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Cryptocurrency Returns Over a Decade: Breaks, Trend Breaks and Outliers

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Abstract: This study finds breaks, trend breaks, and outliers in the last decade returns of five cryptocurrencies Bitcoin, Ethereum, Litecoin, Tether USD, and Ripple that experienced frequent changes. The study uses the indicator saturation (IS) approach to simultaneously identify breaks, trend breaks, and outliers in these returns to gain a deeper understanding in their dynamics. The study found that monthly, weekly and daily breaks existed in these returns as well as trend breaks, and outliers mostly during the market peaks in 2017, 2018, 2020, and 2021 that can be attributed to a number of things, such as the global Covid-19 pandemic in 2020, the 2021 crypto crackdown in China, the 2020 price halving of Bitcoin, and the 2017–2018 initial coin offering (ICO) boom. These returns also have common break segments and outliers. The application of IS technique to cryptocurrencies and simultaneous detection of market breaks, trend breaks, and outliers makes this study unique. This study is limited to considering only returns of five digital coins. These results may help traders, investors, and financial analysts modify their tactics and risk-management techniques to deal with the complexity of the cryptocurrency market.

Keywords: breaks; trend breaks; outliers; cryptocurrency; indicator saturation.

JEL classification: C12; C58; G14.

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1. INTRODUCTION

Finding structural changes in the financial time series data has drawn a lot of attention in the literature. Structural changes in the prices of cryptocurrencies have drawn interest during the last ten years. Thus, its movements must be observed every ten years to record its behavior. A significant emphasis is being placed on adapting traditional approaches to the characteristics of the cryptocurrency market by following the historical evolution of breaks, trend breaks, and outliers in the market. From the beginning of cryptocurrency to the present, the ability to recognize outliers and breaks has changed in reaction to the environment, including technological improvements.

Conversely, analyzing past challenging periods allows for identifying both market instability and coinciding events. Cryptocurrency is a type of electronic cash that can be exchanged through a computer system and is run decentralized. In 2008, Bitcoin was created. A person or organization going by the name Satoshi Nakamoto released the Bitcoin whitepaper in 2008, titled Bitcoin: A Peer-to-Peer Electronic Cash System (Nakamoto, 2008). Since the financial crisis 2008, cryptocurrencies have attracted attention on a global scale and are regarded as a novel type of tradeable speculative asset. Since then, the cryptocurrency market has shown significant price fluctuations over time and the development of other coins. Since computer networks and open-source software govern cryptocurrencies, they are decentralized currencies that are not controlled by any authority. Price changes can greatly impact investors due to its structure. For example, 1 Bitcoin (BTC) cost $767 on January 1st, 2014. In 2015, 1 BTC was substantially cheaper, at $313. In 2017, the price of 1 BTC rose to $998. The price of one bitcoin increased in 2018, reaching $14,093. In 2019, the price of 1 BTC dropped to $3,692. The price of 1 BTC increased to $7,195 in 2020. In 2021, the price of 1 BTC significantly increased to $29,072. The price of 1 BTC increased significantly again in 2022, reaching $46,319 in value. In 2023, the price of 1 BTC fell to $16,540. Other cryptocurrencies released later mostly show similar price fluctuations. Figure no. 1 is an illustration of Bitcoin daily price fluctuations over the last 10 years, totaling 3143 days.

Figure no. 1 – Bitcoin Daily Prices

Throughout this study, we use the following definitions consistently. A structural break refers to a change in how a variable behaves over time, such as a spike in the money stock or a deviation from the prior pattern of relationships between observable variables (Castle and Hendry, 2019). On the other hand, outliers are referred to as data points that do not follow the trend of the other observations and deviate significantly from the fitted model (Brooks, 2019). A trend break is a discrete point in time period *t* when there is a noteworthy deviation or shift in a time series' underlying trend. The trend is expected to follow a given pattern or direction before to the defined date, but at the designated period, a structural change occurs, resulting in a new trend. Structural breaks and outliers are generally connected to financial crashes, wars, natural disasters, and attacks. Breaks in the financial market can be linked to important macroeconomic events (Andreou and Ghysels, 2002; Ahmed, 2018). Some studies have found breaks based on newspaper reports (Zarei *et al.*, 2015). For instance, breakpoints for the Asian Financial Crisis were specified for data between July 1997 and October 1998, while breakpoints for the Global Financial Crisis were set for observations between April 2007 and October 2009. Jiun (2019) divided the sample based on a recognized break date -the Malaysian general election. Even though some finance researchers use news reports of dates or known significant breaks and then specify dummy variables to control the effect of major breaks, relying on event identification using a more rigorous method is preferable to assuming the breaks from newspaper reports, as can be seen in the Dutta and Bouri (2022). So, the dates of breaks are not inferred from news stories but are instead quantified. The news article and known event dates, however, will be added as part of pre-analysis filtering step.

The pressing need to employ advanced methods and the availability of long historical data to identify breaks and outliers in cryptocurrency returns quickly is what motivated this research since it will help with risk reduction and decision-making in the volatile cryptocurrency market. Numerous studies on the detection of breaks and outliers in cryptocurrency have been conducted. These studies highlighted that significant fluctuations and structural breaks in price have occurred in the cryptocurrency market (Sahoo *et al.*, 2019; Evrim Mandaci and Cagli, 2022). Tan *et al.* (2022) detected the structural changes in the return, price, and squared return of the top 10 Cryptocurrencies. They demonstrated that structural changes are most frequently seen in the price series, followed by the squared return and return series, and highlighted that there is a "year-end" influence on the market due to cyclical price changes that occur at the start and end of the year. Canh *et al.* (2019) showed that structural breaks have become common in all well-known cryptocurrencies and that changes have moved from smaller to larger cryptocurrencies (in terms of market capitalization). According to Dutta and Bouri (2022) there is no actual evidence that there are outliers among the biggest cryptocurrencies, except for Bitcoin and considered the existence of some outlying observations in Bitcoin return series. Abdul Rashid and Ismail (2023) found that nonlinear and linear trend patterns were seen in every cryptocurrency closing price data sets. Abdul Rashid *et al.* (2023) also found that top five cryptocurrencies display the yearly phenomenon known as "crypto winter," in which the trend shifts downward after six months. The occurrence of speculative price bubbles and their subsequent bursting can result in economic fluctuations, potentially leading to a crisis (Mgadmi *et al.*, 2022).

Previous research, however, has only been able to identify outliers or breaks using different statistical change tests and has not been able to consider both changes at the same time. So, in literature, breaks are accounted for, trend breaks are not considered, and outliers are often removed from data. However, deleting too many data points in the case of too many outlier observations increases the danger of the final regression model failing to reflect the link that the econometrician wishes to evaluate. Thus, there is a clear knowledge gap in the literature that exists regarding the dynamics of cryptocurrency market breaks, trend breaks and outliers, which is to find an all-encompassing detection methodology that does not place restrictions on the number of breaks, trend breaks, and outliers in this domain to accomplish a simultaneous identification of breaks, outliers, and trends throughout the history of the digital currency market. This calls for examining the whole historical record of digital assets and utilizing advanced techniques like the indicator saturation approach, which have not yet been used but present an unrealized potential for an in-depth understanding of the whole spectrum of breaks, trend breaks, and outliers in this changing financial landscape. This study builds upon the fact that breaks and outliers simultaneously affect the behaviour of the market. So, the Indicator Saturation Approach developed by Hendry (1999) is used in which allows the simultaneous detecting of breaks, trend breaks, and outliers without trimming or removing some observations. IS approach has different types of tests, and it was considered in other studies. According to Castle and Hendry (2022), there are a variety of Indicator saturation estimators (ISEs). These include impulse indicator saturation (IIS) to tackle outliers, step indicator saturation (SIS) to tackle location shifts, and trend indicator saturation (TIS) to tackle for trend breaks. This study aims firstly by employing IS technique to jointly identify breaks, trend breaks, and outliers in the monthly, weekly, and daily returns of the five cryptocurrencies. Secondly, the study finds the common breaks and outliers among cryptocurrencies. The originality of this work is in its application of the indicator saturation technique to cryptocurrencies and jointly detection of breaks, trend breaks, and outliers. In order to achieve all of the aforementioned goals, the study will first convert the prices of each cryptocurrency into returns. It will next visualize and discuss the descriptives to determine whether breaks and outliers exist. Finally, the study will independently apply the indicator saturation approach to each cryptocurrency return. So, SIS is designed to capture these breaks, IIS is designed to capture these outliers and the Trend Indicators (TIS) records this transition by setting a variable to zero until the stated period t and then following the new trend after that.

The results revealed that, over a 10-year period, distinct patterns in outliers, breaks, and trend breaks emerged in the cryptocurrency market for BTC, ETH, LTC, USDT, and XRP. BTC has frequent outliers and disruptions on a daily and monthly basis, with a moderate occurrence weekly. ETH has a balanced distribution of outliers and breaks across daily, weekly, and monthly intervals, with a slight emphasis on weekly trend breaks. LTC has a notable number of daily outliers and breaks, with a higher incidence monthly and a relatively low occurrence of trend breaks. USDT has increased weekly and monthly outliers, moderate daily and weekly breaks, and minimal trend breaks. XRP has a high number of daily outliers, more frequent daily breaks and trend breaks, and a stable trend over weekly and monthly intervals. These findings emphasize the importance of understanding individual cryptocurrency dynamics for effective investment strategies. A balanced approach to policy is required if all historical cryptocurrency breaks, trend breaks and outliers are made public. This entails open disclosure, teaching investors about their patterns, setting risk management policies, working with regulators, encouraging technology development, and guaranteeing ongoing observation. All of these actions are intended to promote a cryptocurrency environment that is more robust, secure, and knowledgeable. The remaining sections of the paper are arranged as follows. The following section provides review of related literature, the methodology and a summary of the data, the results and discussion are then presented, and it ends with conclusion.

2. LITERATURE REVIEW

The detection and study of structural breaks and outliers is becoming more and more important as the cryptocurrency market ages and matures. Consequently, in this quickly evolving financial world, knowing the historical presence and impact of breaks and outliers is crucial for making well-informed decisions. A body of work analyzes these unusual events and their consequences. This literature investigates the approaches to identify structural breaks and outliers in the cryptocurrency market and other associated assets. The previous literature focused on important facets of cryptocurrency connectivity, its relationship to other assets, and the market's behavior during financial crises, given how complicated the cryptocurrency space is. The occurrence of breaks and outliers in cryptocurrency markets during periods of economic crisis provided insights into their behavior under stress. According to Jana and Sahu (2023b), equities and cryptocurrency prices fluctuate in response to various economic conditions. However, currently, most studies consider the COVID-19 pandemic a financial crisis. Fernandes *et al.* (2022) show that these cryptocurrencies demonstrated noticeably stable price dynamics when compared to the periods before and during COVID-19.

Kumar *et al.* (2022) investigated the dynamics of return and volatility connectivity among different cryptocurrencies during the COVID-19 pandemic. They found that volatility connectedness greatly rises throughout the COVID-19 era, and returns connectedness is highest across short-time horizons of one day to one week. James (2021) discovered that whereas cryptocurrencies display more collective dynamics and correlation across the board, stocks act more similarly along their trajectories and extremes and persist longer during anomalies. Sahoo and Sethi (2022) examined return and trading volume data for the top eight cryptocurrencies from August 8, 2015, to October 20, 2022, to investigate the predictability of the cryptocurrency market. Except for XRP, XMR, and DASH, they discovered sustained efficiency after the break. Sahoo *et al.* (2019) conducted a study on the price-volume relationship in the bitcoin market, examining the relationship between returns, return volatility, and trading volume. They stated that new trading volume knowledge causes price changes, and significant price increases drive traders to become more active.

Other studies were conducted to evaluate the distinctive features of cryptocurrencies by contrasting their properties and behavior with a range of conventional and alternative investing options. Jana and Sahu (2023a), who investigated the relationship between cryptocurrencies and the Indian stock market, found that cryptocurrencies do not significantly correlate with the stock market under stable economic conditions. However, Bitcoin, Ethereum, and Cardano show favorable connections during financial crises. Dogecoin, however, provides a haven in times of financial distress. Shahzad *et al.* (2022) compared Bitcoin, gold, and US VIX futures to BRICS stock market indices and considered if these assets are good hedges in high-stress situations like the COVID-19 pandemic. They found that gold and bitcoin are ineffective hedges against BRICS declines. However, Bitcoin, gold, and VIX futures offer diversification advantages for investors in the BRICS stock markets. Gold offers more consistent benefits in China and India, while VIX futures provide more benefits for South Africa, Russia, and Brazil.

In cryptocurrency research, the detection of breaks and outliers have been carried out to identify and comprehend the reasons behind breaks in the dynamic and frequently unpredictable behavior of digital asset markets. According to Kumar *et al.* (2022), the structural shift is evident when examining cryptocurrencies simultaneously with traditional assets as well as when examining them independently. Charfeddine and Maouchi (2019) employed the Bai and Perron (2003) tests known as (BP) for structural breaks in the returns series and the iterative cumulative sum of squares (ICSS) algorithm tests in the volatility series to determine whether structural breaks existed in both series. They came to two significant empirical conclusions: first, the BP test results applied to the returns series provide strong evidence against the presence of structural breaks in the returns series mean; second, the results indicate the presence of at least three breaks in the cryptocurrency volatility series, except for the XRP price volatility series. Tan *et al.* (2022) adopted the structural change model proposed by Bai and Perron (2003) to investigate the number and location of change points in daily price, return, and volatility as measured by the squared return of the cryptocurrency market. According to the results, structural changes in the price series happen often, with the squared return and return series following suit. These changes were constantly noted between December 2017 and April 2018. Telli and Chen (2020) used the Bai-Perron methodology to test several structural cracks in the cryptocurrency markets. Their findings suggested that there are statistically significant structural variations in terms of volatility and returns and that the dynamics of the volatility and return series are distinct. Furthermore, they noticed a grouping of breakpoints between February and March 2017 and December 2017 and March 2018. Sahoo and Sethi (2022) used the Bai and Perron (2003) test and discovered that the break dates of all 13 cryptocurrencies match their real trend values, but LTC and Steller (XMR) did not exhibit any structural breaks.

In addition, numerous scholars have addressed the topic of the consequences of ignoring structural breaks. Aharon *et al.* (2023) found that investors' hedging tactics, risk exposure assessments, and derivatives valuations are all negatively impacted when structural breaks are disregarded in the cryptocurrency markets. Abakah *et al.* (2020) studied the persistence in the absolute and squared returns of twelve major cryptocurrencies using Bai and Perron (1998) fractional integration techniques and long-memory approaches and found a decrease in persistence in the cryptocurrency market after structural breaks were considered. Jiang *et al.* (2023) examined how structural breaks and the dual long memory property affected the persistence level of six significant cryptocurrency markets. They used the iterated cumulative sum of squares (ICSS) technique by Inclán and Tiao (1994), as well as the Bai and Perron (1998) structural break test and found that the conditional volatility of cryptocurrency markets is characterized by long memory and structural breaks. Omane-Adjepong *et al.* (2019) found that the measure of returns, volatility, and regime shift all had a significant impact on informational inefficiency and volatility persistence.

Mostly common multiple break tests used include Bai and Perron (1998, 2003) tests for mean level changes and iterative cumulative sum of squares (ICSS) for variance changes. Sansó and Aragó (2004) pointed out that ICSS has big size distortion for leptokurtic and platykurtic innovations. Gil-Alana (2008) extended the Bai and Perron tests to the fractional case. However, the BP test requires trimming, which means removing some portion of the sample at the beginning and end, which leads to a minimum break length. Trimming also makes it impossible to detect breaks near the start or end of the sample. However, the above test needs the user to employ an individual outlier or break test to find structural breaks or outliers. So, there are still gaps in the literature regarding the accurate and timely detection of past dynamics and shocks in the history of cryptocurrency market. In order to concurrently identify breaks, trend breaks, and outliers that occurred as the cryptocurrency market aged to ten years, this study expands on the prior research on the market by applying the indicator saturation (IS) approach to a high frequency of roughly ten years of cryptocurrency returns. Because the IS technique is superior to earlier testing in its concurrent detection ability, this work is unique because it applies it to cryptocurrency returns. This aids in locating potential outliers and shifts in the market that occur under various financial situations. The indicator saturation technique of Hendry (1999) and its sub-tests were considered in the literature. The indicator saturation approach is a method that saturates the model with a full set of indicators to capture either a break, a trend break, or an outlier and then identifies statistically meaningful ones (Pretis *et al.*, 2015). Some variations of this strategy include the trend indicator saturation (TIS), step-impulse indicator (SIS) produced by Castle *et al.* (2015), and impulse indicator saturation (IIS) developed by Hendry (1999) and Santos *et al.* (2008).

The IS approach was also considered in other studies. Applying the impulse indicator saturation approach, Mohd Nasir and Ismail (2020) discovered that two elements that typically appear in data are outliers and structural breaks. Using the IIS and SIS techniques, Ismail and Nasir (2020) looked for outliers in the volatility of the Malaysian Shariah-compliant index return and discovered 47 of them. IIS was utilized by Russell *et al.* (2010) to pinpoint structural breaks in US inflation and generate precise and perceptive estimates of the Phillips curves in the US. In addition, IIS was also utilized by Reade and Volz (2011) to locate shifts and identify a very specific model for inflation in China. Pretis *et al.* (2015) used a least-squares approach based on (Bai and Perron, 1998) (BP) and the indicator saturation approach of Hendry (1999) to detect breaks. Ghouse *et al.* (2022) used IIS approach to identify structural breaks due to COVID-19 in the returns of Pakistan Islamic banks. Castle *et al.* (2021) used trend and step indicator saturation approaches (TIS and SIS) to detect trend and step shifts in long-run UK production functions. Pretis *et al.* (2015) applied IS approach using two of its types of Step indicator saturation (SIS) and trend indicator saturation (TIS) to evaluate climate models. This approach showed superiority among other change tests available. However, Castle *et al.* (2012) used US real interest rates to compare IIS and BP approaches and found that they give approximately similar results. Outlier detection via impulse indicator saturation is a popular method since it already outperforms existing outlier selection strategies such as least trimmed squares (LTS), M-estimator, and MM-estimator by (Johansen and Nielsen, 2008; Doornik, 2009).

3. METHODOLOGY

3.1 Indicator Saturation Approach

Historically, regression analysis investigated outliers and structural breaks by examining the statistical significance of a small set of associated indicator variables. However, recent general-to-specific (GETS) modeling developments allow for indicator testing at every observation in the estimation sample, including variables indicating outliers, structural breaks, or trend breaks and choosing them for inclusion in the final model. Moreover, the indicator saturation approach of Hendry (1999) saturates the model with a full set of indicators and identifies statistically meaningful ones. This technique has different types, including the impulse indicator saturation (IIS) of Hendry (1999) and Santos *et al.* (2008) used to detect outliers and the step-impulse indicator (SIS) of Castle *et al.* (2015) used to detect breaks, and Trend Indicator Saturation (TIS) used to detect trend breaks. The impulse indicator saturation approach was first created to discover undetermined numbers of outliers with undefined magnitudes at unclear times in the sample (Hendry *et al.*, 2007). Doornik (2009) and Johansen and Nielsen (2008) demonstrated the impulse indicator saturation (IIS) as a robust estimator. The SIS method is a modified version of IIS techniques for multiple break detection.

The IIS and SIS methodologies provide a general procedure for examining model consistency and discovering structural breaks and outliers. Both IIS and SIS are generic tests for an unknown number of structural changes occurring at unknown periods, with unknown duration and amplitude, wherever in the sample (Hendry, 1999; Johansen and Nielsen, 2008). Ericsson and Reisman (2012) merged the two approaches (SIS and IIS). Doornik *et al.* (2013) demonstrate that combining SIS with IIS has no negative impacts when step dummies are present, but it may diminish the power for identifying the impulse indicator. Moreover, one strategy for detecting a trend break (TIS) would be to saturate the model with a number of trend indicators that produce a trend up until a specific observation and 0 subsequently for every observation (Castle and Hendry, 2019). IIS, SIS and TIS have been formulated their mean model y_t as general unrestricted model (GUM) by Pretis *et al.* (2018) as follows:

$$\text{IIS} \quad y_t = \mu + \sum_{j=1}^{n} \delta_j 1_{\{t=j\}} + \varepsilon_t \tag{1}$$

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

$$\text{TIS} \quad y_t = \mu + \sum_{j=1}^{n} \delta_j 1_{\{t>j\}} (t-j) + \varepsilon_t \tag{3}$$

The GUM provides the initial information set and serves as the model reduction process's starting point. Each equation y_t represents the return series of each cryptocurrency, μ stands for the intercept of the regression, δ_j stands for the magnitude of either a break, trend break or outlier, and the ε_t is the error term. The Impulse Indicators (IIS) in equation (1) include a dummy variable that is set to zero in all periods except one, which occurs at period t and takes on a value of one. The Step Indicators (SIS) in equation (2), on the other hand, use a step function variable that remains at zero until period t and then transitions to one. Finally, in equation (3), the Trend Indicators (TIS) provide a trend-break variable that begins at zero and continues until period t, after which it follows a distinct trend.

3.2 IS Application Procedure

The procedure by which the above three equations incorporate the indicators into the regression equation is presented in Table no. 1. We set each return series as a dependent variable on an intercept, and each equation of the IS technique then adds indicators equal to T observations as indicator variables (N). As the number of indicators (N) surely exceeds the number of observations $(N > T)$, the IS techniques will automatically employ blocks; each block contains 30 indicators to look for significant indicators. The blocks constructed and the indicators added when these tests were allowed to run are summarized in Table no. 1. For the three tests – IIS, SIS, and TIS – to discover outliers, breaks, and trend breaks simultaneously, we ran the three tests all at once. Therefore, results will be more accurate, and masking will be less of an issue. We choose to use the sample observations (T) to calculate the alpha value, or (1/T). Each alpha value in the sample is set to be very tight.

Table no. 1 – IS application framework

Returns	Daily		Weekly		Monthly	
	Indicators	Blocks	Indicators	Blocks	Indicators	Blocks
BTC	9423	105	1344	15	303	4
ETH	6162	69	876	10	195	3
LCT	9606	107	1368	16	309	4
USDT	6162	69	876	10	195	3
XRP	6162	69	876	10	195	3

Note: Table no. 1 outlines an indicator-based framework for financial returns of various cryptocurrencies (BTC, ETH, LCT, USDT, XRP) across daily, weekly, and monthly time frames. It also describes the number of indicators created in the regression model and the corresponding blocks into which these indicators were divided. For example, With 9423 indicators created by IIS, SIS and TIS together for BTC daily returns were divided into 105 blocks, 1344 indicators for weekly returns were divided into 15 blocks, and 303 indicators for monthly returns were divided into 4 blocks. Similar procedures were applied to the other coins.

3.3 Datasets

The data set includes the daily, weekly, and monthly 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/*. Table no. 2 gives further information and summarizes the duration of the data and its frequency.

Table no. 2 – Data duration and frequency

Cryptocurrency	Market. Cap.	Start Date	Data begins	Data ends	Frequency
Bitcoin (BTC)	518B	13 July 2010	22 Nov 2014	30 June 2023	3143D, 450W, 103M
Litecoin (LTC)	4B	28 April 2013	22 Sep 2014	30 June 2023	3205D, 458W, 105M
Ripple (XRP)	26B	04 August 2013	13 Nov 2017	30 June 2023	2056D, 294W, 67M
Ethereum (ETH)	196B	07 August 2015	13 Nov 2017	30 June 2023	2056D, 294W, 67M
Tether USD (USDT)	83B	25 February 2015	13 Nov 2017	30 June 2023	2056D, 294W, 67M

Note: D stands for daily, W for weekly and M for monthly.

These cryptocurrencies were chosen based on their ranking in terms of market capitalization or launch. So, for BTC, ETH and USDT were chosen because they are the market leaders in terms of total market capital, and XRP and LTC were chosen because they are the next-oldest cryptocurrencies after BTC. Bitcoin (BTC) is the first cryptocurrency that has ever existed. Of all cryptocurrencies, it has the highest market capitalization at $518 billion. Ethereum (ETH) - With a market capitalization of $196 billion, Ethereum is the second most valued cryptocurrency behind Bitcoin. Tether (USDT) is the third-largest cryptocurrency in the world by market cap, with $83 billion. While Litecoin (LTC) ranks fifteenth with $4 billion and Ripple (XRP) is fifth with $26 billion, both XRP and LTC are older than other ETH and USDT. The study took into account market capitalization and age when choosing cryptocurrencies, allowing for the identification of market leaders as well as an evaluation of how well these coins have weathered changes in the marketplace over time. By considering both established and emerging cryptocurrencies, the combination of market capitalization and age also aids in lowering risk. Information on the market capitalizations was obtained from Yahoo Finance as of September 2023. This study deals with returns by converting each series into log-returns using the formula: $\mathrm{R_t} = \ln\left(\frac{\mathrm{P_t}}{\mathrm{P_{t-1}}}\right) = \ln(\mathrm{P_t}) - \ln(\mathrm{P_{t-1}})$. Where R_t stands for returns, P_t is the current lag of the price at time t, and P_{t-1} is the previous lag price at time $t-1$. Figure no. 2 shows the plots of each cryptocurrency return.

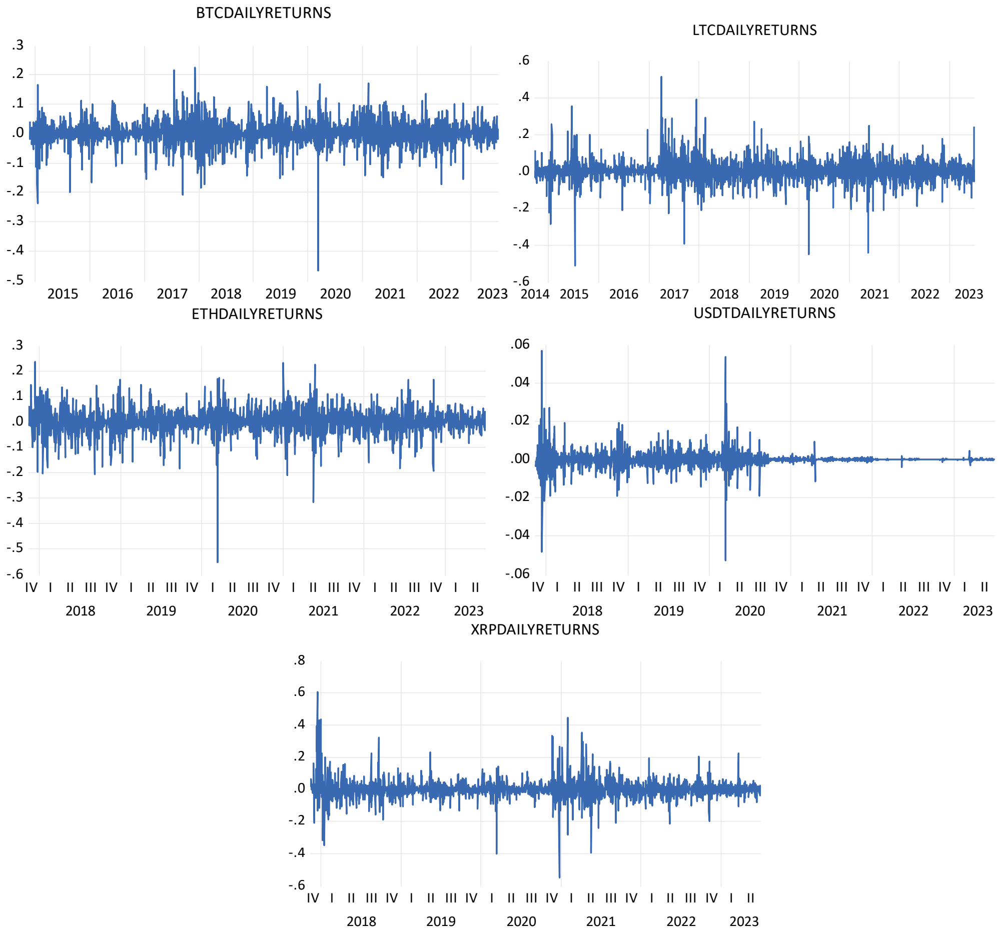

Figure no. 2 – Daily log returns of the five cryptocurrencies

Table no. 3 gives some descriptive information for the cryptocurrency daily log returns. The cryptocurrency market returns demonstrate the traditional features of financial data, namely that a large standard deviation predominates over a modest mean. The returns of LTC and XRP are the most volatile series, whilst the returns of USDT are the least volatile. Returns are also highly negatively skewed and have strong kurtosis, which makes them exceedingly out of the ordinary. According to the kurtosis, which ranges from 13.14 for ETH to 53.30 for USDT, an outlier exists.

Table no. 3 – Descriptive Statistics

Returns	Mean	Std. Dev	Skewness	Kurtosis
BTCDR	0.00	0.04	-0.789	14.2
LTCDR	0.00	0.06	0.103	15.85
ETHDR	0.00	0.05	-0.923	13.14
USDTDR	0.00	0.00	0.745	53.30
XRPDR	0.00	0.06	0.84	20.3

4. RESULTS AND DISCUSSIONS

This section presents the findings and discussions from our comprehensive analysis of breaks, trends, and outliers in the returns on cryptocurrencies over a 10-year period utilising the indicator saturation approach. We use a variety of tables to present our findings and explain them.

4.1 IIS Test Results

Table no. 4 – Outliers and their dates

Series	Alpha	Outlier Dates	Total
BTCDR	0.0003	1/13/2015(-), 1/14/2015(-), 1/15/2015(+), 8/18/2015(-), 1/15/2016(-), 1/11/2017(-), 7/17/2017 (+), 7/20/2017(+) , 9/14/2017(-), 9/15/2017(+), 12/06/2017(+), 12/07/2017(+), 1/16/2018(-), 2/05/2018(-), 4/02/2019(+), 6/27/2019(-), 7/16/2019(-), 10/25/2019(+), 3/12/2020(-), 3/19/2020(+), 1/21/2021(-), 2/08/2021(+), 5/12/2021(-), 5/19/2021(-), 6/13/2022(-)	25
ETHDR	0.0005	12/22/2017(-), 9/05/2018(-), 10/11/2018(-), 9/24/2019(-), 3/08/2020(-), 3/12/2020(-), 3/13/2020(+), 3/19/2020(+), 1/03/2021(+), 1/21/2021(-), 5/19/2021(-), 5/24/2021(+) , 6/21/2021(-)	13
LTCDR	0.0003	1/03/2015(-), 1/14/2015(-), 5/22/2015(+), 6/16/2015(+), 7/10/2015(-), 6/22/2016(-), 12/23/2016(+), 3/30/2017(+), 4/05/2017(+), 5/03/2017(+), 5/23/2017(+) , 9/14/2017(-), 12/08/2017(+) , 12/09/2017(+) , 12/11/2017(+), 12/12/2017(+), 1/16/2018(-), 2/14/2018(+), 2/08/2019(+), 4/02/2019(+), 3/12/2020(-), 1/11/2021(-), 5/12/2021(-), 5/19/2021(-), 5/24/2021(+), 6/21/2021(-), 9/07/2021(-), 6/30/2023(+)	28
USDTDR	0.0005	11/30/2017(+), 12/07/2017(+), 12/08/2017(-), 12/12/2017(+), 12/13/2017(-), 12/14/2017(-), 12/24/2017(-) , 12/30/2017(+), 1/16/2018(+), 1/17/2018(-), 1/19/2018(-), 2/08/2018(+) , 3/24/2018(+), 11/14/2018(-), 11/15/2018(+), 11/23/2018(-), 12/08/2018(+) , 6/28/2019(+), 3/12/2020(+), 3/13/2020(-), 3/17/2020(-), 3/19/2020(+) , 3/27/2020(+), 3/28/2020(-), 5/06/2020(+), 5/07/2020(-), 7/03/2020(-), 8/14/2020(-)	28
XRPDR	0.0005	12/12/2017(+), 12/13/2017(+), 12/14/2017(+), 12/21/2017(+), 12/29/2017(+), 1/03/2018(+), 1/08/2018(-), 1/16/2018(-), 8/17/2018(+), 9/20/2018(+), 9/21/2018(+), 5/14/2019(+), 3/12/2020(-), 11/21/2020(+), 11/23/2020(+), 12/23/2020(-), 12/24/2020(+), 1/07/2021(+), 1/30/2021(+), 2/01/2021(-), 4/10/2021(+) , 4/26/2021(+), 5/19/2021(-), 5/24/2021(+), 5/11/2022(-), 3/21/2023(+)	26
BTCWR	0.0022	12/18/2017(-), 1/29/2018(-), 11/19/2018(-), 3/09/2020(-)	4
ETHWR	0.0034	12/11/2017(+), 1/01/2018(+), 1/29/2018(-), 9/03/2018(-), 11/19/2018(-), 12/17/2018(+), 3/09/2020(-), 5/17/2021(-)	8
LTCWR	0.0022	1/19/2015(+), 3/27/2017(+), 5/01/2017(+), 5/17/2021(-)	4
USDTWR	0.0034	12/04/2017(+), 12/18/2017(+), 1/08/20189(+), 1/29/2018(+), 10/22/2018(+), 11/26/2018(+), 12/03/2018(+), 5/13/2019(+), 11/25/2019(-)	9

Series	Alpha	Outlier Dates	Total
XRPWR	0.0034	12/11/2017(+), 1/08/2018(-), 1/29/2018(-), 9/17/2018(+), 11/16/2020(+), 12/21/2020(-), 1/25/2021(+), 4/05/2021(+), 5/17/2021(-),	9
BTCMR	0.01	No	0
ETHMR	0.015	2018M03 (-)	1
LTCMR	0.01	2015M06(+), 2017M12(+)	2
USDTMR	0.015	2018M01(-), 2018M02(+), 2018M10(-), 2018M12(+), 2019M01(-), 2019M03(-), 2019M06(-), 2019M07(+)	8
XRPMR	0.015	2020M11(+), 2020M12(-), 2021M01(+), 2021M04(+)	4

Note: DR: daily returns, WR: weekly returns, and MR: monthly returns. The table contains daily outliers of the returns, weekly outliers, and monthly outliers. If no outliers were detected in a particular coin, we have written No—otherwise, the provided dates and total of outliers across frequencies.

Table no. 4 displays the results of the IIS approach on daily, weekly and monthly scale, including the outlier dates, total of outliers and alpha values. The sign in the bracket can determine whether the outlier is positive or negative. Positive outliers show that the value was much higher than most of the returns, whilst negative outliers show that the value was significantly lower than others. Regarding the daily returns, the cryptocurrencies LTC, USDT, and XRP each have 28 outliers, which is a significantly greater number. All five cryptocurrencies have a significant number of outliers. This shows that these coins went through fluctuations daily or occurrences that led to outlier values. In terms of weekly returns, ETH, USDT, and XRP have more outliers than BTC and LTC. This shows that, on a weekly basis, ETH, USDT, and XRP had more extreme values compared to BTC and LTC. In the monthly returns USDT cryptocurrency has the most outliers, followed by LTC. There are a small number of outliers for cryptocurrencies ETH and XRP but none for BTC. This implies that these cryptocurrencies perform differently each month, with some experiencing more extreme values than others. Overall, outliers tend to occur most frequently in daily returns. Compared to daily returns, the number of outliers for weekly returns is often smaller while monthly returns have the lowest occurrence of outliers. This suggests that monthly cryptocurrency performance is more likely to be consistent and to experience fewer extreme extremes. Furthermore, there are 169 outliers in total, which is a sizable number. 90 of them have values that are much greater than the rest of the returns, making them positive outliers. 79 of them, however, are negative outliers, with values that are far below the average of the returns. Positive and negative outliers are distributed in an even manner. This shows that extreme numbers can occur in either way, whether it's greater or lower than the expected range. 47% of these outliers coincide with market peaks in 2017, 2018, 2020, and 2021. The China crypto crackdown in 2021, the global covid pandemic, the halving of Bitcoin in 2020, and the initial coin offering (ICO) boom in 2017–2018 can all be blamed for that.

4.2 SIS Test Results

Table no. 5 – Daily Break Segments

SIS output								
Break Segments	**Sign**	**Size**	**Break Segments**	**Sign**	**Size**	**Break Segments**	**Sign**	**Size**
BTCDR			ETHDR			USDTDR		
11/22/2014-11/01/2015	+	344 days	11/13/2017-12/10/2017	+	29 days	11/13/2017-12/23/2017	+	40 days
11/02/2015-11/03/2015	+	2 days	12/11/2017-12/12/2017	+	2 days	12/24/2017-2/4/2018	-	42 days
11/4/2015-6/20/2016	-	229 days	12/13/2017-2/5/2018	-	54 days	2/5/2018-2/6/2018	-	Outlier
6/21/2016-6/22/2016	-	2 days	2/06/2018/11/18/2018	+	285 days	2/7/2018-2/9/2018	-	3 days

			SIS output					
Break Segments	**Sign**	**Size**	**Break Segments**	**Sign**	**Size**	**Break Segments**	**Sign**	**Size**
BTCDR			ETHDR			USDTDR		
6/23/2016-1/4/2017	+	195 days	11/19/2018-11/20/2018	-	2 days	2/10/2018-11/18/2018	+	281 days
1/5/2017-1/06/2017	-	2 days	11/21/2018-5/20/2021	+	911 days	11/19/2018-11/20/2018	-	2 days
1/7/2017-12/6/2017	+	333 days	5/21/2021-6/9/2022	-	384 days	11/21/2018-11/23/2018	+	3 days
12/7/2017-12/16/2017	-	10 days	6/10/2022-6/13/2022	-	3 days	11/24/2018-6/30/2023	-	1,679 days
12/17/2017-11/18/2018	-	336 days	6/14/2022-11/07/2022	+	146 days			
11/19/2018-11/20/2018	-	2 days	11/8/2022-11/9/2022	-	2 days			
11/21/2018-11/7/2022	+	1,447 days	11/10/2022-6/30/2023	+	232 days			
11/8/2022-11/9/2022	-	2 days						
11/10/2022-6/30/2023	+	232 days						
LTCDR			XRPDR					
9/22/2014-1/23/2015	+	123 days	11/13/2017-1/07/2018	+	367 days			
1/24/2015-1/25/2015	+	2 days	1/08/2018-1/16/2018	-	8 days			
1/26/2015-7/04/2015	-	159 days	1/17/2018-1/18/2018	+	2 days			
7/5/2015-5/02/2017	+	667 days	1/19/2018-2/10/2018	-	22 days			
5/03/2017-5/07/2017	+	5 days	2/11/2018-11/23/2020	-	1,016 days			
5/08/2017-5/24/2017	-	16 days	11/24/2020-4/06/2021	+	133 days			
5/25/2017-5/26/2017	-	2 days	4/07/2021-4/08/2021	-	Outlier			
5/27/2017-6/15/2017	+	20 days	4/9/2021-4/13/2021	+	5 days			
6/16/2017-6/17/2017	+	2 days	4/14/2021-5/24/2021	-	40 days			
6/18/2017-5/20/2021	-	1,432 days	5/25/2021-6/20/2021	+	26 days			
5/21/2021-5/24/2021	-	4 days	6/21/2021-6/22/2021	-	2 days			
5/25/2021-6/30/2023	+	766 days	6/23/2021-6/30/2023	+	737 days			

Note: Here in this study, the term break segment refers to a discrete and continuous section of a dataset that is defined by breakpoints that have been found. Each break segment in our situation, for example, BTCDR, got 12 breakpoint dates ($m = 12$). Hence, we have ($m + 1 = 13$) break segments where the returns are divided into 13 segments by 12 breakpoints. These break segments aid in identifying and analyzing changes in patterns or trends during the observation period by highlighting times when the data's behavior departs noticeably from the surrounding intervals. The same idea applies to other segments of the other digital coins. In addition, an outlier is identified by SIS when it detects two consecutive step shifts with opposite signs, as it does in the dates highlighted in the USDTDR and XRPDR (Pretis *et al.*, 2018).

Table no. 6 – Weekly Break Segments

		SIS Output			
Break Segments	**Sign**	**Size**	**Break Segments**	**Sign**	**Size**
BTCWR			LTCWR		
11/22/2017-4/23/2017	+	126 weeks	9/22/2014-6/14/2015	+	38 weeks
4/24/2017-6/11/2017	+	7 weeks	6/15/2015-7/05/2015	+	3 weeks
6/12/2017-7/16/2017	-	5 weeks	7/6/2015-12/03/2017	-	126 weeks
7/17/2017-8/13/2017	+	2 weeks	12/04/2017-12/17/2017	+	2 weeks
8/14/2017-11/12/2017	-	13 weeks	12/18/2017-5/9/2021	-	177 weeks
11/13/2017-12/17/2017	+	5 weeks	5/10/2021-6/30/2023	-	112 weeks
12/18/2017-5/9/2021	-	177 weeks			
5/10/2021-5/23/2021	-	2 weeks			
5/24/2021-6/30/2023	+	110 weeks			
USDTWR			XRPWR		
11/13/2017-12/10/2017	+	4 weeks	11/13/2017-12/17/2017	+	5 weeks
12/11/2017-2/4/2018	-	214 weeks	12/18/2017-1/7/2018	+	3 weeks
2/5/2018-6/30/2023	+	282 weeks	1/8/2018-6/30/2023	-	286 weeks

Table no. 7 – Monthly Break Segments

SIS Output					
Break Segments	**Sign**	**Size**	**Break Segments**	**Sign**	**Size**
BTCMR			ETHMR		
2014M12-2017M03	+	28 months	2017M12-2020M03	+	28 months
2017M04-2017M12	+	9 months	2020M04-2021M04	+	13 months
2018M01-2020M09	-	33 months	2021M05-2023M06	-	26 months
2020M10-2021M03	+	6 months			
2021M04-2023M06	-	27 months			
LTCMR			USDTMR		
2014M10-2017M02	+	28 months	2017M12-2018M10	+	12 months
2017M03-2017M08	+	6 months	2018M11-2019M04	+	6 months
2017M09-2023M06	-	70 months	2019M05-2023M06	-	49 months

The findings of the SIS technique are shown in Tables no. 5, no. 6 and no. 7. Table no. 5 shows daily break dates, break segments, segment signs, and segment sizes. A break segment is a certain timeframe in the cryptocurrency market that reflects a segment or period of similar behaviour. If the break segment is negative suggests that the cryptocurrency market's performance over the period in question declined or suffered. Segment size indicates the segment's duration in days. For instance, BTC's segment from 11/21/2018 to 11/7/2022, which covers 1,447 days, has a positive sign and is the longest segment during which BTC did not exhibit a fall. The longest segment break for ETH is comparable to BTC segments but is shorter at 911 days from 11/21/2018 to 5/20/2021. The longest break for LTC is from 6/18/2017 to 5/20/2021 with 1,432, yet there is a fall in LTC throughout this time. The longest break segment for XRP is 2/11/2018-11/23/2020 with 1,016 days, while the longest break segment for USDT is 11/24/2018-6/30/2023 with 1,679 days with a negative sign. The longest break segments for each cryptocurrency roughly fall in similar segments, showing that the market reacts similarly to each part. The average number of daily break segments detected among all cryptocurrencies is almost the same. However, they all have varying sizes. A similar analysis can be derived from the weekly and monthly break segments shown in Tables no. 6 and no. 7, but the weekly data for ETH did not show any breaks, and the monthly data for XRP did not show any breaks either. On average, the most extended break segments in weekly and monthly data are like daily break segments.

4.3 Common Outliers and Breaks

The daily and weekly outliers that at least three cryptocurrencies share exactly are shown in Table no. 8. Again, Table no. 8 demonstrates that the years 2017, 2018, 2020, and 2021 are among often occurring outliers, indicating that a shock to one cryptocurrency affects at least two others, either positively or negatively. The consistency with which these outliers arise across different cryptocurrencies is interesting, suggesting that there may be a pattern or common component that influences their values or market behavior. It is again interesting to note that cryptocurrencies with frequent outliers also seem to have approximately similar breaks. This implies that their market behavior may be related or correlated. Further investigation into these breaks and their effects on the prices of the cryptocurrencies may offer insightful information about the variables affecting their performance, see Table no. 9.

Table no. 8 – Common Outliers

Outlier date	BTCDR	ETHDR	LTCDR	USDTDR	XRPDR
12/12/2017	No	No	Yes (+)	Yes (+)	Yes (+)
12/13/2017	No	Yes (-)	No	Yes (-)	Yes (-)
1/16/2018	Yes (-)	No	Yes (-)	Yes (+)	Yes (-)
3/12/2020	Yes (-)	Yes (-)	Yes (-)	Yes (+)	Yes (-)
5/19/2021	Yes (-)	Yes (-)	Yes (-)	No	Yes (-)
5/24/2021	No	Yes (+)	Yes (+)	No	Yes (+)
Outlier date	**BTCWR**	**ETHWR**	**LTCWR**	**USDTWR**	**XRPWR**
1/29/2017	Yes (-)	Yes (-)	No	Yes (-)	Yes (-)
5/17/2021	No	Yes (-)	Yes (-)	No	Yes (-)

Note: Yes means share and sign shows whether positively or negatively.

Table no. 9 – Common Break Segments

Break segment	BTCDR	ETHDR	LTCDR	USDTDR	XRPDR
12/17/2017-1/18/2018	Yes	Yes	No	Yes	Yes
2/6/2018-11/18/2018	No	Yes	No	Yes	No
11/19/2018-11/20/2018	No	Yes	No	Yes	No
11/8/2022-11/9/2022	Yes	Yes	No	No	No
11/10/2022-6/30/2022	Yes	Yes	No	No	No
Outlier date	**BTCWR**	**ETHWR**	**LTCWR**	**USDTWR**	**XRPWR**
11/18/2017-12/17/2017	Yes	No	No	Yes	Yes
12/18/2017-5/9/2021	Yes	No	Yes	No	No
1/8/2018-6/30/2023	No	No	No	Yes	Yes
5/10/2021-6/30/2023	Yes	No	Yes	No	No
Outlier date	**BTCMR**	**ETHMR**	**LTCMR**	**USDTMR**	**XRPMR**
2014M9-2017M02	Yes	No	Yes	No	No
2017M04-2021M03	Yes	Yes	No	No	No
2021M04-2023M06	Yes	Yes	No	No	No

4.4 TIS Application Results

The trend break dates determined using the TIS technique are listed in Table no. 10, along with the appropriate alpha value and frequency. The symbol in the bracket indicates whether the trend break is positive or negative. The cryptocurrencies ETH and XRP exhibit a substantially higher number of 8 and 9 trends when it comes to daily returns. LTC and USDT exhibit smaller trends in terms of weekly returns, while others do not exhibit any weekly trends. The monthly returns of the cryptocurrencies show no trend.

Table no. 10 – Trend Break Dates

Series	Alpha	Trend Break Dates	Total
BTCDR	0.0003	7/13/2017 (-), 7/15/2017 (+), 7/17/2017 (-), 12/06/2017 (+), 12/23/2017 (-)	5
ETHDR	0.0005	1/14/2018(-), 1/16/2018(+), 1/20/2018(-), 1/21/2018(+), 1/27/2018(-), 2/06/2018(+), 5/21/2021(+), 5/25/2021(-)	8
LTCDR	0.0003	7/12/2015(-), 7/13/2015(+)	2
USDTDR	0.0005	12/20/2017(+), 12/24/2017(-), 1/18/2018(-), 1/30/2018(+), 2/03/2018(-)	5

Series	Alpha	Trend Break Dates	Total
XRPDR	0.0005	2/05/2018(+), 2/09/2018(-), 11/23/2020(-), 11/26/2020(+), 11/27/2020(-), 4/03/2021(+) , 4/05/2021(-), 5/20/2021(-), 5/25/2021(+)	9
BTCWR	0.0022	No	0
ETHWR	0.0034	No	0
LTCWR	0.0022	1/26/2015(+)	1
USDTWR	0.0034	12/11/2017(-), 2/05/2018(+)	2
XRPWR	0.0034	No	0

The study aligns with actual market events. However, due to varying data, important events may be questioned. The results indicate significant times in 2017, 2018, 2020, and 2021. In 2017, the market experienced BTC halving and planned BTC futures launches. In 2018, Bitcoin and other cryptocurrencies saw a significant price drop. This year also marks the beginning of crypto winter and the initial coin offering (ICO) boom in 2017–2018. In 2020 and 2021, the China crypto crackdown in 2021, the global Covid pandemic, and the halving of Bitcoin in 2020. BTC had its third halving, and prices increased further (Telli and Chen, 2020). Our examination of break, trend break and outlier dates in cryptocurrency markets offers insightful information about market behaviour and its effects. Making wise investment and trading decisions in the dynamic and often changing world of cryptocurrencies requires an understanding of the underlying dynamics behind these breaks.

5. CONCLUSION

In conclusion, this study has investigated the comprehensive detection of breaks, trend breaks, and outliers in historical cryptocurrency data, with a focus on five cryptocurrencies: Bitcoin, Ethereum, Litecoin, Tether USD, and Ripple over a period of 10 years. The findings showed that breaks, trend breaks, and outliers exist in the returns of these digital coins and that the frequency of these changes existed from monthly to weekly to daily. According to the tables, most of these changes happened in 2017, 2018, 2020, and 2021. It can be related to a variety of well-known occurrences, including the global Covid-19 pandemic in 2020, the Chinese crypto crackdown in 2021, the price halving of Bitcoin in 2020, and the rise in initial coin offerings (ICOs) in 2017–2018. Each of the five digital currencies exhibits roughly equal daily, weekly, or monthly returns changes that include both positive and negative shocks. The study also discovered that at least two or three cryptocurrencies have breaks and outliers in common, which indicate existence of common movement during those years. Using the indicator saturation test as a statistical tool for structural change identification, we successfully identified and date weekly, monthly, and daily breaks, trend breaks, and outliers within the cryptocurrency returns.

The study found that running IS estimators like IIS, SIS, and TIS individually can be flexible but running them concurrently increases accuracy, demonstrating the superiority of the IS approach over other tests. The capacity of the SIS method to locate outliers and the ability of the IIS method to identify breaks would both be reduced if all were performed simultaneously. Therefore, SIS is good at break detection, while IIS is good at outlier detection. Some researchers, like Pretis *et al.* (2018), Ghouse *et al.* (2022), and others, that used either SIS or IIS for break and outlier detection will find this to be beneficial. The indicator saturation approach's success in identifying these changes highlights the fact that it can be a useful tool for identifying various changes in financial time series data. For the breaks detected, we have seen that most of the digital coins taken into consideration here exhibit a pattern of break segments throughout the history of the cryptocurrency market. This pattern seems to comprise longer and shorter segments that alternate, with the shorter ones typically lasting two days. The lengthier parts appear to have different particular durations, and their lengths do not exhibit an obvious arithmetic or geometric progression. Instead, the pattern is more erratic, alternating longer and shorter periods. If policymakers wanted to know what was causing the alternating patterns, they would have to keep a tight eye on the market. Policies should also be in place to control and lessen the risks brought on by changes in the market. This study offers practical insights for market participants, highlighting the importance of strong risk management, staying updated on regulations and security measures, and understanding the psychological aspects of market sentiment. The knowledge gained enhances the informed and resilient cryptocurrency market ecosystem, encouraging diversification and risk mitigation strategies among market participants. This study is limited by considering only five digital coins. However, future studies may consider more.

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