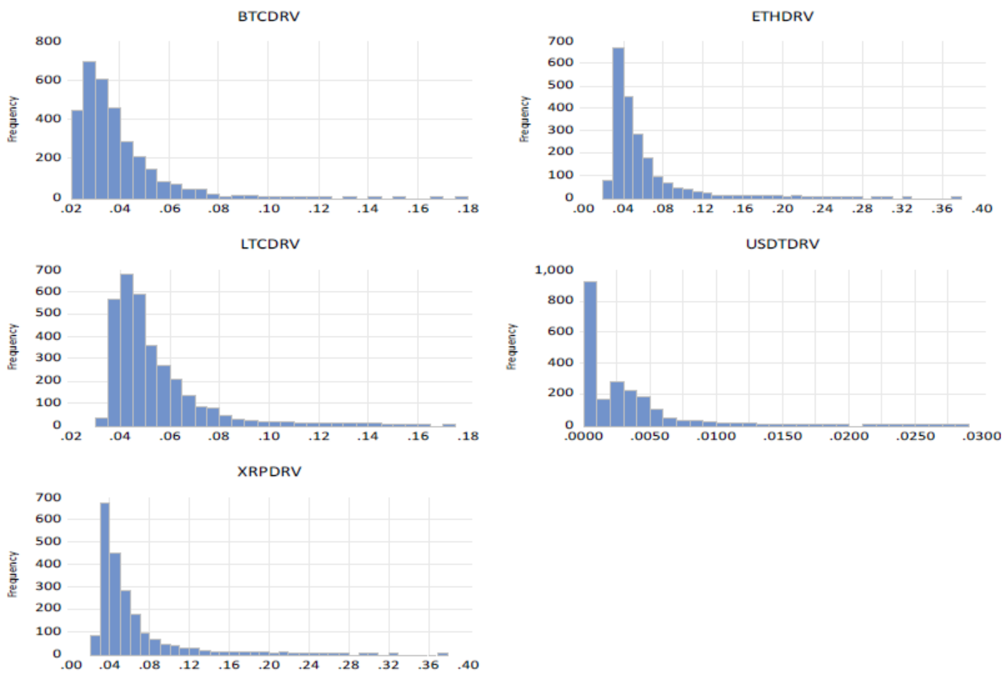

Fig. 1. Histogram for volatility data

We utilized the IS approach that generates dummy variables to detect breaks, trend breaks, and outliers in the volatility data. This was accomplished by considering the volatility data of each cryptocurrency as the response variable and conducting a regression analysis with a constant term. Table 4 demonstrates the overall results, encompassing the utilization of dummy variables (indicators) incorporated within the regression equation and the number of blocks used.

Table 4
IS application framework

Returns	Sample size	Daily		Results		
		Included Observations	Blocks	IIS	SIS	TIS
BTC	3142	9423	105	6	31	74
ETH	2055	6162	69	0	13	61
LCT	3203	9606	107	2	25	74
USDT	2055	6162	69	10	8	45
XRP	2055	6162	69	6	14	51

Table 4 shows that each cryptocurrency's volatility data has more trend breaks than breaks or outliers. When it comes to the return data, this is the opposite. Regarding trend breaks, USDT has 45, XRP has 51, ETH has 61, BTC has 74, and LTC has 74. With an increase in sample size, the trend breaks appear to flow in rising trends, but there will be no difference if the number of trend breaks in each cryptocurrency is divided by its sample size. This would suggest that the market fluctuations are related. The full results for each cryptocurrency are shown in the accompanying tables 5, 6, and 7.

Table 5
IIS Results for Outliers

Series	Alpha	Outliers Dates	Total
BTC	0.0003	12/08/2017(+), 12/09/2017(+), 12/10/2017(+), 3/13/2020(+), 3/14/2020(+), 3/15/2020(+)	6
ETH	0.0005	No	0
LTC	0.0003	7/11/2015(+),12/13/2017(+)	2
USDT	0.0005	12/13/2017(+),12/14/2017(+),12/15/2017(+),12/16/2017(+),12/17/2017(+) 12/18/2017(+),12/25/2017(+),1/20/2018(+),3/13/2020(-),3/14/2020(+)	10
XRP	0.0005	12/15/2017(+),12/16/2017(+),12/17/2017(+),12/22/2017(+),12/23/2017(+), 11/22/2020(+)	6

Table 6
SIS Results (Breaks)

Series	Alpha	Break Dates	Total
BTC	0.0003	1/04/2015(+),8/21/2015(+),8/30/2015(-),11/03/2015(+),11/18/2015(-),1/27/2016(-), 5/29/2016(+), 1/21/2017(-), 3/30/2017(-),7/27/2017(-),9/15/2017(+), 11/10/2017(+), 12/08/2017(+),2/06/2018(+),5/07/2018(-),11/20/2018(+), 4/01/2019(+),5/12/2019(+), 5/29/2019(-),6/28/2019(+),7/25/2019(-),3/13/2020(+), 6/07/2020(-),7/24/2020(+), 10/22/2020(+),5/20/2021(+), 7/04/2021(-),3/20/2022(-),6/15/2022(+), 11/12/2022(+), 4/01/2023(-)	31
ETH	0.0005	12/15/2017(-),4/03/2019(+),7/26/2019(-),3/13/2020(+),4/25/2020(-),1/04/2021(+), 2/12/2021(-),3/17/2021(-),5/20/2021(+),6/06/2021(-),10/08/2021(-),6/14/2022(+), 9/28/2022(-)	13
LTC	0.0003	1/04/2015(+),2/21/2015(-),5/21/2015(+),6/17/2015(+),8/29/2015(-),10/18/2015(+), 8/13/2016(+),12/24/2016(+),3/31/2017(+),6/17/2017(+),9/15/2017(+), 12/09/2017(+), 12/12/2017(+),2/04/2018(+),2/27/2018(-),5/06/2018(-),11/02/2018(-),8/04/2019(-), 3/13/2020(+),4/04/2020(-),7/23/2020(+),1/19/2021(-),5/13/2021(+),5/20/2021(+), 5/14/2022(+)	25

USDT	0.0005	12/01/2017(+),12/15/2017(+),4/06/2018(-),8/12/2018(+),11/15/2018(+),1/16/2019(-), 12/04/2019(-),3/13/2020(+)	8
XRP	0.0005	12/13/2017(+),1/09/2019(-),7/20/2019(-),3/13/2020(+),11/29/2020(-), 12/24/2020(+), 1/31/2021(+),4/06/2021(+), 4/16/2021(-),4/27/2021(+), 5/20/2021(+),5/27/2021(-), 6/22/2021(+),6/26/2021(-)	14

As evidenced by the results in Tables 5, 6, and 7, utilizing the SIS estimator allowed us to successfully identify and timestamp 91 daily breaks across the five coins. Moreover, employing the IIS estimator led to the detection 24 daily outliers, while the TIS estimator revealed 305 daily trend breaks over the previous years. It is worth noting that all 24 outliers detected were positive. Specifically, BTC exhibited six outliers in 2017 and 2020, LTC had two outliers in 2015 and 2017, USDT had ten outliers in 2017, 2018, and 2020, and XRP had six outliers in 2017 and 2020. Conversely, ETH displayed no outliers during the analyzed period. Of the 91 breaks identified, 53 were positive, whereas 38 were negative. BTC demonstrated 31 breaks in 2015, 2016, and 2017, while ETH exhibited 13 breaks in 2017, 2019, 2020, 2021, and 2022, indicating a recurring pattern of breaks in ETH almost every year. Similarly, LTC displayed 25 breaks consistently throughout the years. USDT demonstrated eight breaks in 2017, 2018, 2019, and 2020, while XRP exhibited 14 breaks, primarily in 2017, 2019, 2020, and 2021. Regarding the 305 trend breaks, with 145 being positive and 120 being negative, BTC and LTC each displayed 74 breaks, while ETH exhibited 61, XRP had 51, and USDT had 45. These trend breaks were observed on an almost yearly basis. Overall, the analysis conducted on the coins illustrates the effectiveness of the SIS, IIS, and TIS estimators in identifying daily breaks, outliers, and trend breaks, respectively. By doing so, we have responded to the subsequent inquiry regarding the possibility of identifying them simultaneously.

Table 7

TIS Results (Trend Breaks)

Series	Alpha	Trend Break Dates	Total
BTC	0.0003	1/13/2015(+),1/16/2015(-),1/22/2015(+),2/13/2015(+),3/17/2015(+),3/25/2015(-), 4/04/2015(+),6/21/2015(+),8/21/2015(-),9/17/2015(+),11/13/2015(-),1/15/2016(+), 1/16/2016(-),3/16/2016(+),6/12/2016(+),6/23/2016(-),8/02/2016(+),8/03/2016(-), 9/12/2016(+),11/12/2016(-),12/12/2016(+),1/04/2017(+),1/07/2017(-),2/08/2017(+), 3/16/2017(+), 3/19/2017(-),5/08/2017(+),5/11/2017(-),6/13/2017(-),7/14/2017(+), 7/21/2017(-),9/02/2017(+),9/15/2017(-),10/06/2017(+), 12/08/2017(-),2/06/2018(-), 3/07/2018(+),7/18/2018(-),11/04/2018(+),11/30/2018(-),12/02/2018(+),1/31/2019(+), 2/26/2019(-),9/23/2019(+),9/25/2019(-),10/25/2019(+),10/26/2019(-),11/21/2019(+), 3/13/2020(-),4/06/2020(+),10/22/2020(+),1/01/2021(+),1/14/2021(-),1/21/2021(+), 1/22/2021(-),4/18/2021(+),5/22/2021(-),6/19/2021(+),9/23/2021(-),11/16/2021(+), 12/06/2021(-),1/15/2022(+),3/02/2022(-),4/15/2022(+),5/12/2022(-),6/16/2022(-), 7/01/2022(+),8/14/2022(+),9/15/2022(-),10/13/2022(+),11/12/2022(-),11/20/2022(+), 12/12/2022(+), 4/11/2023(-)	74
ETH	0.0005	12/13/2017(+),12/15/2017(-),1/13/2018(+),2/11/2018(-),3/06/2018(+),3/15/2018(-) 4/27/2018(-),5/15/2018(+),6/13/2018(-),8/06/2018(+),8/11/2018(-),9/04/2018(+), 9/15/2018(-),10/09/2018(+),10/13/2018(-),11/11/2018(+),11/21/2018(-), 12/17/2018(+),30/2018(-),1/08/2019(+),1/11/2019(-),2/05/2019(+),2/17/2019(-),5/08/2019(+),5/16/2019(-),6/08/2019(+),7/15/2019(-),9/06/2019(-),9/07/2019(+), 9/26/2019(-), 11/07/2019(+),2/02/2020(+),3/13/2020(-), 4/02/2020(+), 7/21/2020(+), 7/31/2020(-), 8/30/2020(+),9/06/2020(-), 9/30/2020 (+), 11/01/2020(+),11/28/2020(-),1/28/2021(-), 1/29/2021(+),4/26/2021(+),5/20/2021(-),6/20/2021(+),6/28/2021(-),7/27/2021(+), 9/26/2021(-),12/24/2021(-),12/26/2021(+),1/22/2022(-),4/24/2022(+), 5/13/2022(-), 6/20/2022(-),6/24/2022(+),11/08/2022(+),11/11/2022(-),11/20/2022(+), 12/13/2022(+), 3/19/2023(-)	13

LTC	0.0003	11/21/2014(-),12/16/2014(+),12/17/2014(-),1/03/2015(+),1/20/2015(-),1/22/2015(+), 1/26/2015(-), 2/09/2015(+),5/21/2015(-),6/17/2015(-),6/22/2015(+), 7/08/2015(+), 7/12/2015(-),7/22/2015(+), 8/08/2015(+), 1/15/2016(+),1/16/2016(-),2/16/2016(+), 6/22/2016(+),6/23/2016(-),8/13/2016(+),12/24/2016(-),2/09/2017(+), 3/31/2017(-), 5/03/2017(+),5/04/2017(-),5/11/2017(+), 5/27/2017(-),7/02/2017(+),8/23/2017(+), 9/08/2017(-),10/06/2017(+), 11/05/2017(+),12/13/2017(-),1/05/2018(+),1/07/201 (-), 3/06/2018(+),9/03/2018(-),11/01/2018(+),11/21/2018(-),6/11/2019(+),7/18/2019(-), 1/14/2020(+), 1/15/2020(-),3/13/2020(-),3/28/2020(+),9/03/2020(+),9/04/2020(-), 9/22/2020(+), 11/16/2020(+), 11/18/2020(-),2/24/2021(-),4/03/2021(+),4/12/2021(-), 5/20/2021(-),6/16/2021(+),6/22/2021(-),7/19/2021(+),9/21/2021(-),10/17/2021(+), 11/17/2021(-),1/15/2022(+), 2/14/2022(-),3/16/2022(+),5/12/2022(-),8/13/2022(+), 9/12/2022(-),10/12/2022(+), 11/11/2022(+),11/12/2022(-),12/12/2022(+), 2/09/2023(+), 3/16/2023(-),4/10/2023(+)	74
USDT	0.0005	11/29/2017(+),12/14/2017(-),1/13/2018(+),2/11/2018(-),3/03/2018(+), 3/15/2018(+), 3/16/2018(-),5/14/2018(-),5/15/2018(+),7/13/2018(-),8/12/2018(+),10/10/2018(+), 11/13/2018(+),11/24/2018(-),12/09/2018(+),2/06/2019(+),5/09/2019(-),6/08/2019(+), 7/18/2019(-),8/04/2019(+),8/08/2019(-),9/03/2019(-),9/07/2019(+),10/13/2019(-), 11/05/2019(+),12/19/2019(-),2/04/2020(+),3/13/2020(-),4/04/2020(+), 5/06/2020(+), 5/07/2020(-),6/01/2020(+),7/01/2020(+),7/05/2020(-),7/31/2020(+), 8/14/2020(+), 8/15/2020(-),8/30/2020(+),10/01/2020(+),3/30/2021(+),4/28/2021(+),5/10/2021(+), 2/18/2023(+),3/19/2023(-),4/18/2023(+)	45
XRP	0.0005	12/13/2017(-),12/29/2017(+),12/30/2017(-),1/08/2018(+),1/09/2018(-),1/16/2018(+), 1/17/2018(-),1/26/2018(+),2/11/2018(-),2/17/2018(+),4/14/2018(-), 7/14/2018(+), 8/18/2018(-) ,9/18/2018(+),9/22/2018(-),10/02/2018(+),10/13/2018(-),10/23/2018(+), 1/09/2019(-), 5/14/2019(+),5/15/2019(-),5/25/2019(+-),3/13/2020(-),3/25/2020(+), 5/31/2020(+), 7/31/2020(-), 11/20/2020(+),11/24/2020(-),12/24/2020(-), 12/30/2020(+), 1/31/2021(-), 2/10/2021(+),3/20/2021(+),3/26/2021(-), 6/28/2021(+),9/08/2021(-), 10/16/2021(+), 2/26/2022(-), 3/24/2022(+), 5/09/2022(+), 5/12/2022(-),5/23/2022(+),8/21/2022(+), 9/23/2022(-), 11/08/2022(+),11/11/2022(-),11/18/2022(+),11/29/2022(+), 3/21/2023(+),3/22/2023(-), 4/07/2023(+)	51

The summarized results from tables 5, 6, and 7 are as follows: First, cryptocurrency returns exhibit high volatility persistence values, indicating the existence of breaks and outliers. Second, the standard GARCH (1,1) model will provide volatility data with higher fluctuations, which can be attributed to the high persistence resulting from ignoring breaks and outliers in the returns. Thirdly, each cryptocurrency volatility data has shown breaks, trend breaks, and outliers (except for ETH). Fourthly, the conditional volatility data has fewer outliers and breaks but significantly more trend breaks. In addition, the yearly total of breaks found throughout five coins, as well as the yearly total of outliers found over the course of five coins and the yearly total of trend breaks found over the course of five coins, are shown in the accompanying figure 2.

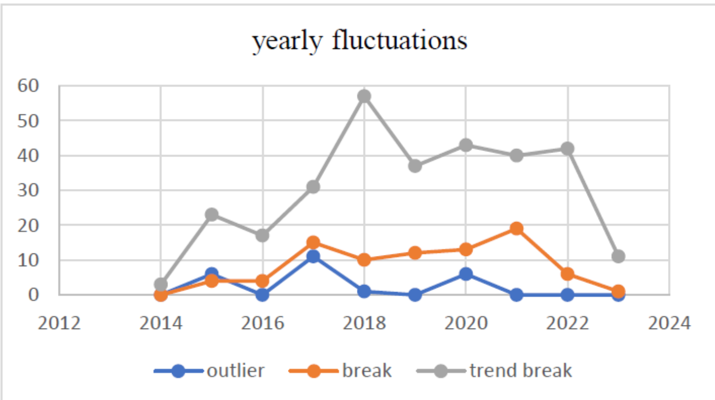

Fig. 2. Cryptocurrency Market Yearly Fluctuations

Figure 2 illustrates the fluctuations in volatility observed in the digital currency market. Every year, there are variations in the level of market volatility. The figure also illustrates the overall outcomes of the IIS methodology across the five markets, along with the aggregate results of the SIS and TIS methodologies for the same markets. We measure the totals annually. Consequently, we observe that the TIS approach produces the highest results when considering the yearly performance of the three estimators. Additionally, regarding annual fluctuations, 2018, 2020, and 2021 exhibit the most variability.

These dates line up with times when there were more volatility swings and market turmoil in the digital coin space. For instance, in 2015-2016, there was a significant rebound in the oil price, which fell from 106 USD to 45 USD [39]. Similarly, in 2017, both ETH and BTC began their ascent to reach their consistently high values. In 2018, the market capitalization of the crypto market decreased by 80%, as reported by Harbe et al. [40]. In 2019, the occurrence of the first cryptocurrency hack in New Zealand and the investment in an initial coin offering (ICO) coincided [39]. The COVID-19 pandemic began on March 11, 2020, and continued throughout 2021. In 2022, the Bitcoin market had significant declines in June and November, resulting in losses of $18,000 and $20,000, respectively, due to unfavorable news and threats. In addition, in 2020 for the COVID-19-related events, the dates mentioned in the input coincide with significant occurrences. China implemented lockdowns in Wuhan and other cities in late January 2020, followed by many countries in Europe, North America, and other regions implementing their own lockdowns in March and April 2020. The first major cryptocurrency market crash, known as "Black Thursday," happened on March 12, 2020, as the COVID-19 pandemic escalated globally. This crash resulted in major cryptocurrencies experiencing price declines of over 30-40%. The lockdowns and movement restrictions imposed in early 2020 also had an impact on crypto trading and usage patterns. March 19, 2020, marked the first outbreak of COVID-19.

Although traders may be able to profit from volatility fluctuations due to this phenomenon, there is also an increased risk involved. On the other hand, low volatility may point to a more secure and less unstable environment for the coin market. Gaining knowledge about the causes and events of volatility greatly impacts trading and investing techniques. In the financial markets, identifying historical breaks, trend breaks, and outliers in volatility data is essential for several reasons, such as risk management, trading strategy creation, and comprehension of market behavior. Investors may manage risk effectively, traders can spot profit opportunities during stormy times, and long-term investors can make wise asset allocation decisions by recognizing these breaks, trend breaks, and outliers. It supports the development of hedging strategies, event analysis, and quantitative modeling, all leading to better investing results. It also contributes to market stability and regulatory compliance, making it a crucial component of financial decision-making and risk assessment for various financial products. All these benefits increase market trust.

4. Conclusions

This study detected and dated breaks, trend breaks, and outliers in the cryptocurrency volatility data. The study first used a typical GARCH (1,1) model under a normal distribution to model each cryptocurrency's returns, and it found that these returns are highly persistent. The study was based on the fact that breaks and outliers simultaneously impact volatility persistence. The study next applied the indicator saturation technique to the volatility data produced from the GARCH (1,1) model. It simultaneously ran the IIS, SIS, and TIS estimators to find breaks, trends, and outliers in the volatility data. The result discovered the existence of breaks, trend breaks, and outliers in each cryptocurrency volatility dataset. The three years 2018, 2020, and 2021 show the most fluctuations related to the fact that BTC reached its all-time high, together with the COVID-19 pandemic in 2021 and initial coin offers (ICO) in 2017. The volatility data also revealed that positive trends outnumbered negative ones.

However, one can acquire insights about increased market risk and uncertainty by finding breaks, trend breaks, and outliers in the volatility data. These insights can be important for risk management methods, portfolio allocation, and option pricing. It helps investors identify critical moments associated with monetary crises, significant market occurrences, or government policy announcements. The findings of this study contribute to the field of financial econometrics by providing empirical evidence of frequent breaks and outliers in the volatility data for cryptocurrencies. Understanding how different events affect financial markets can help strengthen volatility models. Decision-makers and authorities may also ensure financial stability. This study is limited to using standard GARCH and only considering five coins.

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