sciendo

UDC: 336.743.3:336.76
DOI: 10.2478/jcbtp-2024-0012

Journal of Central Banking Theory and Practice, 2024, 2, pp. 41-70
Received: 28 February 2023; accepted: 15 June 2023

Bilgehan Tekin *

** Çankırı Karatekin University, Çankırı, Türkiye*

E-mail: btekin@karatekin.edu.tr

Structural Breaks and Co-Movements of Bitcoin and Ethereum: Evidence from the COVID-19 Pandemic Period

Abstract: This study examined the structural breakdowns and co-movements of Bitcoin (BTC) and Ethereum (ETH) cryptocurrencies from the onset of the COVID-19 pandemic. The Bai-Perron test was used to determine the change in the mean and variance of the two principal actors regarding market capitalization in the cryptocurrency market. Wavelet coherence analysis was also used to detect the co-movements between BTC and ETH. As a result of the study, several similar breaks were seen in each BTC and ETH series. Only one break could be directly associated with the pandemic process. This means that the pandemic is internalized and normalized in the process. The wavelet coherence results indicate a strong positive dependency (dark warm colours) between BTC and ETH and in phase (in the same direction) in the short and long bandgaps.

Keywords: Structural Break, Co-Movement, Cryptocurrency.

JEL Classification: C22, C50, G10

1. Introduction

Following the meteoric rise in BTC and ETH in 2017, cryptocurrencies have become a critical investment instrument followed by media, financial and government institutions because they provided new perspectives on volume, forms of payment, and the ability to use pseudonyms in transactions. It is also notable that cryptocurrencies have little resemblance to those linked to traditional assets

such as bonds and stocks (Beneki et al., 2019). Also, their markets are known to be volatile, as BTC and ETH are still not regulated by a central authority (Mensi, Al-Yahyaee and Kang, 2019).

Many nations have noticed changes in consumer behaviour across many industries due to fear and restrictions. COVID-19 has caused stocking and cautious saving practices worldwide (Özbay and Özcan, 2021). Especially with the emergence of the pandemic, cryptocurrencies have become more remarkable as a means of savings. The pandemic has drawn people's entire lives to the internet/virtual environment, and turning to cryptocurrencies has been seen as a quick and easy alternative option for investors (Zeren and Hızarcı, 2020). The increase in cases during the pandemic has been seen to have a powerful impact on the cryptocurrency market. It is stated that the COVID-19 pandemic has played an essential role in the change in the crypto money market.

One of the main effects of COVID-19 was that it revealed the global economy's vulnerability and its apparent dependence on external shocks (Bentes, 2022). The non-stableness of the cryptocurrency is mainly attributed to structural breaks (Wu, 2021). Structural breaks are observed in financial and economic indicators and policies that show continuity. Structural breaks can occur in timing, trend, change point, and date shifts. The analysis of structural breaks or change points has its origins in quality control studies (Page, 1954, 1955) but has since grown in economics, finance (Andreou and Ghysels, 2009), climatology (Reeves, Chen, Wang, Lund and Lu, 2007), and engineering (Stoumbos, Reynolds, Ryan and Woodall, 2000) has become an integral part of a wide variety of fields (Aue and Horváth, 2013; Perron, 2006; Telli and Chen, 2020). The structural break came to the fore and began to be researched, especially in the late 1970s. The literature on structural break is devoted to detecting parameter instability or changes occurring at an unknown time. It emphasizes the instability of parameters, especially in dynamic models with biased regressors, cointegrating variables, varying variance disorders and perhaps unit roots (Bai and Perron, 1998). Testing for unknown structural breaks or change points can be identified in single and multiple structural breaks. Once the structural break is known, the Chow test is used. Various alternative procedures exist under the Bai-Perron test class to estimate an unknown number of multiple fractures. These procedures are global, maximizing sequential analysis and hybrid versions with both components.

The literature on BTC financing should be expanded, particularly concerning the analysis of the persistence in the level and volatility of the BTC price (Bouri, Gil-Alana, Gupta and Roubaud et al., 2019). In addition, examining ETH, another leading cryptocurrency in terms of trading volume, enables the expan-

sion and comparison of the results obtained and increases consistency. It also expands the literature. Identifying possible structural breaks in these two major cryptocurrencies, which we can define as pioneers in cryptocurrencies, and determining their importance will provide important predictability for investors. In this study, the structural breaks of BTC and ETH, the two main elements of the cryptocurrency market, are examined to have made significant movements during the pandemic. The literature has focused on the BTC economy and finance in general, and studies examining the BTC and ETH market breaks in the Covid-19 period have been neglected. This study aims to contribute to filling this gap in the literature and advancing information, policy, and discussions about cryptocurrencies. It focuses on the structural breaks, especially considering the pandemic period. For this purpose, detailed analyses developed by Bai-Perron, in which multiple breaks can be detected, were carried out. Considering significant volatile movements in the crypto money market even during the day, it is vital to investigate structural breaks in the context of daily series (Esteve & Requena, 2006). At the same time, it is crucial to investigate structural breaks in the pandemic period, given that there are severe increases in cryptocurrencies, especially during the pandemic.

This study evaluates whether BTC and ETH experienced statistically significant structural breaks during the pandemic (31.12.2019-03.07.2022). The primary purpose here is to determine the timing of possible breaks and their relationship with each other. In the study, Bai & Perron's test (Bai & Perron, 2003, 1998), which is widely used and allows the detection of multiple breaks, was used to determine the timing of structural breaks of BTC and ETH for more than one endogenous breakpoint. The wavelet coherence analysis was also used to detect the co-movements between BTC and ETH.

2. Previous Studies

Numerous studies have been conducted to examine the characteristics of cryptocurrency prices. Some of these studies have investigated and documented whether crypto money markets are based on speculation and the existence of bubbles in cryptocurrencies (Cheah and Fry, 2015; Corbet, Lucey & Yarovaya, 2018; Bouri, Shahzad and Roubaud, 2019;? Hafner, 2020). In addition, Makarov and Schoar (2020) highlighted that cryptocurrencies exhibit arbitrage opportunities against stock markets for weeks. Yermack (2015) discusses the extent to which Bitcoin can become a currency.

There are various studies on structural breaks during the pandemic, but few of them investigate structural breaks of cryptocurrencies. However, some studies consider the pre-pandemic period and the structural breaks in cryptocurrency markets. During the pandemic period, it is seen that there is a particular focus on stock markets rather than cryptocurrencies. While the co-movements of cryptocurrencies had been frequently studied before the pandemic, they were not adequately studied during the pandemic. However, it is essential to examine such relationships in terms of informing investors and raising awareness about similar situations in the future, such as in the economic crisis environment created by the pandemic, which considers the crisis periods. On the other hand, Marashdeh & Shrestha (2010) report that studies examining the co-movements of asset prices are essential for risk management, asset pricing and allocation, and policy formulation.

According to Mensi et al. (2019) investigated the effects of structural breaks on the binary long memory levels of BTC and ETH price returns. As a result, they detected long bilateral memory and structural changes in crypto money markets. Abakah, Gil-Alana, Madigu and Romero-Rojo (2020) analyzed 12 leading cryptocurrencies (BTC, Bitshare, Bytecoin, Dash, Ether, Litecoin, Monero, Nem, Ripple, Siacoin, Stellar, and Tether) by taking into account the persistence of volatility and the possibility of a structural break. As a result, they stated that the returns showed extended memory features with integration sequences supporting the long memory hypothesis. However, when structural breaks are considered, they observed a decrease in the level of permanence in the cryptocurrency market.

Kumar and Ajaz (2019) examined the co-movement patterns of four leading cryptocurrencies: BTC, ETH, Lite and Dashcoin. It was found that the correlation follows a non-periodic cyclical structure, and cryptocurrency prices are affected by BTC price movements. They discovered that BTC prices drive cryptocurrency prices.

Katsiampa (2019) provided evidence of the interdependencies of BTC and Ethereum. Additionally, he found that ETH could be an effective hedge against BTC. Thies and Molnár (2018) found that structural breaks in BTC's average returns and volatility are frequent.

Telli & Chen (2020) aimed to test multiple structural breaks using the Bai-Perron methodology for crypto markets. Their results indicate statistically significant structural changes in returns and volatility.

Qiao, Zhu & Hau (2020) examined the co-movement between 12 cryptocurrencies and BTC. As a result of the study, there are positive correlations between BTC and other cryptocurrencies in short and medium-investment horizons. Moreover, BTC's returns and volatility are ahead of other cryptocurrencies at low frequencies. A hedge effect across BTC against other cryptocurrencies is more pronounced in the long run.

As a result of the Zivot-Andrews unit root test, one of the structural break unit root tests conducted by Avşarlıgil (2020) concluded that there was no structural break at the beginning of the Covid-19 pandemic for both WTI, BTC, and EUR.

Panagiotis, Efthymios Anastasios-Taxiarchis and Athanasios (2020) explored the impacts of twelve large-capitalization cryptocurrencies during bearish markets, focusing on the influence of Bitcoin, Ethereum, and Ripple. The findings highlight the positive relationships between most cryptocurrencies, including Bitcoin and Ethereum, suggesting limited hedging possibilities for portfolio managers and investors during distressed times.

James & Menzies (2021) examined overbearing distribution endpoints and erratic behaviour in 51 cryptocurrencies with structural breaks to evaluate the impact of Covid-19 on cryptocurrency market dynamics. They observed a reduction in self-similarity due to Covid-19, particularly concerning structural breaks in variance. While Tether (USDT) and TrueUSD (TUSD) are consistent outliers in terms of returns, Holo (HOT), NEXO (NEXO), Maker (MKR), and NEM (XEM) often behave abnormally in both behaviour and time.

Karavias, Narayan and Westerlund (2022) conducted a study covering 61 countries between January 3 and September 25, 2020, with a new fracture detection toolbox. As a result of the study, they determined that the Covid-19 pandemic was negative before the fracture and zero after it. They explained this situation by saying that although the markets reacted, the reaction took a short time. They emphasized that there may have been quantitative easing programs announced by central banks worldwide in the second half of March 2020.

Mandaci & Cagli (2022) used a new Granger causality methodology with the Fourier approach to determine the relationship between herd and volatility, taking into account structural breaks. As a result, they suggested that it points to a vital herd behaviour intensified during the Covid-19 outbreak. The causality test results show that herd significantly affects market volatility. As a result, it has been argued that the efficient market hypothesis is not supported.

Lee & Rhee (2022) examined the BTC price of BTC using structural break analysis. They stated that the number of structural breaks in BTC was five and that the pandemic had little impact on BTC price. They suggested that BTC was more susceptible to underlying economic factors during the pandemic than Covid-related variables alone or combined. They concluded that BTC had reached a certain maturity as an investment vehicle.

On the other hand, the study by Luburić (2021) delves into the global crisis triggered by the COVID-19 pandemic and emphasizes the need for a comprehensive approach to crisis prevention and management. This research contributes valuable insights into the broader context of crisis prevention, particularly in the face of unprecedented global challenges. By exploring the cryptocurrency market's reactions during the pandemic, this study complements the Luburić's study by extending the discussion to the financial realm and exploring the implications of crisis dynamics on novel and volatile assets like cryptocurrencies.

Examining the studies on the stock exchange and financial markets during the Covid-19 period is also essential. Especially in studies, it is necessary to understand the assumption that cryptocurrencies behave differently from other markets.

Kılcı (2021) analyzed the trend of confidence indices for Turkey in the range of 2012:05 - 2020:09. Carrion-I-Silvestre, Kim and Perron`s (2009) unit root test was used. As a result of the study, it was determined that the financial and real sector confidence indices followed a stable course. In contrast, the consumer confidence index did not show a consistent approach. Our analysis also provides information on the dates of structural breaks.

Bhatia (2022) investigated the impact of the coronavirus pandemic on India's stock market efficiency during multiple breakout periods. His study using the automated portmanteau test showed that the stock returns of the two indices deviated from market efficiency during some analysis periods, particularly during the peak of nationwide lockdown and coronavirus cases in India. These findings suggest that the changing stock market behaviour is becoming more speculative and making abnormal profits.

Erol and Saghaian (2022) investigated the impact of the Covid-19 pandemic on vertical price transmission dynamics in the US beef industry using monthly farm, wholesale and retail prices over the period 1970-2021. They investigated possible asymmetries and structural breaks in price transmission along the beef supply chain with contemporary time series techniques and historical decomposition

graphs. The results showed that the impact of Covid-19 was unequal in the beef marketing channel where consumers and farmers share the burden of the shock.

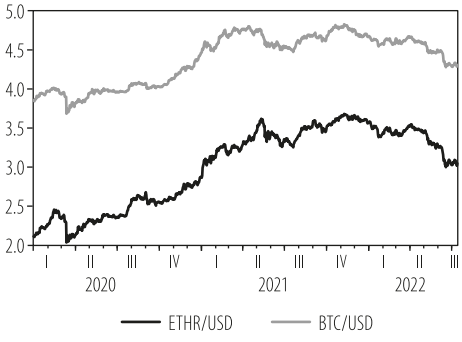
Fabris and Ješić (2023) investigated the role of gold and Bitcoin as safe havens for European indices, challenging the traditional notion that gold serves as a reliable safe haven. However, the findings reveal that Bitcoin, despite being considered the best representative of cryptocurrencies, was rejected as a safe haven during turbulent periods. This brings attention to the need for a deeper understanding of the dynamics and behaviour of cryptocurrencies during crises.

The literature on the characteristics of the cryptocurrency market has shown that the market behaves differently from other financial markets, such as stocks, commodities and exchange rates (Nitithumbundit & Chan, 2022). In the following period, it is essential to examine the relations of these variables with each other to understand this difference. In this context, it may be beneficial for investors to analyse structural breaks while considering future volatility and applying hedging strategies (Avşarlıgil, 2020). Examining the structural change periods in cryptocurrencies, which have become an essential investment tool today, with detailed analyses, will guide investors and those lacking information on the subject. Understanding the key breakpoints and interdependencies of price movements in cryptocurrency markets over time is important for successful and profitable investment management. Therefore, our study can help cryptocurrency users make more informed decisions.

3. Data and Methodology

First, to detect the structural changes or breaks in the BTC/USD and Ethereum/USD cryptocurrency series, three different methods of the Bai-Perron structural break test were used. The logarithmic values of the series were used in the study. Analyses include daily price data for the period 12/31/2019 – 7/13/2022. The prices considered in the study are the closing prices as of 11:59:00 at night. Figure 1 shows the time series of LogBTC/USD and LogETH/USD exchange rates during the analysis period.

Figure 1: Time Series of Variables



Source: Author

3.1. Bai-Perron Structural Breaks Test

We consider the standard model of linear regression:

$$y_i = X_i^T \beta_i + \mu_i (i = 1 \ldots .... n) \quad (1)$$

Where at the time i, y_i is the observation of the dependent variable (*BTC* and *ETH*), $x_i = (1, x_i \ldots .... x_{ik})^T$ is a k x 1 vector of observations of the independent variables, with the first component equal to unity, $\mu_i (0, \sigma^2)$, and βi is the k x 1 vector of regression coefficients. Tests on structural change are premised on analyzing the null hypothesis of "no structural change" (Zeileis, Leisch, Hornik and Kleiber, 2002).

$$\beta_0 : \beta_1 = \beta_0 (i = 1 \ldots .... n) \quad (2)$$

contrary to the alternative hypothesis that the coefficient vector varies over time, certain tests are more or less suitable (i.e., having good or poor power) for certain patterns of deviation from the null hypothesis (Phiri and Wang, 2022).

3.2. Wavelet Coherence Analysis

The next section used the wavelet coherence analysis to detect the co-movement between BTC and ETH. The wavelet model consists of scale parameters, position, and a main wavelet function (Torrence and Compo, 1998; Zhang and Wu, 2019). Choosing the appropriate master wavelet is key when converting return series and volatility series in the cryptocurrency market. Therefore, the Morlet wavelet (Morlet, Arens, Fourgeau and Giard, 1982) is applied because it is not orthogonal, which means it can be applied to continuous variables. The Daubechies 4 wavelet is the master wavelet to decompose the return and volatility series (Qiao et al., 2020). In the literature on the use and derivation of wavelets, it is seen that two types of wavelets are mostly mentioned, which vary according to the normalization methods. These are father ϕ and mother wavelets ψ (Yang, Cai, Zhang and Hamori, 2016). $1(\int \phi(t)dt = 1)$ represents the integration of the father wavelet and $0(\int \psi(t)dt = 0)$ represents the integration of the mother wavelet. The detail and high-frequency components are the mother wavelet, and the flat and low-frequency parts of the signal (raw data) are the father wavelet.

By transforming any $y(t)$ function in $L^2(\mathbb{R})$ (area for square summable functions) into different frequency components with a resolution appropriate to its scale,

the wavelet function can be constructed as a series of projections on the mother and father wavelets generated from ϕ and ψ scaling and translation are as follows (Yang et al., 2016):

$$\phi_{j,k}(t) = 2^{-j/2}\,\phi(2^{-j}\,t - k),$$
$$\psi_{j,k}(t) = 2^{-j/2}\,\psi(2^{-j}\,t - k), \tag{3}$$

$j = 1, 2, \ldots, j$: scaling parameter in a J-level decomposition and k: translation parameter. We can express the wavelet representation of the signal $y(t)$ in $L^2(\mathbb{R})$ as:

$$y(t) = \Sigma_k\, s_{J,k}\,\phi_{J,k}(t) + \Sigma_k\, d_{J,k}\,\psi_{J,k}(t) + \Sigma_k\, d_{J-1,k}\,\psi_{J-1,k}(t) + \ldots + \Sigma_k\, d_{1,k}\,\psi_{1,k}(t) \tag{4}$$

in above equation $s_{j,k} = \int y(t)\,\phi_{j,k}(t)dt$ and $d_{j,k} = \int y(t)\,\psi_{j,k}(t)dt$, J: the number of multi-resolution components, $s_{j,k}$: smooth coefficients, and $d_{j,k}$ illustrates the detailed coefficients. The value of coefficients $(s_{j,k}, d_{j,k})$ measures the contribution of the corresponding wavelet function relative to the total signal.

The scale factor 2^j in Eqs. (1) and (2) denote the dilation factor during the translation parameter $2^j k$ refers to the location parameter. The larger the index j, the larger the value of the scale factor 2^j. Thus, the function becomes more expansive and more spread out. As the functions $\phi_{J,k}(t)$ and $\psi_{J,k}(t)$ become wider, their translation parameters $2'k$ also rise correspondingly.

The decomposed signals for a multi-resolution decomposition are represented as follows:

$$S_j(t) = \Sigma_k^{\,5}\, j_{J,k}\,\phi_{J,k}(t),$$
$$D_j(t) = \Sigma_k\, d_{J,k}\,\psi_{J,k}(t) \tag{5}$$

The functions $S/(t)$ and $D_j(t)$ in Eqs. (4) and (5) are smooth and detailed signals. They constitute a decomposition of a signal into orthogonal components at different scales. Thus, a signal $y(t)$ can be rewritten as:

$$y(t) = S_j(t) + D_j(t) + D_{j-1}(t) + \ldots + D_1(t) \tag{6}$$

The highest-level approximation $S/(t)$ is the smooth signal and the detail signals $D_1(t), D_2(t), \ldots, D_1(t)$ are associated with oscillations of lengths 2–4, 4–8, ... $2' - 2^{/+1}$, respectively. A real-valued function $y(t)$ for the discrete wavelet transform (DWT) is defined as follows:

$$\omega = Wy, \tag{7}$$

Where the coefficients are ordered from coarse scales to fine scales in the vector ∞. *W* is introduced as a set of low-pass a filter and *y* is called by the band-pass filter. *W* and *y* are orthogonal vectors with *N* x 1 elements. The type of the mother wavelet determines the coefficients in the filter. As *n* is divisible by 2′,*ω* can be specified as:

$$\omega = \begin{pmatrix} s_j \\ d_j \\ d_{j-1} \\ \vdots \\ d_1 \end{pmatrix} \tag{8}$$

where,

$$\begin{aligned} \boldsymbol{s_j} &= (\boldsymbol{s}_{j,1}, s_{j,2}, \cdots, \boldsymbol{s}_{j,2,2})', \\ \boldsymbol{d_j} &= \left(\boldsymbol{d}_{l,1}, d_{j,2}, \cdots, \boldsymbol{d}_{j,4/22'}\right)', \\ \boldsymbol{d_{j-1}} &= \left(d_{j-1,1}, d_{j-1,2}, \cdots, d_{j-1,8/2}\right)', \\ \boldsymbol{d_1} &= \left(\boldsymbol{d}_{1,1}, d_{1,2}, \cdots, d_{1,1/2i}\right)' \end{aligned} \tag{9}$$

Each set of coefficients s_1, d_1, d_j-1, w_1, ′, d_1 is called a crystal in which the wavelet coefficients corresponding to a set of translated wavelet functions arranged on a regular lattice.

Definition of the cross wavelet power of two-time series *x*(*t*) and *y*(*t*) is as follows (Ercan & Karahanoğlu, 2019):

$$Wxy(u, j) = Wx(u, j) \cdot Wy*(u, j) \tag{10}$$

Wx(*u, j*) and *Wy*(*u, j*) represent continuous wavelet transforms of time series *x*(*t*) and *y*(*t*). The star (*) signifies a complex conjugate, parameter *j* allocates a time position, and parameter *j* symbolizes the scale parameter. A low wavelet scale denotes the high-frequency part of the time series-a short investment horizon (Torrence and Webster, 1999).

Whenever the time series exhibit a typical high power, the cross-wavelet power reveals areas in the time-frequency space. In the co-movement analysis, we search for places where the two-time series in the time-frequency space co-movement do not necessarily have high power. A proper wavelet technique for finding these co-movements is wavelet coherence.

Torrence and Webster (1999) define the squared wavelet coherence coefficient as follows:

$$R^2(u,j) = \frac{|s[j^{-1}Wxy(u,j))|^2}{s\left[[j^{-1}(Wx(u,j))^2]\right] s\left[j^{-1}|Wy(u,j)|^2\right]}. \quad (11)$$

S represents a smoothing operator. The coefficient $R^2(u,j)$ lies in the interval [0,1]. When there is a low correlation the R^2 becomes closer to zero, whereas a stronger correlation is shown with the values more relative to one. Therefore, R^2 explains the local linear correlation between two stationary time series at each scale and is analogous to the squared correlation coefficient in linear regression. The following formula shows the phase differences according to Torrence and Webster's (1999) definition:

$$\theta_{xy}(u,j) = \tan^{-1}\left(\frac{\mathcal{F}\left\{s(j^{-1}w_{xy}(u,j))\right\}}{\Re\left\{s(j^{-1}w_{xy}(u,j))\right\}}\right) \quad (12)$$

$\mathcal{F}$ is imaginary, and $\Re$ is a fundamental part operator in this formulation. Black arrows in the wavelet coherence figures with significant coherence display the Phase differences. Once the two analyzed time series move together on a particular scale, the arrows direct to the right showing the positive correlation. On the other hand, if the correlation is negative between time series, then the arrows point to the left (Yang et al., 2016).

The result of wavelet coherence analysis is usually a shape with five main parts: eight-sided black arrows (←, →, ↑, ↓, ↘, ↗, ↙, ↖), warm and cool colours, black contours, two axes, and a cone. → (←) black arrows indicate an in-phase (out-of-phase) relationship or positive (negative) correlation, while arrows ↗ (↙) indicate the maximum effect of the first (second) series. For example, black arrows with the '↘' direction in wavelet coherence graphs show an in-phase relationship or positive co-movement between the two-time series with the maximum effect of the second time series. Black arrows with the '↖' direction in wavelet coherence plots indicate an out-of-phase relationship or negative co-movement between two-time series with the maximum effect of the first time series. A phase difference of zero means that both time series move together. The black curves in the graphs show regions with coherence significance at the 5% level, and the solid white bell-shaped line in the wavelet coherence graphs is the cone of influence (Rubbaniy et al., 2021).

4. Findings

4.1. Unit Root Test

First, the stationarity levels were examined. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests (Dickey & Fuller, 1979; Phillips, 1987; Phillips & Perron, 1988) are two widely applied unit-root tests (Cheung & Lai, 1997). In this study, these two tests were used for unit root research. Table 1 shows that since the null hypothesis suggesting that there is a unit root in the level values of the series could not be rejected at the 1% significance level using the ADF and PP tests, it was determined that the series contained unit root in the level values but became stationary in the difference values.

Table 1: PP and ADF Unit Root Test Results

			BTC	ETH
PP	*I(0)*	Constant	-1.6207 (**0.4715**)	-1.8699 (**0.3467**)
		Constant & Trend	-0.1396 (**0.9942**)	0.0937 (**0.9972**)
		Trend	0.7049 (**0.8674**)	1.0064 (**0.9176**)
			d(BTC)	d(ETH)
	I(I)	Constant	-33.2015 (**0.0000**)	-33.3934 (**0.0000**)
		Constant & Trend	-33.3311 (**0.0000**)	-33.5678 (**0.0000**)
		Trend	-33.1933 (**0.0000**)	-33.3455 (**0.0000**)
			BTC	ETH
ADF	*I(0)*	Constant	-1.5943 (**0.4851**)	-1.7654 (**0.3979**)
		Constant & Trend	-0.2193 (**0.9926**)	0.0229 (**0.9965**)
		Constant & Trend	0.6456 (**0.8555**)	0.8634 (**0.8959**)
			d(BTC)	d(ETH)
	I(I)	Constant	-13.8750 (**0.0000**)	-8.9085 (**0.0000**)
		Constant & Trend	-14.0175 (**0.0000**)	-9.1499 (**0.0000**)
		Constant & Trend	-13.8572 (**0.0000**)	-8.8303 (**0.0000**)

Notes: The values in the table are t statistics. Values in parentheses are probability values.
* MacKinnon (1996) one-sided p-values.

In the next stage of the study, the structural break tests recommended by (Bai and Perron, 2003, 1998) were carried out to detect the structural breaks of the BTC series. The tests were carried out in *R* and *Eviews 10* package programs. Three optimization procedures are included to identify multiple breaks for the Bai-Perron test performed in Eviews. Test statistics from each test are compared with their critical values to determine whether there are statistically significant breaks (Bumpass, Douglas, Ginn and Tuttle , 2019).

In this section, firstly, the procedure of "Bai-Perron Tests of 1 to k Globally Determined Breaks" is given. This procedure specifies the maximum number of k breaks that will be allowed, and the number of breaks that maximizes the test statistic is reported. Bai & Perron (1998) presented two test statistics that test for an unknown number of breaks versus zero breaks. These are the double maximum tests (***UDmax*** ve ***WDmax***) and the **supF_t (k)** tests. In the ***UDmax*** and ***WDmax*** tests, the null hypothesis is that there is no break, and the alternative hypothesis is the presence of an unknown number of breaks. In the **supF_t (k)** test, the null hypothesis is that there is no break, and the alternative hypothesis is that there are ***k*** breaks. The advantage of Bai-Perron tests over conventional tests is that they do not require a predetermined number of breaks and stop points.

Bai and Perron (2003) stated that **supF_t (k)**, ***UDmax*** and ***WDmax*** statistics should be looked at first among the test statistics used to determine the number of breaks and ***supFt(l+1/l)*** to test more breaks because the statistical significance indicates the presence of at least one break.) suggested that the test statistic be taken into account.

Table 2 shows the results of the **supF_t (k)**, ***UDmax*** and ***WDmax*** tests. Table 2 shows that both maximum statistics are significant at traditional levels. In addition, the null hypothesis of "no breaks" against the "**k number of breaks**" alternative hypothesis proposed for performing the **supF_t (k)** test is rejected at the 1% significance level. In summary, the data strongly supports structural break(s) in the mean of the BTC series.

The Bai-Perron test results in Table 2 showed the leading hypothesis is no structural break according to the **supF_t (k)** tests was rejected at a 5% significance level for 1, 2, 3, 4 and 5.

According to the UDMax and WDMax tests, the existence of at least 1 break cannot be rejected at the 5% significance level against the null hypothesis that there is no structural break. The double maximum statistics indicate a structural break, and the break date is 12/16/2020.

Table 2: BTC Bai-Perron Tests of 1 to M Globally Determined Breaks

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
supFt(1)*	5514.018	**5514.018**	**5514.018**	8.58
supFt(2)*	3643.420	3643.420	4329.715	7.22
supFt(3)*	3126.666	3126.666	4501.140	5.96
supFt(4)*	2510.151	2510.151	4316.052	4.99
supFt(5)*	2062.479	2062.479	4525.850	3.91
Estimated break dates:				
1: 12/16/2020				
2: 7/27/2020, 12/24/2020				
3: 7/27/2020, 12/26/2020, 2/20/2022				
4: 7/27/2020, 12/25/2020, 8/19/2021, 1/20/2022				
5: 7/27/2020, 12/26/2020, 5/16/2021, 10/01/2021, 2/18/2022				
UDMax statistic*		5514.018	UDMax critical value**	8.88
WDMax statistic*		5514.018	WDMax critical value**	9.91

Notes: * Significant at 0.05; ** Bai-Perron (Econometric Journal, 2003) critical values; Break test options: Trimming 0.15, Max. breaks 5, Sig. level 0.05; Sequential F-statistic determined breaks: 5; Significant F-statistic most extensive breaks: 5; UDmax determined breaks: 1; WDmax determined breaks: 1

In the method of sequentially determined breaks from 0 to m, the Bai-Perron test with the information criteria of Schwarz and Liu, Wu and Zidek (LWZ) reports the optimal number of breaks that minimizes the two information criteria. Bai-Perron test, Schwarz (Yao, 1988) and (Liu, Wu and Zidek, 1997) information criteria show 5 and 4 structural breaks, respectively. The final selection can be made based on the LWZ criterion (Liu et al., 1997), which is robust against serial correlation problems. Since the LWZ information criterion performs relatively better, it can be said that the number of breaks is 4. In this case, the structural break dates are 7/27/2020, 12/25/2020, 8/19/2021, and 1/20/2022.

Table 3: BTC Compare Information Criteria for 0 to M Globally Determined Breaks

Breaks	Sum of Sq. Residents.	Log-L	Schwarz* Criterion	LWZ* Criterion
0	95.78077	-263.4770	-2.261436	-2.249473
1	13.74669	635.3282	-4.187946	-4.152056
2	10.76826	748.3907	-4.417388	-4.357566
3	8.572111	853.9957	-4.630723	-4.546964
4	8.047552	883.2323	-4.679115	**-4.571415**
5	7.845015	895.0341	**-4.689852**	-4.558204
Estimated break dates:				
1: 12/16/2020				
2: 7/27/2020, 12/24/2020				
3: 7/27/2020, 12/26/2020, 2/20/2022				
4: 7/27/2020, 12/25/2020, 8/19/2021, 1/20/2022				
5: 7/27/2020, 12/26/2020, 5/16/2021, 10/01/2021, 2/18/2022				

* Minimum information criterion values displayed with shading; Break test options: Trimming 0.15, Max. breaks 5; Schwarz criterion selected breaks: 5; LWZ criterion selected breaks: 4

Structural changes in BTC/USD were determined by the Bai-Perron structural break sequential test. Another Bai-Perron structural break test procedure is L+1 vs. L sequentially determined breaks ($supF_t(l+1/l)$) tests for an unknown break and additional breaks that most reduce the sum of the squares of the residues. The $supF_t(l+1/l)$ test is a sequential test in which the null hypothesis expresses the existence of 1 break and the alternative hypothesis expresses the existence of 1+1 breaks. Table 4 shows the estimated F statistic, scaled F statistic, Bai-Perron critical values, and break dates.

In the last stage of the study, based on the results of the $supF_t(1+1/l)$ tests, it is seen that 1 structural break is rejected against 0 structural breaks, 2 structural breaks against 1 structural break, 3 structural breaks against 2 structural breaks, 4 structural breaks against 3 structural breaks.

As a result, the sequential Bai-Perron test in Table 4 reveals four structural breakpoints. Structural break dates; 7/27/2020, 12/16/2020, 8/09/2021 and 2/21/2022. The null hypothesis suggesting that there are no five structural breakpoints (m=5) cannot be rejected at the 5% significance level (F-statistic is 0 and is lower than the critical value of 12.25).

Table 4: BTC Bai-Perron Tests of L+1 Vs. L Sequentially Determined Breaks

Break Test	F-statistic	Scaled F-statistic	Critical Value**
supFt(l/0)*	5514.018	5514.018	8.58
supFt(2/1)*	249.8459	249.8459	10.13
supFt(3/2)*	212.4004	212.4004	11.14
supFt(4/3)*	63.42854	63.42854	11.83
supFt(5/4)	0.000000	0.000000	12.25
Break Dates:			
	Sequential	Repartition	
1	12/16/2020	7/27/2020	
2	7/27/2020	12/26/2020	
3	2/21/2022	8/09/2021	
4	8/09/2021	1/21/2022	

* Significant at the 0.05 level. ** Bai-Perron (Econometric Journal, 2003) critical values. Break test options: Trimming 0.15, Max. breaks 5, Sig. level 0.05 Sequential F-statistic determined breaks: 4

Considering other optimization methods, the procedures consistently suggest similar break dates. The LWZ criterion shows that the most significant breakouts consist of 4 breaks that occurred on 7/27/2020, 12/16/2020 or 12/26/2020, 8/09/2021, and 2/21/2022. However, the sequential procedure outperforms BIC and LWZ because the sequential approach can easily account for the effects of possible serial correlation in errors (Bai and Perron, 2003, 1998). In this study, sequential procedures and criteria gave similar results.

When the breaking dates are examined, while the exchange rate of ₿/$ was 9,9481 on 7/26/2020, it became 11,044 on 7/27/2020. Therefore, on the date of the first breakout, the ₿/$ rate increased by 11% for the first time in the last 7 years. During this period, there were developments such as the depreciation of the dollar and the appreciation of gold. It can be said that the measures governments took to combat the economic recession and recession caused by the worldwide coronavirus pandemic during the same period also supported BTC. Again, it is expected that BTC, which has been in a bear market trend since 2017, will enter a bull market trend after this break. The exchange rate, 19,459 on 12/15/2020, increased to 21,322 on 12/16/2020 (9.57%). It enormously exceeded the $20,000 limit for the first time in history. Likewise, the exchange rate, 24,717 on 12/25/2020, increased to 26,412 on 12/26/2020 (6.86%). After this date, it entered an intense rising period and exceeded the limit of 40 thousand dollars in 13 days. In 2021, it increased to approximately 70 thousand dollars. There was an increase of 5.76%

on 8/09/2021. For the date of 2/21/2022, we can say that the decline from the peak point ended for a while and then approximately 49 thousand dollars were seen again.

To strengthen the analyses, Bai-Perron structural break tests were repeated in the Rstudio program, and the analyses performed were included. According to the sup F type test results in Table 5, since the p-value is less than 1% and 5%, the hypothesis of "H0: There is no structural change in the series" is rejected. Therefore, there is a structural break in the series of BTC. To assess the goodness of fit and determine an optimal number of k breakpoints, we use sequential tests and compare the criteria based on the Bayes Information Criterion (BIC) and Residual Sum of Squares (RSS) is the sum of the differences between observed and expected outcome values. Table 5 also shows the summary of BIC, a criterion used for model selection and RSS, a statistical technique used to measure the amount of variance in a data set that the regression model does not explain. The RSS and BIC values were smaller than the mono-exponential model ($p<0.001$). It is common to consider information criteria to select the number of breaks. According to the minimum values of RSS and BIC criteria, there are 5 breaks in the BTC series. The breaking dates are 07/14/2020, 12/25/2020, 08/08/2021, 01/19/2022 and 07/13/2022.

Table 5: R Output of Sequentially Determined Breaks Bai-Perron Test (BTC)

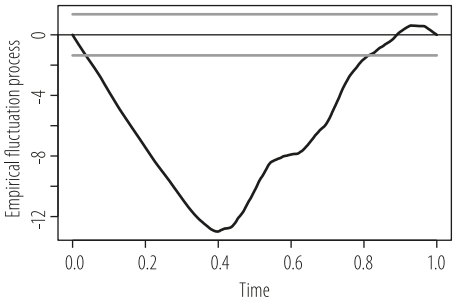
Number of Fractures	Observation Values	Break Dates				
1	321	11/15/2020				
2	351 926	12/15/2020 - 07/13/2022				
3	196 360 926	07/13/2020 – 12/24/2020 - 07/13/2022				
4	197 361 752 926	07/14/2020 - 12/25/2020 – 01/20/2022 - 07/13/2022				
5	**197 361 587 751 926**	**07/14/2020 - 12/25/2020 – 08/08/2021 - 01/19/2022 - 07/13/2022**				
Dates observed by Eviews: 7/27/2020 - 12/16/2020 - 12/26/2020 - 8/09/2021 - 2/21/2022						
Goodness of Fit:						
m	0	1	2	3	4	5
RSS:	127.879	77.399	14.692	11.979	9.856	**9.266**
BIC:	769.735	233.426	-1573.766	-1783.553	-1983.330	**-2036.978**
sup. F = 5514, p-value < 2.2e-16						

As a result of the analysis, it was statistically confirmed that there were many structural breaks. However, there are minor deviations from the Eviews program results in the break dates.

In Figure 2, the empirical fluctuations overflow the process. A suitable empirical fluctuation process of a particular type is constructed using the formula that defines a linear regression model to be tested. When the grey lines enclose the black lines of the plotted graph, the structural break hypothesis is rejected. However, there is a structural break in the model of the series as the graph drawn in Figure 2 is outside the boundary lines. It can be seen that the OLS-based CUSUM process exceeds its boundary; hence, there is evidence of a structural change. Furthermore, the process seems to indicate four changes.

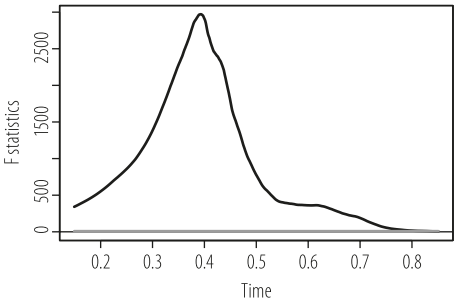
In Figure 3 below, peaks are the parts of the time series with structural changes. The computation of boundaries and plotting of *F* statistics is similar to that of empirical fluctuation processes introduced in the previous section. Under the null hypothesis of no structural change, limits can be computed such that the asymptotic probability that the supremum (or the mean) of the statistics F_i (for $\underline{i} \leq i \leq \overline{i}$) exceeds this boundary is α. The process of *F* statistics with its limit can be seen in Figure 3. As the *F* statistics cross their border, there is evidence again for a structural change (at the level $\alpha = 0.05$).

Figure 2: OLS-Based Cusum Test



Source: Author

Figure 3: F Statistics



Source: Author

4.2. ETH Structural Breaks

Below are the analyzes for ETH. Table 6 shows the results of $\mathbf{sup}F_t$ **(k)**, ***UDmax*** and ***WDmax*** tests. Table 6 shows that both maximum statistics are significant. In addition, the null hypothesis of "no breaks" against the "k number of breaks" alternative hypothesis proposed for performing the $\mathbf{sup}F_t$ **(k)** test is rejected at the 1% significance level. In summary, the data strongly supports structural break(s)

in the mean of the ETH series. When the Bai-Perron test results in Table 6 are examined, the main hypothesis, no structural break, according to the $\mathbf{sup}F_t$ (**k**) tests, was rejected at a 5% significance level for 1, 2, 3, 4 and 5. On the other hand, according to the ***UDMax*** and ***WDMax*** tests, the existence of at least 1 break cannot be rejected at the 5% significance level against the null hypothesis that there is no structural break. ***UDmax*** and ***WDmax*** criteria indicate 1 and 4 breaks. When 1 break is taken into account, the break date is 1/03/2021. On this date, ETH rose by a significant 26.19%. Considering the 4 break dates, the break dates are 7/25/2020, 1/03/2021, 8/04/2021, 1/21/2022.

Table 6: ETH Bai-Perron Tests of 1 to M Globally Determined Breaks (Supft(K))

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
$supF_t(1)$*	6120.171	**6120.171**	6120.171	8.58
$supF_t(2)$*	5120.849	5120.849	6085.441	7.22
$supF_t(3)$*	4128.307	4128.307	5943.100	5.96
$supF_t(4)$*	4170.561	4170.561	**7171.025**	4.99
$supF_t(5)$*	3203.954	3203.954	7030.671	3.91
Estimated break dates:				
1: 1/03/2021				
2: 7/25/2020, 1/05/2021				
3: 7/25/2020, 1/03/2021, 7/30/2021				
4: 7/25/2020, 1/03/2021, 8/04/2021, 1/21/2022				
5: 7/25/2020, 1/03/2021, 5/21/2021, 10/06/2021, 2/21/2022				
UDMax statistic*		6120.171	UDMax critical value**	8.88
WDMax statistic*		7171.025	WDMax critical value**	9.91

Notes: * Significant at the 0.05 level; ** Bai-Perron (Econometric Journal, 2003) critical values; Break test options: Trimming 0.15, Max. breaks 5, Sig. level 0.05; Sequential F-statistic determined breaks: 5; Significant F-statistic largest breaks: 5; UDmax determined breaks: 1; WDmax determined breaks: 4

Table 7 shows L+1 vs. another procedure of the Bai-Perron structural break test. The results of L sequentially determined breaks (supFt(l+1/l)) method are shown. Based on the results of the supFt (l+1/l) tests in the ETH/USD exchange rate, it is seen that 1 structural break was rejected against 0 structural breaks, 2 structural breaks against 1 structural break, 3 structural breaks against 2 structural break, 4 structural breaks against 3 structural break.

As a result, the sequentially determined breaks in Table 7 reveal four structural breakpoints. Structural break dates: 1/03/2021, 7/25/2020, 7/30/2021, 1/21/2022.

The null hypothesis suggests that no five structural breakpoints (m=5) cannot be rejected at the 5% significance level (F-statistic is 0 and is lower than the critical value of 12.25).

Table 7: ETH Bai-Perron Tests of L+1 Vs. L Sequentially Determined Breaks

Break Test	F-statistic	Scaled F-statistic	Critical Value**
supFt(l/0)*	6120.171	6120.171	8.58
supFt(2/1)*	537.4995	537.4995	10.13
supFt(3/2)*	181.1129	181.1129	11.14
supFt(4/3)*	291.0705	291.0705	11.83
supFt(5/4)	0.000000	0.000000	12.25
	Break Dates:		
	Sequential	Repartition	
1	1/03/2021	7/25/2020	
2	7/25/2020	1/03/2021	
3	7/30/2021	8/04/2021	
4	1/21/2022	1/21/2022	

* Significant at the 0.05 level.
** Bai-Perron (Econometric Journal, 2003) critical values.
Break test options: Trimming 0.15, Max. breaks 5, Sig. level 0.05
Sequential F-statistic determined breaks: 4

Table 8 shows the analysis results according to the method based on comparing information criteria for globally determined breaks between 0 and k. Schwarz and LWZ information criteria show that there are 4 structural breaks. Considering other optimization methods, the procedures consistently suggest similar break dates. LWZ criterion shows that the most critical breaks consist of 4 on 7/25/2020, 1/03/2021, 8/04/2021, and 1/21/2022. As a result, the sequential selection procedure approach and LWZ criterion gave similar results.

Table 8: ETH Compare Information Criteria for 0 to K Globally Determined Breaks

Breaks	Sum of Sq. Residents.	Log-L	Schwarz* Criterion	LWZ* Criterion
0	232.8057	-674.6868	-1.373293	-1.361331
1	30.53766	265.7790	-3.389783	-3.353894
2	19.24635	479.5179	-3.836669	-3.776847
3	16.13047	561.2890	-3.998527	-3.914768
4	12.18037	691.3384	**-4.264658**	**-4.156957**
5	12.64369	674.0533	-4.212571	-4.080924
Estimated break dates:				
1: 1/03/2021				
2: 7/25/2020, 1/05/2021				
3: 7/25/2020, 1/03/2021, 7/30/2021				
4: 7/25/2020, 1/03/2021, 8/04/2021, 1/21/2022				
5: 7/25/2020, 1/03/2021, 5/21/2021, 10/06/2021, 2/21/2022				

* Minimum information criterion values displayed with shading; Break test options: Trimming 0.15, Max. breaks 5
Schwarz criterion selected breaks: 4
LWZ criterion selected breaks: 4

Considering the breaking dates, ETH increased from $279.85 to $305.87 on 7/25/2020. On 1/03/2021, ETH rose by a significant 26.19%. There was an increase of 8.62% on 08/04/2021. Around this time, the London upgrade took place, overhauling ETH's fee structure to make it easier and cheaper to estimate transaction costs. At the same time, ConsenSys founder and ETH co-founder Joseph Lubin made statements implying that ETH had passed to the status of "ultrasound money" before the London hard fork. It declined rapidly below $3,000 with a decline. During this period, Russia is deploying troops to Ukraine's borders. In the same period, sharp decreases were experienced in the stock values of technology companies in the USA.

In this section, the results obtained in the *R* program are given. According to the sup F type test results in Table 9, since the p-value is less than 1% and 5%, the hypothesis of "H0: There is no structural change in the series" is rejected. Therefore, there is a structural break in the series of ETH series. The RSS and BIC values were smaller than the mono-exponential model ($p<0.001$).

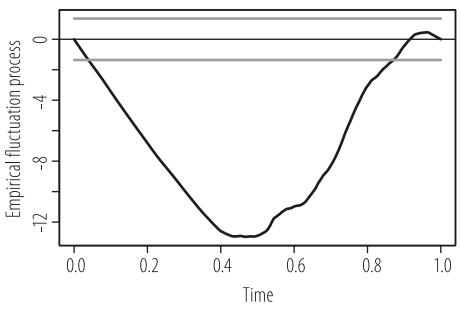
Table 9: R Output of Sequentially Determined Breaks Bai-Perron Test (ETH)

Number of Fractures	Observation Values	Break Dates				
1	369	01/02/2021				
2	207 371	07/24/2020 - 01/04/2021				
3	207 369 582	07/24/2020 - 01/02/2021 - 08/03/2021				
4	207 363 487 611	07/24/2020 - 12/27/2020 - 04/30/2021 09/01/2021				
5	206 337 461 585 709	07/23/2020 – 12/01/2020 - 04/04/2021 – 08/06/2021 - 12/08/2021				
Goodness of Fit:						
m	0	1	2	3	4	5
RSS:	224.345	25.826	14.488	11.979	**8.588**	8.862
BIC:	1284.631	-502.701	-970.763	-1392.912	**-1459.483**	-1339.914
sup. F = 5514, p-value < 2.2e-16						

As a result, it was statistically confirmed that there was a structural break in the series, and it was determined that there were many structural breaks. In Figure 4, the empirical fluctuations overflow the process. A suitable empirical fluctuation process of a particular type is constructed using the formula that defines a linear regression model to be tested. When the grey lines enclose the black lines of the plotted graph, the structural break hypothesis is rejected. However, there is a structural break in the model of the series as the graph drawn in Figure 4 is outside the boundary lines. It can be seen that the OLS-based CUSUM process exceeds its boundary; hence there is evidence of a structural change. Furthermore, the process seems to indicate four changes.

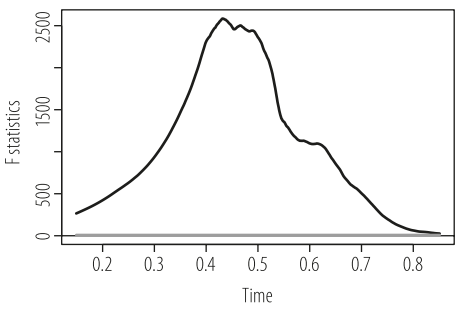
In Figure 5, peaks are the parts of the time series with structural changes. The computation of boundaries and plotting of *F* statistics is similar to that of em-

Figure 4: OLS Based CUSUM test



Source: Author

Figure 5: F Statistics



Source: Author

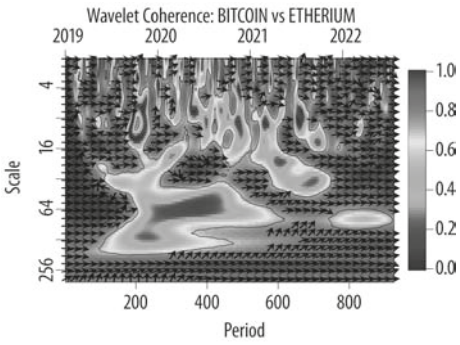
pirical fluctuation processes introduced in the previous section. Under the null hypothesis of no structural change, boundaries can be computed such that the asymptotic probability that the supremum (or the mean) of the statistics F_i (for $\underline{i} \leq i \leq \overline{i}$) exceeding this boundary α. The process of *F* statistics with its boundary can be seen in Figure 5. As the *F* statistics cross their boundary, there is evidence again for a structural change (at the level $\alpha = 0.05$).

4.3. Wavelet Coherence Results

The findings obtained from the analysis are shown in Figure 6. Figure 6 shows the analysis period daily on the horizontal axis. The analysis period consists of a total of 926 days. The vertical axis shows the frequency (the lower the frequency, the larger the scale); regions in the time-frequency space where the two-time series change is accommodated by wavelet coherence. Warmer colours (red) represent regions with significant correlation, while more perfect colours (blue) represent lower levels of dependency between series. The cold (blue) regions outside the areas expressing significant relationships represent time and frequencies that are not dependent on the series. An arrow in wavelet coherence plots represents the series' forward/lag phase relationships. Zero phase difference means that two-time series move together on a specific scale. Arrows point right (left) when the time series is in phase (anti-phase). If two series are in phase, they move in the same direction, while anti-phase means moving in the opposite direction. Arrows pointing right down or left up indicate that the first variable is leading, and arrows pointing right up or left down indicate that the second variable is leading (Kalmaz & Adebayo, 2020).

Figure 6 shows the Wavelet Consistency heat maps reflecting the most important of the typical movements of BTC and ETH. Since the analysis period is relatively short (two years and seven months), the short term is defined as fluctuations in the frequency bands of 0–32 days, while the long term ranges between the frequency bands 64–256 and > 256 days. As seen in Figure 6, there are arrows to the right between January 2020 and July 2022. Most arrows are to the right, indicating a strong link between BTC and ETH. Figure 6 reveals that BTC mainly triggers ETH. The wavelet coherence heat maps indicate a strong dependency (dark warm colours) between BTC and ETH and in phase (in the same direction) in the short and long bandgaps. During this period, ETH follows BTC prices. They exhibit zero phase features at a 32-128-day scale (which means that two-time series move together on a specific scale). The series are positively correlated in this process. However, it is seen that ETH prices follow BTC prices (↘) in band gaps of 32 days and below. At the beginning of the pandemic, while there was a zero

Figure 6: R Package Wavelet Coherence Output



Source: Author

phase feature and ETH prices followed BTC prices, it is seen that BTC prices started to follow ETH prices intensively in the long term and on a 128-256-day scale. The reason for this may be the bursting of the bubble in BTC and the increase in demand for ETH, which has been neglected compared to BTC, and the attempt to gain profits by taking advantage of price differences (Arbitrage). In the long term, on the 4-64-day scale, the direction of joint movements is quite complex. These results also suggest that BTC and ETH are seen as safe havens for each other for investors who do not want to give up their crypto investment during the pandemic period.

5. Discussion and Conclusion

Testing structural changes in time series is a crucial topic in econometrics. Numerous factors cause changes in financial and economic indicators over time. Bai and Perron (2003, 1998) discussed estimating multiple structural breaks or changes in a linear model estimated by the least squares method. This study aims to detect multiple structural breaks using the methodology developed by Bai & Perron (1998) and the co-movements using wavelet coherence analysis in BTC and ETH prices. As a result of the analyses carried out, it is seen that consistent results have been achieved. Our empirical findings point to the existence of change points in cryptocurrency prices. In general, similar breakpoints were determined as a result of the analyses made in Eviews and R programs. It is seen that there are 4-5 breaks in the BTC and ETH series during the pandemic period. Structural breaks point to general economic, political, and pandemic developments and cryptocurrencies. These breaks show that cryptocurrencies are reacting to essential developments. The results showed that cryptocurrencies were affected by the developments related to the pandemic in their own particular and other economic and political developments during the pandemic. It was seen that there was only one break that could be directly associated with the pandemic process. In this period of rupture, states are subject to restrictions. This means that the pandemic is internalized and normalized in the process. Parallel to our

result, Ghabri, Ben Rhouma, Gana, Guesmi and Benkraiem (2022) show that the pandemic did not influence BTC Futures. At the same time, Özbay and Tosun (2022) pointed out that the fear of Covid-19 on the markets was temporary.

This article also sheds light on the typical movements of cryptocurrencies during a particular period, such as the pandemic. Investors' movements of the two most preferred major cryptocurrencies during the pandemic are analyzed in this context. It explains the relationship between variables on issues such as possible balloons and arbitrage opportunities. The joint movement and association between the two major cryptocurrencies were examined in the study. The joint movement between cryptocurrencies has been studied across multiple time scales. Wavelet coherence analysis proposed by Morlet et al. (1982) was used in the study. Cross-wave consistency testing of cryptocurrencies has been carried out. The local correlation between cryptocurrencies was measured using wavelet coherence, and the phase difference arrow vectors showed the direction of the correlation and the leading (lagged) causal relationship between the crypto pair. According to the results obtained in the study, we can say that BTC and ETH had a strong positive relationship during the pandemic period. While ETH followed BTC at the beginning of the pandemic, BTC started to follow ETH in the long term. Although the existence of a bubble cannot be mentioned here, it can be said that ETH is preferred as the safe haven of BTC and for hedging purposes against BTC.

The findings documented in this study can guide market participants, investors and policymakers who want to profit, hedge and regulate the cryptocurrency market. In particular, considering the general and special developments experienced during the structural break periods, future decisions and policies can be guided by considering the possibility of similar situations or developments. The study's findings show market participants and analysts the inefficiency in the cryptocurrency market and state that they should take advantage of this situation. Investors and portfolio managers can improve the risk-adjusted performance of their portfolios based on the findings of this study. In addition, based on the study's results, integrating the structural break method into financial modelling seems useful in forecasting processes, especially for those who want to model the return or volatility in cryptocurrencies. These findings support broad applications in financial modelling to respond to relevant structural breakpoints.

Future studies must work with a more extensive data reservoir, especially in cryptocurrency market research. Today's inflation, along with the interest policies implemented by governments, can have a significant impact on the cryptocurrency market. In this context, it is essential to pay attention to future studies as the data in this area strengthens.

References

1. Abakah, E.J.A., Gil-Alana, L.A., Madigu, G. and Romero-Rojo, F. (2020). Volatility persistence in cryptocurrency markets under structural breaks. *Int. Rev. Econ. Financ.* 69, 680–691. https://doi.org/10.1016/j.iref.2020.06.035
2. Andreou, E. and Ghysels, E. (2009). Handbook of Financial Time Series. *Handb. Financ. Time Ser.* 839–840. https://doi.org/10.1007/978-3-540-71297-8
3. Aue, A. and Horváth, L. (2013). Structural breaks in time series. *J. Time Ser. Anal.* 34, 1–16. https://doi.org/10.1111/j.1467-9892.2012.00819.x
4. Avşarlıgil, N. (2020). Covid-19 Salgınının Finansal Sisteme Etkileri Üzerine Bir İnceleme. *Alanya Akad. Bakış* 665–682. https://doi.org/10.29023/alanyaakademik.735214
5. Bai, J. and Perron, P. (1998). Estimating and Testing Linear Models with Multiple Structural Changes. *Econometrica* 66, 47. https://doi.org/10.2307/2998540
6. Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural change models. *J. Appl. Econom.* 18, 1–22. https://doi.org/10.1002/jae.659
7. Beneki, C., Koulis, A., Kyriazis, N.A. and Papadamou, S. (2019). Investigating volatility transmission and hedging properties between BTC and Ethereum. *Res. Int. Bus. Financ.* 48, 219–227. https://doi.org/10.1016/j.ribaf.2019.01.001
8. Bentes, S.R. (2022). On the stylized facts of precious metals' volatility: A comparative analysis of pre- and during COVID-19 crisis. Phys. A Stat. Mech. its Appl. 600, 127528. https://doi.org/10.1016/j.physa.2022.127528
9. Bhatia, M. (2022). Stock Market Efficiency and COVID-19 with Multiple Structural Breaks: Evidence from India. *Glob. Bus. Rev.* 1–12. https://doi.org/10.1177/09721509221110372
10. Bouri, E., a, L.A., Gupta, R. and Roubaud, D. (2019). Modelling long memory volatility in the BTC market: Evidence of persistence and structural breaks. *Int. J. Financ. Econ.* 24, 412–426. https://doi.org/10.1002/ijfe.1670
11. Bouri, E., Shahzad, S. J. H., & Roubaud, D. (2019). Co-explosivity in the cryptocurrency market. *Finance Research Letters*, 29, 178-183.
12. Bumpass, D., Douglas, C., Ginn, V. and Tuttle, M.H. (2019). Testing for short and long-run asymmetric responses and structural breaks in the retail gasoline supply chain. *Energy Econ.* 83, 311–318. https://doi.org/10.1016/j.eneco.2019.07.021

13. Carrion-I-Silvestre, J.L., Kim, D. and Perron, P. (2009). GLS-based unit root tests with multiple structural breaks under both the null and the alternative hypotheses. *Econom. Theory* 25, 1754–1792. https://doi.org/10.1017/S0266466609990326
14. Cheah, E. T., and Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics letters*, 130, 32-36.
15. Cheung, Y. and Lai, K.S. (1997). Bandwidth Selection , Prewhitening , and the Power of the Phillips-Perron Test Author (s): Yin-Wong Cheung and Kon S . Lai Published by : Cambridge University Press Stable URL : https://www.jstor.org/stable/3532622 Bandwidth Selection , Prewhitening, A 13, 679–691.
16. Corbet, S., Lucey, B., & Yarovaya, L. (2018). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters*, 26, 81-88.
17. Dickey, D, A. and Fuller, W.A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *J. Am. Stat. Assoc*. 74, 427–431. https://doi.org/https://doi.org/10.1080/01621459.1979.10482531
18. Ercan, H. and Karahanoğlu, İ. (2019). A Wavelet Coherence Analysis: Contagion in Emerging Countries Stock Markets. *Periodica Polytechnica Social and Management Sciences*, 27(2), 99-107.
19. Erol, E. and Saghaian, S.H. (2022). The COVID-19 Pandemic and Dynamics of Price Adjustment in the US Beef Sector. Sustain. 14. https://doi.org/10.3390/su14084391
20. Esteve, V. and Requena, F., 2006. A cointegration analysis of car advertising and sales data in the presence of structural change. *Int. J. Econ. Bus.* 13, 111–128. https://doi.org/10.1080/13571510500520036
21. Fabris, N. and Ješić, M. (2023). Are Gold and Bitcoin a Safe Haven for European Indices?. *Journal of Central Banking Theory and Practice*, 12(1), 27-44.
22. Ghabri, Y., Ben Rhouma, O., Gana, M., Guesmi, K. and Benkraiem, R. (2022). Information transmission among energy markets, cryptocurrencies, and stablecoins under pandemic conditions. *Int. Rev. Financ. Anal.* 82, 102197. https://doi.org/10.1016/J.IRFA.2022.102197
23. Hafner, C. M. (2020). Testing for bubbles in cryptocurrencies with time-varying volatility. *Journal of Financial Econometrics*, 18(2), 233-249.
24. James, N. and Menzies, M. (2021). Efficiency of communities and financial markets during the 2020 pandemic. *Chaos* 31. https://doi.org/10.1063/5.0054493
25. Kalmaz, D.B. and Adebayo, T.S. (2020). Ongoing debate between foreign aid and economic growth in Nigeria: a wavelet analysis. *Soc Sci Q*, 101(5):2032–2051

26. Karavias, Y., Narayan, P.K. and Westerlund, J. (2022). Structural Breaks in Interactive Effects Panels and the Stock Market Reaction to COVID-19. *J. Bus. Econ. Stat*. 0, 1–14. https://doi.org/10.1080/07350015.2022.2053690
27. Katsiampa, P. (2019). Volatility co-movement between BTC and Ether. *Finance Research Letters*, 30, 221-227.
28. Kılcı, E.N. (2021). A study on confidence indexes in Turkey under structural breaks for the period covering the Covid-19 pandemic. Ömer Halisdemir Üniversitesi İktisadi ve İdari Bilim. *Fakültesi Derg.* 14, 948–960. https://doi.org/10.25287/ohuiibf.795657
29. Kumar, A.and Ajaz, T. (2019). Co-movement in crypto-currency markets: evidences from wavelet analysis. *Financial Innovation*, 5(1), 1-17.
30. Lee, Y. and Rhee, J.H. (2022). A VECM analysis of BTC price using time-varying cointegration approach. *J. Deriv. Quant. Stud*. 선물연구 30, 197–218. https://doi.org/10.1108/jdqs-01-2022-0001
31. Liu, J., Wu, S. and Zidek, J. V. (1997). On Segmented Multivariate *Regression*. *Stat. Sin*. 7, 497–525.
32. Luburić, R. (2021). Crisis Prevention and the Coronavirus Pandemic as a Global and Total Risk of Our Time. *Journal of Central Banking Theory and Practice*, 10(1), 55-74.
33. Makarov, I. and Schoar, A. (2020). Trading and arbitrage in cryptocurrency markets. *Journal of Financial Economics*, 135(2), 293-319.
34. Mandaci, P.E. and Cagli, E.C. (2022). Herding intensity and volatility in cryptocurrency markets during the COVID-19. *Financ. Res. Lett*. 46, 102382. https://doi.org/10.1016/j.frl.2021.102382
35. Marashdeh, H. A. and Shrestha, M. B. (2010). Stock market integration in the GCC countries. International Research *Journal of Finance and Economics*, 37, 104–114.
36. Mensi, W., Al-Yahyaee, K.H. and Kang, S.H. (2019). Structural breaks and double long memory of cryptocurrency prices: A comparative analysis from BTC and Ethereum. *Financ. Res. Lett.* 29, 222–230. https://doi.org/10.1016/j.frl.2018.07.011
37. Morlet, J., Arens, G., Fourgeau, E. and Giard, D. (1982). Wave propagation and sampling theory; Part II, Sampling theory and complex waves. *Geophysics*, 47(2), 222-236.
38. Nitithumbundit, T. and Chan, J.S.K. (2022). Covid-19 impact on Cryptocurrencies market using Multivariate Time Series Models. *Q. Rev. Econ. Financ*. 86, 365–375. https://doi.org/10.1016/j.qref.2022.08.006
39. Özbay, F. and Özcan, A. (2021). The examined of the influence of Covid-19 on e-commerce and consumer behaviour: A study on Turkey. *Aydın İktisat Fakültesi Derg.* 6, 21–33.

40. Özbay, F. and Tosun, N. (2022). The Fear Impact of COVID-19 on Stock Markets and Exchange Rates: An Empirical Application on Turkey, in: Handbook of Research on Global Networking Post COVID-19. *IGI Global Publısher of Tımely Knowledge*, pp. 1–22. https://doi.org/10.4018/978-1-7998-8856-7.ch001
41. Panagiotis, A., Efthymios, K., Anastasios-Taxiarchis, K., & Athanasios, P. (2020). GARCH Modelling of High-Capitalization Cryptocurrencies' Impacts During Bearish Markets. *Journal of Central Banking Theory and Practice*, 9(3), 87-106.
42. Perron, P. (2006). Dealing with Structural Breaks, Palgrave handbook of econometrics.
43. Phillips, P.C.B. (1987). Time Series Regression with a Unit Root. *Econometrica* 55, 277. https://doi.org/10.2307/1913237
44. Phillips, P.C.B. and Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika* 75, 335–346. https://doi.org/https://doi.org/10.1093/biomet/75.2.335
45. Phiri, E. and Wang, W. (2022). Time Series Analysis and structural break detection: A case of Zambia's CPI. *Int. J. Econ. Policy* 2, 33–43. https://doi.org/10.47941/ijecop.914
46. Qiao, X., Zhu, H., & Hau, L. (2020). Time-frequency co-movement of cryptocurrency return and volatility: Evidence from wavelet coherence analysis. *International Review of Financial Analysis*, 71, 101541.
47. /repeated
48. Reeves, J., Chen, J., Wang, X.L., Lund, R. and Lu, Q.Q. (2007). A review and comparison of changepoint detection techniques for climate data. *J. Appl. Meteorol. Climatol*. 46, 900–915. https://doi.org/10.1175/JAM2493.1
49. Rubbaniy, G., Khalid, A. A.and& Samitas, A. (2021). Are cryptos safe-haven assets during Covid-19? Evidence from wavelet coherence analysis. *Emerging Markets Finance and Trade*, 57(6), 1741-1756.
50. Stoumbos, Z.G., Reynolds, M.R., Ryan, T.P. and Woodall, W.H. (2000). The state of statistical process control as we proceed into the 21st century. *J. Am. Stat. Assoc*. 95, 992–998. https://doi.org/10.1080/01621459.2000.10474292
51. Telli, Ş. and Chen, H. (2020). Structural breaks and trend awareness-based interaction in crypto markets. *Phys. A Stat. Mech. its Appl*. 558, 124913. https://doi.org/10.1016/j.physa.2020.124913
52. Thies, S. and Molnár, P. (2018). Bayesian change point analysis of BTC returns. *Financ. Res. Lett*. 27, 223–227. https://doi.org/10.1016/j.frl.2018.03.018
53. Torrence, C. and Compo, G. P. (1998). A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society*, 79(1), 61-78.

54. Torrence, C. and Webster, P. J. (1999). Interdecadal changes in the ENSO–monsoon system. *Journal of Climate*, 12(8), 2679-2690.
55. Wu, C. (2021). Window effect with Markov-switching GARCH model in cryptocurrency market. *Chaos, Solitons and Fractals* 146, 110902. https://doi.org/10.1016/j.chaos.2021.110902
56. Yang, L., Cai, X. J., Zhang, H. and Hamori, S. (2016). Interdependence of foreign exchange markets: A wavelet coherence analysis. *Economic Modelling*, 55, 6-14.
57. Yao, Y.-C. (1988). Estimating the number of change-points via Schwarz' criterion. *Stat. Probab. Lett. 6*, 181–189. https://doi.org/https://doi.org/10.1016/0167-7152(88)90118-6
58. Yermack, D. (2015). Is Bitcoin a real currency? An economic appraisal. In *Handbook of digital currency* (pp. 31-43). Academic Press.
59. Zeileis, A., Leisch, F., Hornik, K., and Kleiber, C. (2002). Strucchange: An R package for testing for structural change in linear regression models. *J. Stat. Softw.* 7, 1–38. https://doi.org/10.18637/jss.v007.i02
60. Zeren, F. and Hızarcı, A. (2020). the Impact of Covid-19 Coronavirus on Stock Markets: Evidence From Selected Countries. *Muhasebe ve Finans İncelemeleri Derg.* 1, 78–84. https://doi.org/10.32951/mufider.706159.
61. Zhang, Y. J.and& Wu, Y. B. (2019). The time-varying spillover effect between WTI crude oil futures returns and hedge funds. *International Review of Economics & Finance*, 61, 156–169.