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Interrelation of Bitcoin and Some Traditional Assets

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Abstract

In the research, the causal relationships between Bitcoin, gold and oil prices were examined. The data of the research covers the period from 2015 to July 2020 and consists of daily price values. Augmented Dickey-Fuller Unit Root Test was used to see whether the stochastic process changes with time. Bitcoin and gold series do not contain a unit root since the oil series is stationary at the level while the difference is stationary. The reason why the series containing unit roots are not stationary is due to structural breaks or not, was investigated by Bai-Perron Unit Root Test with Multiple Structural Breaks. According to the test, it was determined that the Bitcoin series has one break and two regimes, while the gold series has two structural breaks and three different regimes. Whether the research series are cointegrated or not was investigated with the Gregory and Hansen test. The causality between the series was examined with the Toda-Yamamoto causality test, which is based on the VAR (Vector Autoregression) model and examines the causality in the series regardless of the unit root. A two-way causality relationship was determined between the eight lag-long Gold series and the Bitcoin series. In other cases, a causal relationship has not been established. As a result, we give an evidence that Bitcoin and gold prices series followed a parallel pattern while with oil not. Therefore, investors can add Bitcoin into their portfolios to make balance of the risk and return.

Keywords: Bitcoin; gold prices; oil prices; Toda-Yamamoto causality test.

JEL classification: G15; G11.

1. INTRODUCTION

The difference between a counterfeiter and a state is having seigniorage rights. If a person prints money, he is called a counterfeiter; if a state, does it, it is called a state. So, to stay within the legal limits is important. Bitcoin, like all other cryptocurrencies, breaks this rule.

As anyone's money, Bitcoin is traded all over the world. Although there are several risks (e.g., speculation, 51% attack) related to cryptocurrencies, billions of dollars are invested in

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them, because of their transparency, traceability, low transaction cost, and highly profitable potential (Narman & Uulu, 2020, p. 187). Regarding a Twitter account, namely "glassnote", the % of supply owned by entities holding ≤ 10 $BTC grew from 5.1% to 13.8% in 5 years, while the percentage held by entities with 100-100k BTC declined from 62.9% to 49.8% (6th August 2020, accessed 18th October 2020). With advantages and disadvantages, Bitcoin is very popular in social networks and according to (Narman & Uulu, 2020, p. 187), positive comments are higher than negative ones for six cryptocurrencies in social networks. On the other hand, Covid-19 helps its popularity and forces digital payments and cryptocurrencies to be applied (Avdjiev, Eren, & Mcguire, 2020). The top 10 cryptocurrencies by market capitalisation are $178.43 bn, and with 71.7% of market share, Bitcoin is far ahead of the others (Bagshaw, 2020). So, as in this research, almost all research studies about cryptocurrencies cover and apply Bitcoin data.

As we know men are more risk seekers than women so, cryptocurrency investors are to a greater extent male and have higher portfolio wealth (Lammer, Hanspal, & Hackethal, 2019, p. 22). Bitcoin traders, who we can define as risk lovers (Pelster, Breitmayer, & Hasso, 2019, p. 100), should estimate its value before trading but not all investors can do this small investors who are called whales in cryptocurrency jargon follow big investors. This causes herd behavior in the cryptocurrency markets, which negatively affects the efficiency of the market (Bouri, Gupta, & Roubaud, 2019; Hotar, 2020).

In the literature there are plenty of cryptocurrency research studies mainly focused on Bitcoin and portfolio diversification. Some of the studies are focused on the relationships among the cryptocurrencies while others focus on traditional investment assets.

This research mainly focuses on the causality relationship between Bitcoin and gold prices, and Bitcoin and oil prices. The reason for choosing these three price variables is the lack of research about the same topic in the literature. Secondly, we assume that these investment instruments have an important position, especially in some terroristic organisations' activities. Because world trade is dominated by the U.S. dollar as a currency, the organisations could prefer to buy illegal guns directly or by Bitcoin. Taking ISIS as an example, it has been known that the terrorist organisation pays salaries to its soldiers in U.S. dollars and also accepts donations mainly in dollars. On the other hand, oil is one of the main incomes of ISIS. So, when the organisation sells oil, it usually receives U.S. dollars. Because of all these relations, we especially prefer to choose these three variables, but this does not mean that there are no other effective factors. On the other hand, Covid19 pandemic has been changing our lifestyles and investment attitudes. Investors have been considering to ad Bitcoin to portfolios. It is not just about adding bitcoin to portfolios, but also companies and countries that matter. With this perspective the research has an avant-garde characteristic. In addition to this, Bitcoin has been accepted as a national currency by El Salvador, and some countries have started to create their own crypto currencies. So, Bitcoin officially becomes an asset and will compete with real assets and country based created crypto currencies. Will Bitcoin loose or increase its power in the future? Can the developed countries control it? These are the questions, make the topic hot.

2. LITERATURE REVIEW

There are plenty of research on Bitcoin and other crypto currencies. Bitcoin not just unsettles economies in the world but also changes traditional economy theories. Countries are in risk to loose seniorage rights. The power slightly shifts from the (wealthy) politicians to unknown people. As a risk or hedging factor, Bitcoin has a relationship with either real assets or other crypto currencies.

Cryptocurrencies go hand in hand in the market in terms of returns and trading volumes (Bouri et al., 2019). As a leader of the cryptocurrencies market Bitcoin price series can affect and lead the market, and other cryptocurrencies follow it. It macroscopical at the graphics that some crypto currencies such as Dogecoin, Holo and Bittorrent co-act with Bitcoin. We can assert that some whales as big investors manipulate the cryptocurrencies prices like wealthy businessmen Elon Musk's tweets effecting the Dogecoin.

In this case, regarding the Efficient Market Hypothesis (EMH), information efficiency cannot be observed Urquhart (2016). In literature, there are both side favourite evidences: Kang, Lee, and Park (2021) and Kristoufek and Vosvrda (2019) give efficiency evidence while Kyriazis (2019) and World Health Organization et al. (2020) gives inefficiency of cryptocurrencies.

Even though there are evidences in literature about cryptocurrencies close relations, it would seem reasonable to expect that Bitcoin tends to dominate the other cryptocurrencies in terms of information transmission, given its dominance in terms of trading volume, market capitalization and exchange trading volume but Bação, Duarte, Sebastião, and Redzepagic (2018)'s report is given some evidence against this hypothesis with the lagged information transmission occurring mainly from the other cryptocurrencies, especially from Litecoin, to Bitcoin.

Smales (2020) examined the relationship between 100 big coin prices and returns and reported that as a leader coin, Bitcoin prices affect other cryptocurrencies, and this can be beneficial for investors while they make diversification decisions for their portfolios. Further evidence for diversification comes from (Bouri, Lucey, & Roubaud, 2020). They noted that leading cryptocurrencies, namely Bitcoin, Ethereum, and Litecoin, are hedges especially against Asian Pacific and Japanese equities. For instance, Ji, Bouri, Gupta, and Roubaud (2018) added Litecoin next to Bitcoin for portfolio diversification and claimed that "…Regardless of the sign of returns, the results show that Litecoin is at the centre of the connected network of returns, followed by the largest cryptocurrency, Bitcoin. This finding implies that return shocks arising from these two cryptocurrencies have the most effect on other cryptocurrencies…".

Bitcoin as an intangible leader coin can have a relationship with traditional assets such as currencies, stock exchange indices, oil and crop prices. Evidence from this relationship can give us some clues about who the cryptocurrency investors are and what is the aim to invest. Cryptocurrencies vs traditional assets relation is more essential than in the past, because some experts are expecting that central banks will hold bitcoin sooner or later Hydzik and Smith (2021). If so, will they continue to hold gold or replace with cryptocurrencies is the question. El Salvador as being the first nation in the world to adopt bitcoin as its legal currency along the U.S. dollar, seems to accelerate the process (McGlurg, 2021).

In addition, can some private investment funds and individual investors add Bitcoin to their portfolio for hedging? To add Bitcoin to a portfolio its relationship with other traditional assets should be known. Regarding this issue there are evidence for both. By adding Bitcoin, portfolio performance increase as the meaning of return but not to reduce risk Kajtazi and Moro (2018). Except during the extreme bearish and bullish markets, both gold and Bitcoin can act as a weak hedge and weak safe haven against economic policy uncertainty (Wu, Tong, Yang, & Derbali, 2019). Similar research was done by Bouri, Das, Gupta, and Roubaud (2018) about return and volatility spillovers between four asset classes (equities, stocks, commodities, currencies and bonds) and Bitcoin in bear and bull market conditions. The researchers report significant evidence that Bitcoin returns are related quite closely to those of most of the other assets, particularly commodities. Interestingly, they also added that Bitcoin receives more volatility than it transmits and "…in stable periods, S&P 500 returns, VIX returns, and sentiment influence Bitcoin volatility…" (López-Cabarcos, Pérez-Pico, Piñeiro-Chousa, & Šević, 2021). In contrast, Baur, Dimpfl, and Kuck (2018) asserted that Bitcoin has unique risk-return characteristics and there is no correlation between Bitcoin and assets. As a risk proxy, volatility has an importance when adding a financial instrument to a portfolio. Cebrián-Hernández and Jiménez-Rodríguez (2021) report that Bitcoin volatility is inversely correlated with that of USD/EUR while there is no significant correlation observation for gold and oil which supported by Klein, Pham Thu, and Walther (2018).

Volatility as a risk proxy has a great importance to create a portfolio but some external factors such as Covid19 pandemic have also big impact too. The pandemic causes economic disruption and developed markets indicators strongly influenced from the pandemic than emerging markets. Dong, Song, and Yoon (2021) profound that …to reduce overall losses, emerging Asian market investors could hold more gold assets and developed market investors could hold more gold and bitcoin assets in their portfolios during the COVID-19 pandemic…which Bitcoin reacts significantly not just gold prices but also the federal funds, so it can be a useful tool for risk averse investors in anticipation of bad news (Dyhrberg, 2016).

Conversely, Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) gave evidence against Wu and Bouri's research about the relation of cryptocurrencies and mainstream assets, and recommend adding cryptocurrencies into the portfolio for diversification in short investment horizons. A study which was done by Kurka (2019) coincided with the research by Corbet et al. (2018). The researcher reports that the unconditional connectedness between cryptocurrencies and traditional assets is negligible. Further evidence about the relation between cryptocurrencies and other assets comes from Turkey by Vardar and Aydogan (2019). The researchers note that there are positive unilateral return spillovers from the bond market to the Bitcoin market. Aslanidis, Bariviera, and Martínez-Ibañez (2019) also examined the relationships of cryptocurrency with cryptocurrency and cryptocurrency with other assets and claimed that correlations among cryptocurrencies were positive while correlations between cryptocurrencies and traditional financial assets were negligible. In addition to this, we can say that extreme correlation increases in bear markets, yet not in bull ones for these pairs.

Bullish and bearish market conditions can have an impact on the relationship between Bitcoin and traditional assets (Ji et al., 2018). The researchers, especially during the bear market of Bitcoin, found evidence of lagged relationships between Bitcoin and some assets, such as gold and the U.S. dollar. Bouraoui (2020) attempted to determine the drivers of Bitcoin trading volume in 21 emerging countries and reported significant relationships between the local Bitcoin trading volume in each country and the associated banking system access. Kajtazi and Moro (2019) aimed to give evidence for whether Bitcoin should be added into portfolios or not. They noted that by adding Bitcoin, the portfolio performance improved. To assert this, one should know the investors aim. If they are risk averse adding gold to the portfolio as a diversifier can be recommended if risk seeker Bitcoin (Pho, Ly, Lu, Hoang, & Wong, 2021). Not just Bitcoin but also other cryptocurrencies could be incorporated to financial portfolios like traditional currencies and gold (Hsu, Sheu, & Yoon, 2021). On the other hand, cryptocurrencies can replace gold in portfolios in financial markets, could be a safe haven (Maghrebi & Abid, 2021) (López-Cabarcos et al., 2021). If so, we can say that information transfer occurs between cryptocurrencies and traditional investment instruments or between cryptocurrencies (Bação et al., 2018).

In the literature, some research studies give evidence about the relationship between Bitcoin and traditional assets and recommend adding it into portfolios for diversification. In this study, we have added oil and gold prices into the analysis and examined the relationship with Bitcoin, which many of the others have not done before.

The paper is structured as follows: The following Section 2 discusses the methodology and illustrates the variables used. Section 3 gives the empirical results and discusses the results, and finally, Section 4 concludes the paper.

2. DATA AND METHODOLOGY

2.1 The Dataset

We use daily price data of Bitcoin and two traditional assets (WTI crude oil and gold prices). All data were obtained from https://investing.com. The period under examination runs from 02.01.2015 to 16.07.2020. By the way, Bitcoin is traded 24 hours a day, 7 days a week. However, oil and gold are traded in organized markets that are open only during the working week. We have obtained 1,394 observations. All price data are reorganized as working days of the week. In the research, the dependent variable is Bitcoin prices in U.S. dollars, while the explanatory variables are gold prices (U.S. $) and oil prices (U.S. $). The data set is shown in Table no. 1.

Table no. 1 – Bitcoin, Gold and Oil Prices Data Explanations

Variable	Contraction	Explanation	Recourse	Period
Bitcoin	BITC	U.S. Dollar	https://investing.com	02.01.2015 to 16.07.2020
Gold	GOLD	U.S. Dollar Unit per Troy Ounce	https://investing.com	02.01.2015 to 16.07.2020
Oil	OIL	U.S. Dollar	https://investing.com	02.01.2015 to 16.07.2020

The model applied is shown in Equation (1):

$$\mathrm{BITC}_{it} = \propto_{it} + \beta_1 \mathrm{GOLD}_{it} + \beta_2 \mathrm{OIL}_{it} + \varepsilon_{it} \tag{1}$$

Table no. 2 shows the descriptive statistics. Whether the variables for all three-time series have normal distribution was examined by the Jarque-Bera fit test, which was calculated based on kurtosis and skewness coefficients. According to the Jarque-Bera fit test, none of the series have normal distribution and have a sharper distribution compared to the normal distribution series, with positive asymmetry.

Table no. 2 – Variables and Descriptive Statistics (n=1394)

Parameters/ D. Statistics	Bitcoin	Gold	Oil
Mean	4390.902	453.0110	556706.2
Median	3677.550	442.2500	533000.0
Maximum	18972.30	629.6000	1035520.
Minimum	164.9000	364.6000	262100.0
Standard Dev.	4010.578	52.82724	129131.4
Skewness	0.597257	1.278934	1.145850
Kurtosis	2.424765	4.459411	5.120434
Jarque-Bera	102.0965	503.7315	566.2038
P	0.000000	0.000000	0.000000

2.2 The Methodology

The Unit Root Tests

When any time series model is developed, it must be known whether the resulting stochastic process changes with time. If its characteristic changes through time, in that case the time series is non-stationary. So, it is impossible to state past and future structures of time series with a mathematical model. If the stochastic process is stable through time, then by using past values of the series, a model with a constant coefficient can be obtained. If a series is non-stationary, autocorrelations significantly deviate from zero (Kutlar, 2005, p. 252). Both series can be non-stationary, and consequently, the relation between two time series can be based on trends. In this paper, firstly it was examined whether there is stationarity or not.

To investigate stationarity, the Augmented Dickey-Fuller unit root test and KP unit root test were applied. The Augmented Dickey-Fuller unit root test is an improved version of the Dickey-Fuller test and is used for examining whether a series has a unit root or not. In this method, according to the H_0 hypothesis (H_0: $\emptyset = 1$), series containing a unit root are non-stationary and the variable Yt is affected by its previous value. On the other hand, the alternative hypothesis ($H_1: \emptyset < 1$) claims that series having no unit root are stationary. Past shocks carry out their effects for a while, and then they gradually decrease and after a short period they will disappear (Sarıkovanlık, Koy, Akkaya, Yıldırım, & Kantar, 2019, p. 20).

The models in this test can be shown below as Equations with constant (2) and trend with constant (3):

$$\Delta Y_t = \beta_0 + \theta Y_{t-1} + \sum_{j=1}^{k} \lambda_i \Delta Y_{t-1} + u_t \tag{2}$$

$$\Delta Y_t = \beta_0 + \beta_1 t + \theta Y_{t-1} + \sum_{j=1}^{k} \lambda_i \Delta Y_{t-1} + u_t \tag{3}$$

Where, these (2) and (3) equations ΔY_t indicates first difference of the analysed variable while β_0 constant term and t trend. ΔY_t Y_{t-1} is the difference term with lag, k is the optimal lag length while u_t indicates error term. In stationarity tests, it is examined whether the coefficient of θ is equal zero or not.

3. EMPIRICAL RESULTS

Here, the stationarity situation for all three series was examined, and the results are given below:

Table no. 3 – ADF and Unit Root Test Results

Variables	ADF Test Statistics	Critical Values		
		1%	5%	10%
Bitcoin	-1.677007	-3.434896	-2.863435	-2.567828
ΔBitcoin	-8.753694***	-3.434896	-2.863435	-2.567828
Gold	1.224754	-3.434906	-2.863440	-2.567830
ΔGold	-8.631878***	-3.434910	-2.863441	-2.567831
Oil	-3.781844**	-3.434842	-2.863411	-2.567815

Note: *, **,*** indicates 1%, 5% and 10% significance levels, respectively, while Δ indicates the first difference of the analysed variables.

Regarding the ADF test results, Bitcoin and gold variables are non-stationary at "level", where the values in Table no. 3 do not exceed the MacKinnon critical values at 1%, 5% and 10% significance levels. The series also have unit roots. When taking account of the first differences of the Bitcoin and gold series results, because the calculated values in the ADF Test statistics results exceed the MacKinnon critical values at 1% significance level, hypothesis H_0: "The series have a unit root" is rejected and hypothesis H_1: "The series have no unit root" is accepted. Hence, it is accepted that both series are stationary and have no unit root. In addition, the oil series is stationary at "level" and has no unit root.

3.1 Bai-Perron (BP) Unit Root with Structural Break Test

Multiple breaks and also non-stationarity may exist in the trend function of many economic time series (Bai, 1997). One reason for non-stationarity in econometric time series is that the population shows changes in terms of different samples (structural breaks) along the regression equation. Usually, reasons for structural breakdowns in the economy are shown as changes of economic policies, changes of economic structure or changes caused by an important event which occurs in any industry.

If such structural changes or breakdowns have occurred in the economy in a certain way, but if such changes are not taken into account within the framework of a regression model, or if estimations are neglected, it is clear that the results obtained and reporting based on these results will be systematically biased (Sevüktekin & Nargeleçekenler, 2010, pp. 399-400).

Multiple breaks may exist in the trend function of many economic time series (Bai, 1997, p. 315), and economic, political or natural disaster shocks hitting a series with a deterministic underlying trend will have transitory effects and the series will exhibit a trend-reversion characteristic (Reyes & Villaseñor, 2011, p. 9).

Bai (1997, p. 335) developed an underlying theory for estimating multiple breaks one at a time. One year later they improved the methodology and investigated each breakpoint successively (Bai, 1997).

Their model is given as follows:

$$y_t = x_i\,\beta + z_i\delta_j + u_i \qquad t = T_{j-1} + 1, \dots\dots, T_j \qquad j = 1, \dots\dots, m+1 \tag{4}$$

where, y_t indicates dependent variable while x_t (p x 1) and z_t (q x 1) indicate independent variables (covariates) vector, β ve δ_j (j=1, ……., m+1) vector of corresponding coefficients and u_i indicates error term (disturbance). In addition, $(T_1, \dots, T_m)$ indicates times of unknown breaks. Here, the main purpose is to calculate the break times (T_1,….,T_m) and the unknown; using T observations,, (y_1, x_t, z_t) data set; and β and δ_j (j = 1, ……., m + 1) are to estimate the parameters (Mert & Çağlar, 2019).

"…In this method, three tests for break counts and hypotheses are offered. These are:

1. Sup Ft (n; k) test: There is no break under the H_0 hypothesis. There are k structural breaks under the alternative hypothesis.
2. UDMaxFt (M, q) and WDMaxFt (M, q) tests: There is no break under the zero hypothesis in these tests, which are referred to as double maximum tests. Under the alternative hypothesis, there are at most m (1≤m≤M) structural breaks.
3. Sup Ft (L + 1 | L) test: In the consecutive F test, the null hypothesis shows that there is L breakage, while the alternative hypothesis shows L + 1 breaks…" (Çiçen, 2020).

According to Bai and Perron (2003), at the beginning of the analysis, the first two tests are considered. If there is at least one break, then the number of breaks is investigated by the sequential test. In addition to this, determination is also possible with Schwarz and LWZ information criteria (Çiçen, 2020).

In this research, breaks in Bitcoin series at level are investigated, as explained above. The significance of UDMax and WDMax statistics was also examined, and only five breaks were allowed. As a result, it can be reported that the "H_0: m = 0 there is no break" hypothesis is rejected with the assumption that M is the maximum number of breaks count, while m is the number of breaks. Consequently, there is at least one break in the Bitcoin series. Because UDMax = 130.0866 > 8.88 and WDMax = 154.5904 > 9.91 we can claim that there is at least one break and that it is statistically significant.

The global L=5 breaks test results can be examined. We tested the H_1: j, j=1, 2, 3, 4, 5 hypothesis and because a (Sup FT (J) = Scaled F-statistic>Critical value was obtained, five breaks for Bitcoin series were determined. The results are shown in Table no. 4.

Table no. 4 – First Phase of BP Breaks Results

Breaks	F-statistic	Scaled F- statistic	Weighted F- statistic	Critical Value
1	33.998	33.998	33.998	8.58
2	130.086	130.086	154.590	7.22
3	38.768	38.768	55.811	5.96
4	5.0712	5.0712	8.719	4.99
5	65.713	65.713	144.199	3.91
UDMax statistic* 130.0866			UDMax critical value* 8.88	
WDMax statistic** 154.5904			WDMax critical value** 9.91	

Note: *Significant at the 0.05 level, **Bai-Perron (2003) critical values.

To search for breakpoints and number of breaks, the sequential BP test was applied and the date of T1 = 10/09/2017 was obtained as the breakpoint. There are two different regimes in the Bitcoin series, as there is only one significant level of breakout of consecutive BP. These regimes were between 1/2/2015-10/06/2017 and 10/09/2017-7/16/2020 and consist of 697 variables. After the break, the level of the second regime (mean) was δ2 = 7862.780 and its standard error was found to be 1047.048 P<0.0001, which is statistically significant. On the other hand, the break that covers the dates 1/02/2015-10/06/2017 and consists of 697 variables with δ1= 919.0241 mean and 567.3457 standard error obtained is statistically not significant. The results are shown in Table no. 5.

Table no. 5 – Sequential BP Test Statistics

Variable	Coefficient	Std. Error	t- Statistic	Prob
1/02/2015-10/06/2017 697 obs				
C	919.0241	567.3457	1.6198	0.1055
10/09/2017-7/16/2020 697 obs				
C	7862.780	1047.049	7.50947	0.0000

In this paper, breakpoint specification was also applied. We have rejected H_0 and obtained one break (o vs.1*) even though it was given the maximum number of breaks of 5. The statistic of this test was Sup FT (1/0) = 33.998, and it was found to be greater than the

8.58 critical value at 0.05 error level. The date of the break was determined as 10/09/2017. The results can be seen in Table no. 6.

Table no. 6 – F-Statistic Determined Breaks

Sequential F-statistic determined breaks: 1

Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs 1*	33.998	33.998	8.58
1 vs 2	0.8752	0.8753	10.13
Break dates	**Sequential**	**Repartition**	
1	10/09/2017	10/09/2017	

Note: *Significant at the 0.05 level **Bai-Perron (2003) critical values.

The results of the BP test are also investigated in Figure no. 1. Regarding the results, we can report that there is one break on the actual line and according to fitted line, two different regimes have been obtained. The residual graph is also seen at the bottom of Figure no. 1. It can be claimed that the residuals are heterogenous and differ from regime to regime.

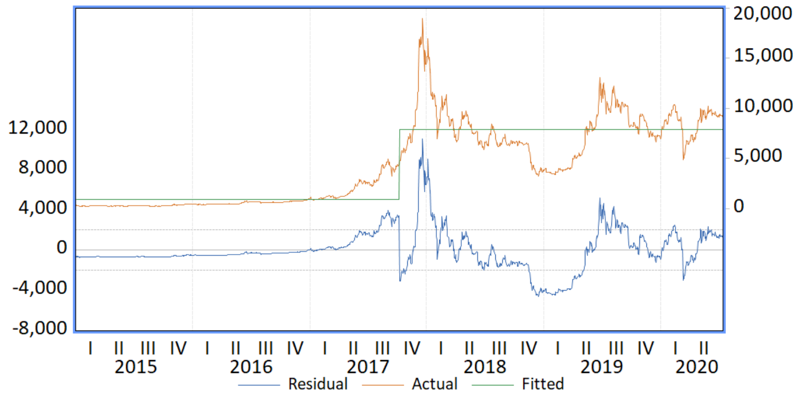

Figure no. 1 – Long-term variations in BP Break Results and Regimes for Bitcoin Series

The same procedures were applied for gold series by allowing five breaks and the statistical significance of UDMax and WDMax was examined. Because we obtained the result (Sup FT (J) = Scaled F-statistic > Critical value, five breaks were determined and at least one of them is statistically significant (UDMax = 105.0618 > 8.88 and WDMax = 161.8638 > 9.91). The results are shown in Table no. 7.

Table no. 7 – First Phase BP Test Break Results for Gold Series

Breaks	F-statistic	Scaled F- statistic	Weighted F- statistic	Critical Value
1	24.719	24.719	24.719	8.58
2	105.062	105.062	124.852	7.22
3	39.291	39.291	56.563	5.96
4	79.966	79.966	137.498	4.99
5	73.763	73.763	161.864	3.91
UDMax statistic*	105.0618	UDMax critical value*	8.88	
WDMax critical value**	161.8638	WDMax critical value**	9.91	

Note: *Significant at the 0.05 level **Bai-Perron (2003) critical values.

As previously applied for Bitcoin series, the BP Test it was applied to determine times and numbers of breaks, and we found two structural breaks. The date of the break is T_1 = 2/10/2016. Because two significant breaks at level were obtained, there are three regimes in the gold series. The first regime covers 279 variables and was obtained for the dates 1/2/2015-2/10/2016, while the second regime covers 875 variables and the dates 2/10/2016-8/01/2019. In addition to this, the last regime covers 240 variables and the dates 8/02/2019-7/16/2020. Before the break, the level of the regime (mean) was found to be $\delta 1 = 401.1978$ with 5.8435 standard error at $P<0.0001$ significance level. The second regime results were realized as mean $\delta 2 = 442.6345$ and 2.3515 standard error with $P<0.000$ significance level, while the last regime has a $\delta 3 = 551.075$ mean value and 10.5101 standard error with $P<0.000$ significance level. The results can be seen in Table no. 8.

Table no. 8 – Sequential BP Test Results for Gold Series

Variable	Coefficient	Std. Error	t- Statistic	Prob
1/02/2015-2/10/2016	279 obs			
C	401.1978	5.8435	68.6564	0.0000
2/11/2016-8/01/2019	875 obs			
C	442.6345	2.3515	188.2324	0.0000
8/02/2019-7/16/2020	240 obs			
C	551.0750	10.51011	52.4328	0.0000

Breakpoint specification was also applied to determine the breakpoints, and if appropriate, re-compute and display the test statistics used to obtain the optimal breaks. Regarding the method, two breaks were obtained with Sup FT (1/0) = 56.8842 test statistics, which exceeds the 8.58 critical value at 0.05 significance level. The second break was also obtained at Sup FT (2/1) = 66.1597 test statistics which also exceeds the 10.13 critical value at 0.05 significance level. Different from this, a result of Sup FT (3/2) = 10.0558<11.14 (critical value) was obtained for the third break, indicating no statistically significance. According to the method, the first regime period continued until the date of 2/11/2016, while second regime period turned into the last regime with the break at 08/02/2019. The results are shown in Table no. 9.

Table no. 9 – F-Statistic Determined Breaks for Gold Series

Sequential F-statistic determined breaks: 2

Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1*	56.8842	56.8842	8.58
1 vs. 2*	66.1597	66.1597	10.13
2 vs. 3	10.0558	10.0558	11.14
Break dates	**Sequential**	**Repartition**	
1	7/11/2019	2/11/2016	
2	2/11/2016	8/02/2019	

Note: *Significant at the 0.05 level **Bai-Perron (2003) critical values.

As a graphical view, the gold series breaks can be seen in Figure no. 2 below. According to actual line, two breaks can be seen, and regarding the fitted line three different regimes can be seen. Residuals differ from regime to regime and have a heterogeneous character, and can be seen at the bottom of Figure no. 2.

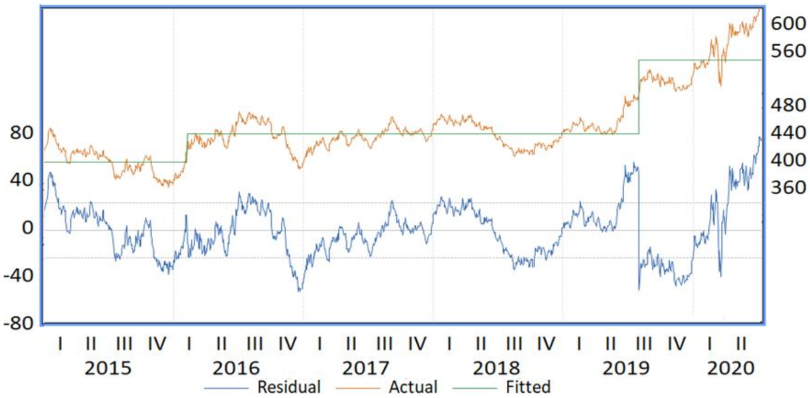

Figure no. 2 – Long-term variations in BP Break Test and Regimes for BP Gold Series

According to the ADF unit root test, the oil series has no unit root, and consequently, the BP multi-breaks test was not applied. Since the cointegration test can be applied if the series differences are stationary, then all three series were not dealt with together.

3.2 Gregory and Hansen (1996) Cointegration Test with Breaks (Co-Integration with Structural Breaks)

To investigate the long-term relationship among variables the Gregory-Hansen Cointegration Test (Gregory & Hansen, 1996) was applied, and the FMOLS and CCT estimators and long-term coefficients were found. Gregory and Hansen (1996) and Engle and Granger (1987) added a dummy variable, which represents a structural break, to the cointegration test and so, a new, improved cointegration test was developed. In this test there are three alternative models. These are: (C) break at the level, (C/T) break at the trend level, and change in regime (C/S). It is assumed that the time of the structural break is determined internally. The models are:

$$y_t = \mu_1 + \mu_2\, \varphi_{t\tau} + \delta^T y_{2t} + \varepsilon_t \quad t = 1, \dots, n \tag{5}$$

$$y_t = \mu_1 + \mu_2\, \varphi_{t\tau} + \beta_t + \delta^T y_{2t} + \varepsilon_t \quad t = 1, \dots, n \tag{6}$$

$$y_t = \mu_1 + \mu_2\, \varphi_{t\tau} + \delta_1^T y_{2t} + \delta_1^T y_{2t}\varphi_{t\tau} + \varepsilon_t \quad t = 1, \dots, n \tag{7}$$

In these Equations, (5) indicates at the level while (6) level with trend and (7) break and changes in regime. At the first model, constant term is represented by μ_1 while μ_2 indicates the change that breakage has made in the constant term. The last model which shows break and break in regime δ_1 indicates trend coefficient of just before break while δ_2 explained changing of trend coefficient after break. On the other hand, α^T indicates vector of coefficient of independent variables. In the model, $\varphi_{t\tau}$ indicates dummy variable while $\varphi_{t\tau}$ indicates dummy variable for breaking point (Gregory & Hansen, 1996, p. 103).

The dummy variable for the breakpoint can be described as follows:

$$\varphi_{t\tau} = \begin{cases} 0, & t \leq [nt] \\ 1, & t > [nt] \end{cases} \tag{8}$$

In the test there is no cointegration at H_0. If the test statistics which are obtained according to the Gregory and Hansen (1996) approach exceeded the critical values, H_0 is refused and it is accepted that there is a cointegration which considers structural changes among the variables (Mert & Çağlar, 2019, pp. 377-379). According to the FMOLS estimation results for the Gregory and Hansen (1996) test level model, the cointegration relationship between gold and Bitcoin variables under structural breaks was determined. The results are shown in Table no. 10.

Table no. 10 – Gregory and Hansen Test FMOLS Estimation Results

	Coefficient	Std. Error	t-Statistic	Prob.
	FMOLS Estimation results for the Level Break Model			
Gold	36.6682	4.8888	7.5003	0.0000
C	-14428.0	2024.95	-7.1251	0.0000
Du1	2747.301	646.013	4.2527	0.0000
	FMOLS Estimation results for the Break in the Regime Model			
Gold	-2.8675	25.4680	-0.1126	0.9104
Gold*Du1	40.8861	25.9441	1.5759	0.1153
C	1434.44	10229.4	0.1402	0.8885
Du1	-13746.49	10488.97	-1.3106	0.1902

3.3 Toda-Yamamoto Causality Test

This test differs from other causality tests by adding extra lags intentionally in the estimation and without examining the existence of a unit root and cointegration.

"…Most hypothesis tests can be conducting using the standard asymptotic theory. But this requires pretests of a unit root and cointegrating rank, which one may wish to avoid if the cointegrating relation itself is not one's interest since those tests are known to have low power." The Toda-Yamamoto Causality Test "…proposed a simple way to test economic hypotheses expressed as restrictions on the parameters of VAR models without pretests for a unit root(s) and a cointegrating rank(s)…" (Toda & Yamamoto, 1995, p. 246).

On the other hand, "…To apply the test a VAR model at (k+dmax) level has to be established. In this VAR model k indicates the optimal lag length which provides equation conditions while dmax indicates the degree of maximum integration of a series in the model. The test denotes k lag length and χ^2 asymptotic distribution. The TY causality test for X and Y variables is shown in Equations (9) and (10)…" (Mert & Çağlar, 2019).

$$y_t = \delta + \sum_{i=1}^{k+dmax} \alpha_i \, y_{t-1} + \sum_{i=1}^{k+dmax} \theta_i x_{t-1} + e_{1t} \tag{9}$$

$$x_t = \delta + \sum_{i=1}^{k+dmax} \gamma_i \, x_{t-1} + \sum_{k=1}^{k+dmax} \vartheta_i y_{t-1} + e_{2t} \tag{10}$$

In Equations (9) and (10) it is assumed that e_{1t} and e_{2t} error terms indicate white noise and that there is no autocorrelation. The hypotheses are shown below:

H_0: There no causality from Y to X.

H_1: There is a causality from Y to X.

Lag length determined by VAR in the model is shown in Table no. 11. VAR Lag Order Selection Criteria are: Endogenous variables: BITCOIN GOLD OIL, Exogenous variables: C BITCOIN(-9) GOLD(-9) OIL(-9). Date: 11/13/20. Time: 22:01. Sample: 1/02/2015, 7/16/2020. Included observations: 1385.

Table no. 11 – Optimum Lag Length Determination in VAR Model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-33332.26	NA	1.64e+17	48.15056	48.19591	48.16752
1	-28843.37	8932.422	2.54e+14	41.68139	41.76075*	41.71107*
2	-28829.01	28.51336	2.52e+14	41.67365	41.78701	41.71605
3	-28820.84	16.18236	2.52e+14	41.67486	41.82222	41.72997
4	-28814.66	12.20249	2.53e+14	41.67894	41.86031	41.74678
5	-28808.67	11.82430	2.54e+14	41.68328	41.89866	41.76384
6	-28798.62	19.78528	2.54e+14	41.68176	41.93115	41.77504
7	-28794.09	8.886151	2.56e+14	41.68822	41.97162	41.79422
8	-28773.04	**41.24944***	**2.51e+14***	**41.67082***	41.98823	41.78954

Note: *Indicates lag order selected by the criterion, LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion.

According to LR, FPE and AIC information criteria, the lag length is determined as 8. In the study, the Toda-Yamamoto causality test was applied within the framework of k + dmax = (8 + 1) = 9th order VAR model, and the results are given in Table no. 12.

A one-way causality was determined between the gold and Bitcoin variables with 8 lag lengths ($\chi^2 = 18.4849, P = 0.0179$), which is shown in Table no. 12. Similar results were obtained for the Bitcoin and gold variables ($\chi^2 = 15.2412, P = 0.0456$). Consequently, it can be claimed that there is a two-way causality between the gold and Bitcoin variables. A one-way causality relation between the oil and Bitcoin variables for 8 lag lengths was also investigated. A one-way causality relation was not found either from the oil variable to the Bitcoin variable ($\chi^2 = 7.9893, P = 0.4345$) or from the Bitcoin variable to the oil variable ($\chi^2 = 7.9800, P = 0.4354$).

Table no. 12 – Toda Yamamoto (1995) Causality Test Results

Direction of causality	Lag length	χ^2	P
$\boldsymbol{Gold \rightarrow Bitcoin}$	8	18.4849	0.0179*
$\boldsymbol{Bitcoin \rightarrow Gold}$	8	15.2412	0.0456*
$\boldsymbol{Oil \rightarrow Bitcoin}$	8	7.98930	0.4345
$\boldsymbol{Bitcoin \rightarrow Oil}$	8	7.98002	0.4354
$\boldsymbol{Oil \rightarrow Gold}$	8	8.6037	0.3768
$\boldsymbol{Gold \rightarrow oil}$	8	1.1450	0.9972

The same procedure was also repeated for the oil and gold variables, and a one-way causality relationship could not be established either from the oil to gold variables ($\chi^2 = 8.6037, \mathrm{P} = 0.3768$) or from the gold to oil variables ($\chi^2 = 1.1450, \mathrm{P} = 0.9972$).

4. CONCLUSIONS

The causality relationship between Bitcoin, gold and oil prices were investigated. In addition, it has also been investigated whether Bitcoin can be a safe haven. Some interesting findings are reported. First, there is no relation between Bitcoin and oil prices. Second, there are time-delayed causal relationships between Bitcoin and other asset classes during the bearish Bitcoin market. Third, instead of Bitcoin, gold is a safe haven.

As a leading investment tool among cryptocurrencies, Bitcoin is gaining more importance especially for portfolio diversification decisions. Regarding portfolio diversification Bouri et al. (2018) and Vardar and Aydogan (2019) have given significant evidence that Bitcoin returns are related with most of the other assets, particularly commodities. Bouri et al. (2018) report that rather than volatility transmission to other assets, Bitcoin receives it from other assets, but more important evidence reports that Bitcoin is connected with the other assets to a greater extent via return than volatility. Vardar and Aydogan (2019) report unilateral return spillovers from the bond market to Bitcoin market.

Regarding the relation between commodities and Bitcoin, our research is divergent from the findings of Bouri et al. (2018). We have not found evidence of a relation between "Bitcoin and oil" prices, while there is support for the "gold and Bitcoin" price relation. Our findings are partly in line with the research by Wu et al. (2019), which reports that gold and Bitcoin can be considered for portfolio diversification during the normal market, because they are correlated with their bearish or bullish market situation. A similar result to our findings has been reported by Ji et al. (2018), who claim that except for a time-lagged causality structure, there is no causality relation between Bitcoin and all the asset classes under study (some stock exchange indexes, gold and the US dollar). The reason why there is no correlation between oil and Bitcoin prices can be explained as the aim of the investors. Bitcoin investors seem to be hasty and risk taker investors and focus on short term (instant) return. Oil prices do not escalate like Bitcoin prices. Therefore, Bitcoin investors could not choose oil as a high return investment opportunity. We assumed that terrorist organisations such as ISIS, were trading oil with Bitcoin which is highly probable. In conclusion, there must be a correlation between Bitcoin and oil prices but there is no substantial evidence.

On the other hand, Bitcoin and gold prices series followed a parallel pattern. Main characteristic of the two instruments is a better hedge against the inflation and a decline in the U.S. dollar. Gold serves as a safe haven for oil markets amid the COVID-19 outbreak but Bitcoin acts only as a diversifier during this phase (Dutta, Das, Jana, & Vo, 2020).

The findings of Corbet et al. (2018) and Kurka (2019) about the relationship between Bitcoin and other assets differ from the findings of Bouri et al. (2018) and our findings. Corbet et al. (2018), Bouri, Azzi, and Dyhrberg (2017); Bouri et al. (2019) and Aslanidis et al. (2019) report that cryptocurrencies are strongly connected each other but disconnected from mainstream assets, while Kurka (2019) reports that the connectedness can be negligible.

Bitcoin prices were likely manipulated by a big investor called a "whale" in cryptocurrency parlance in 2017. Griffin and Shams (2020, p. 6) investigated the Bitcoin and Tether stable coin relationship and report that "…A further detailed analysis for the single largest player on Bitfinex shows that the 1%, 5%, and 10% of hours with the highest lagged flow of Tether by this one player are associated with 55%, 67.2%, and 79.2% of Bitcoin's price increase over our March 1, 2017 to March 31, 2018 sample period…". This allegation is given enough evidence to explain the Bitcoin breakpoint which was observed on 10/09/2017.

The first breakpoint of the gold price series was observed on 02/11/2016. Although we cannot explain it by a certain event and date, we can claim some reasons such as the stock exchange crisis in China which began in 2015 and ended early in 2016. The second reason could be the British Brexit referendum announcement which was made by British Prime Minister David Cameron in February 2016. This announcement led to uncertainty in stock markets around the world. These two events and the observed low oil prices may have caused investors around the world to rush to gold.

The second breakpoint was observed in gold prices on 08/02/2019. Although we cannot give evidence for an exact date, the reason could be Covid-19. Because a positive, mildly explosive episode was detected in the gold market by Gharib, Mefteh-Wali, and Ben Jabeur (2020) in July-August 2019 due to the collapse of the U.S. dollar, we can explain the breakpoint with the weakness of the U.S. dollar. During economic crises, investors and central banks prefer to buy gold as a safe heaven.

Focusing on the contemporaneous causality between empirical results suggests the isolation of the Bitcoin market. However, based on the time-lagged causality structure, the causal relationships seem to be time-variant. Specifically, there is evidence of time-lagged causal relations between Bitcoin and other asset classes during the bearish state of the Bitcoin market.

Even we cannot generate that Bitcoin is a safe haven for markets regarding bearish and bulls market types, we can say that Bitcoin investors also prefer to invest gold rather than oil. There is a great suspicion that terror organisations are trading oil with Bitcoin, but there is no statistical evidence. This may be due to the volume of Bitcoin trading. Since the relationship between the three instruments has different characteristics, they can be used as a risk balance. Therefore, we can recommend investors to add Bitcoin, gold and oil to their portfolios. Interestingly, oil prices also have nothing to do with gold prices. The research has some limitations regarding the darkness of the transition from Bitcoin to other investment instruments. We have also selected only three price series that can affect each other and ignore the others. A potential future area of research would be to examine whether adding the top ten highly traded cryptocurrencies to the search changes the outcome. In addition, the impact of the Covid19 pandemic on cryptocurrencies can be investigated.

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