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Testing the Price Bubbles in Cryptocurrencies using Sequential Augmented Dickey-Fuller (SADF) Test Procedures: A Comparison for Before and After COVID-19

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Abstract: Bubbles in asset prices have attracted the attention of economists for centuries. Extreme increases in asset prices, followed by their sudden decline, create a turbulent effect on the economy and even invite crises in time. For this reason, some measurement techniques have been employed to investigate the price bubbles that may occur. This study explores the possible speculative price bubbles of Bitcoin, Ethereum, and Binance Coin cryptocurrencies, compares them with the pre-and post-COVID-19 period, and examines asymmetric causality relationships between variables. Therefore, we analyzed the price bubbles of these cryptocurrencies using the closing price for daily data between 16.01.2018 and 31.12.2021 by the Supremum Augmented Dickey-Fuller (SADF) and the Hatemi-J (2012) asymmetric causality test. In this context, 1446 observations, 723 of which were before COVID-19 and 723 after COVID-19, were employed in the study. Looking at the SADF analysis results, we detected 103 price bubbles before COVID-19 for the three cryptocurrencies, while we determined 599 price bubbles after COVID-19. The common finding in the asymmetric causality test results is that there is a causality relationship between the negative shocks faced by one cryptocurrency and the positive shocks faced by the other cryptocurrencies.

Keywords: price bubbles; COVID-19; SADF; Asymmetric Causality.

JEL classification: A1; C01; E37.

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1. INTRODUCTION

Throughout history, the characteristic of money has changed in parallel with economic activities and technological developments. At the beginning of the economic activity, commercial activity was carried on through barter. In this period, commodity money was used, that is, the exchange of goods with goods was the center of commercial activities. Then there are various materials utilized as money such as stones and seashells. Afterward, metal coins were employed in the processing of precious metals. Over time, as social requirements increased and trade activities developed, the usage of money through mines was replaced by paper money or banknotes. Nowadays, it can be said that digital currencies, and especially cryptocurrencies, are gaining popularity (Anbugeetha & Nandhini, 2021; König, 2021; Ogachi *et al*., 2021). This situation has created the conditions for many academic studies examining cryptocurrencies from various aspects in recent years (Aliu *et al.*, 2020; Aliu *et al.*, 2021; Y. Liu *et al.*, 2022; Lucey *et al.*, 2022). Cryptocurrencies are generally not issued or controlled by any government or other central authority. Cryptocurrencies are managed by peer-to-peer networks of computers running free and open-source software. In short, it is a computer-based decentralized currency that is not under the control of the government or any authority. The fact that it is open to manipulation and speculation due to its decentralized structure leads to the formation of price bubbles that can deeply affect investors. For this reason, examining the existence of price bubbles in cryptocurrencies is also important for portfolio managers, investors, and monetary authorities. In this study, we examined Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNC) cryptocurrencies, which have an important place in terms of transaction volume. Looking at the development process of related cryptocurrencies, respectively, BTC, a mystery person named Satoshi Nakamoto published a manifesto in 2009. Nakamoto mentioned Peer to Peer and the blockchain system, which we used to know before. According to Nakamoto, “what is needed is an electronic payment system based on cryptographic proof instead of trust, allowing any two willing parties to transact directly with each other without the need for a trusted third party” (Nakamoto, 2009). BTC has the highest market share compared to other cryptocurrencies today. BTC is created through a computational process called mining. ETH is the second-largest cryptocurrency by market share. Like Bitcoin, Ethereum is a public blockchain network. They both rely on a blockchain to operate. “Ethereum is a technology that allows you to send cryptocurrency to anyone for a small fee. It also powers applications that everyone can use and no one can take down” (Ethereum, 2022). Finally, BNC has its chain, although it primarily uses the Ethereum network that is called the Binance Chain (Investopedia, 2022).

As stated, the fact that cryptocurrencies are open to risk and speculation, especially due to their decentralized nature, highlights the necessity of detecting price bubbles. In economic theory, price bubbles are defined as a market phenomenon, which is expressed as the rise in asset prices to levels significantly above the intrinsic value of the asset). (Kindleberger, 1996; Jarrow *et al*., 2010). Extreme increases in asset prices and they explode after a certain point bring along vital problems in the economy. There have been many important price bubbles in history, caused by the extreme increase in asset prices. Tulip Speculative Frenzy in the Netherlands in 1637 (Goldgar, 2007; Thompson, 2007); The South Sea Bubble, which occurred in the 1720s, was caused by the overvaluation of the stock prices of the South Sea Company, which aims to continue trade with South America more profitably (Paul, 2011; Frehen *et al*., 2013), the Mississippi Bubble in the French in the 1720s (Quinn & Turner, 2020), the pre-Great Depression price bubble and the Wall Street crash (Galbraith, 2009), the Dotcom tech bubble that started before the Millennium (Ljungquist & Wilhelm, 2003; Ofek & Richardson, 2003), the Mortgage crisis caused by the real estate bubble in the US (Mayer, 2011; McCarthy *et al*., 2013) and lastly, the Chinese bubble that occurred in the stock market covering the period 2007-2015 (Quinn & Turner, 2020) are the best-known examples of price bubbles. From a historical viewpoint, it can be said that the first place where the crises showed themselves was the finance and banking sector, and then it was reflected in the real sector. Price bubbles also burst after a certain stage in their nature. The time when price bubbles burst, they undoubtedly affected the real sector at a very high level and destroyed the financial markets. It even leads to the formation of crisis conditions. If the economic structure is considered as a whole, it is seen that when there is a malfunction in any element of this structure, it is reflected in other sectors and markets. Price bubbles and volatility trends in financial markets reveal the level of uncertainty and risk, and then the dynamics of the crisis. In this respect, price bubbles that are not easy to catch can be detected with the help of econometric techniques. These techniques are predictive dating algorithms that not only detect occurring outcomes but also provide market actors or policy-makers with an early warning diagnosis that can assist them in monitoring the market (Phillips *et al.*, 2015). It should also be noted that some researchers emphasize that econometric techniques are insufficient to detect price bubbles (Gürkaynak, 2008).

The originality of this study is to examine the price bubbles in cryptocurrencies with increased risk levels and high price volatility, together with their pre- and post-COVID-19 effects. The empirical detection of price bubbles in cryptocurrencies is of vital importance, especially in terms of investors avoiding risk and preventing possible bankruptcies. For this reason, in particular, this study is expected to contribute theoretically to investors, portfolio managers, businesses, and individuals that use cryptocurrencies in their transactions.

This study aims to investigate the potential speculative price bubbles in the Bitcoin, Ethereum, and Binance Coin cryptocurrencies with the right-tailed unit root tests proposed by Phillips and Yu (2011) and Phillips *et al.* (2015). For this purpose, we analyze the price bubbles employing the Supremum Augmented Dickey-Fuller (SADF) test for price bubble detection, while we observe the asymmetric causality analysis between variables applying the Hatemi-J (2012) test. In this context, the study continues with a literature review. Following that, the empirical method is discussed and then the data set and analysis results are presented. The study is completed with the discussion, conclusion, and recommendations sections.

2. LITERATURE REVIEW

In the literature, we can find lots of examples that investigate price bubbles in different markets. After the Mortgage Crisis studies cluster around the housing market. Pavlidis *et al.* (2017) used the SADF and Generalized Supremum Augmented Dickey-Fuller Test (GSADF) unit root tests of Phillips and Yu (2011). The study focuses on different levels of aggregation by using simulated data and actual housing data for both U.S. metropolitan areas and international housing markets (Pavlidis *et al*., 2017). Similarly, Güler and Gökçe focus on price bubbles in housing markets. They find that the legal procedures and the percentage share of house sales to foreigners in total house sales create price bubbles (Güler & Gökçe, 2020). We can witness multiple bubbles in crude oil prices from 1990 to 2019. Herrera and Tourinho (2019) used the SADF and GSADF right-tail unit root tests to study multiple bubbles in WTI and Brent petroleum prices from January 1990 to March 2019. The result of the study showed many price bubbles for both series. The results of the GSADF test were found to be more successful in detecting price bubbles compared to the results of the SADF test.

On the other side, price bubbles are also an important research topic for financial markets, another area where price volatility is relatively high. "When a stock market bubble bursts, it can trigger financial crises that spread to the real economy." (Z. Liu *et al*., 2016). Çağlı and E. (2018) examined the multiple rational bubbles in developed and emerging stock markets employing the GSADF unit root test. The findings of the study show that rational bubbles exist in all markets except Brazil, Chile, India, and South Korea. Z. Liu *et al*. (2016) focused on the Shanghai A-share index, they find out the origins and evolution of each periodically collapsing bubble. Chang *et al*. (2016) used the BRICS stock market as a case study. The results based on the GSADF test statistic indicate that there are multiple bubbles in the BRICS countries, and the bubbles in the stock markets have important policy implications. El Montasser *et al*. (2018) acknowledged the differences between rational speculative bubbles and explosive fundamentals in the US Stock market using the SADF unit root test.

Arshanapalli and Nelson (2016) examined price bubbles in historical stock prices from 1871 through 2014. They explored the characteristics of every price bubble through historical data. Another historical analysis of price bubbles was applied by Phillips, Shi, & Yu. Empirical tests were conducted on S&P 500 stock market data over the period from January 1871 to December 2010 (Phillips *et al*., 2015). Monschang and Wilfling (2021) investigated the performance of the SADF, GSADF, and backward SADF (BSADF) tests for detecting and date-stamping financial bubbles by using the NASDAQ data period of 45 years.

Mete *et al*. (2019) analyzed the formation of speculative bubbles in Bitcoin, Ethereum, and Ripple cryptocurrencies employing SADF and GSADF methods. The results showed that Bitcoin is particularly susceptible to speculative movements, with price bubbles formed between 2013-2014, 2017-2018 and 2019, Ethereum in 2013-2016 and 2017-2018, and Ripple between 2014-2015 and 2017-2018.

Şak (2021) investigated the investment motives of cryptocurrencies by employing Hatemi-J Asymmetric Causality Analysis. As a result of the analysis, it has been observed that people can diversify their investment instruments, especially in the winning periods, and invest in cryptocurrencies, which are seen as less risky in the losing periods. During negative shock periods, the most preferred cryptocurrencies are Ripple, Binance coin, Bitcoin cash, and Monero; during periods of positive shock, they are Bitcoin, Ripple, Binance coin, Dash, and Bitcoin cash. Özdemir (2021) investigated the bubble behavior in the prices of selected five cryptocurrencies (Bitcoin, Ethereum, Ripple, Stellar, and Tether) using daily data of the closing level during the COVID-19 pandemic. The time interval was chosen from January 2, 2020, to January 2, 2021. The empirical results highlight that bubble behavior is not a diverse and stable feature of Bitcoin, Ethereum, Ripple, and Stellar prices, except for Tether prices, which indicates the emergence of a potential crisis through an increased degree of financial risk in the digital assets market. instability.

Güleç and Aktaş (2019) conducted a study on the eight most traded cryptocurrencies. The existence of speculative price bubbles in the 8 most traded cryptocurrencies in the market was subjected to the Sup Augmented Dickey-Fuller test, which was verified with 1000 repetitions of Monte Carlo Simulation using daily frequency data. As a result of the study, they determined the existence of non-speculative price bubbles in the market. Cryptocurrencies have similarities with precious metals in theory, but the volatility of crypto markets increases the potential risks. Mensi *et al*. (2019) showed evidence of significant volatility spillover effects between Bitcoin and precious metals. According to the conclusion of the article, it greatly affects the good and bad volatility of Bitcoin, which is in its good and bad volatility. Cryptocurrencies can be used universally, they are not national currencies. So they can work as so-called reserve money. Mokni and Ajmi (2021) compared cryptocurrencies to US dollars for the time span between January 1, 2018, and September 26, 2019, applying Granger causality analysis. The COVID-19 pandemic has had a significant impact on the relationship between cryptocurrencies and has established an important place for cryptocurrencies in the financial system. Another research about asymmetric relationships between BTC and other financial assets is studied by Erdaş and Çağlar (2018). This study investigates the asymmetric causality relationship between Bitcoin and Brent oil, the U.S. dollar, S&P 500, and BIST 100 indices employing the Hatemi-J (2012) test. The time range was chosen between November 2013 and July 2018. The result showed that According to the results of the analysis, there is a one-way causality relationship from the Bitcoin price to S&P 500 index. Bouri *et al*. (2019) analyzed the date-stamp price explosivity in leading cryptocurrencies and revealed that all cryptocurrencies investigated here were characterized by multiple explosivity. In the study, date-stamp price explosiveness in seven large cryptocurrencies revealed evidence of multiple periods of explosivity in all cases, especially in 2017. In particular, it can be seen that Bitcoin was exposed to long-lived explosions.

Price bubbles are studied in many different areas in the literature. The commodity market is one of these areas. Yildirim (2021) examined a study on the commodity market. In the study in which the SADF test was used, price bubbles were found in 2 commodities, but not in 14 commodities. Cryptocurrency markets are volatile and they are getting bigger so studies are focusing on bubbles in cryptocurrencies. Enoksen *et al*. (2020) examined which variables can determine the price bubbles of the eight cryptocurrencies. According to the result, it was observed that studies were conducted, especially during 2017 and 2018. Corbet *et al*. (2018) examined the existence and dates of pricing bubbles in Bitcoin and Ethereum, two popular cryptocurrencies using the methodology. The results helped form an idea for the analysis of the main explanatory variables. Geuder *et al*. (2019) studied bubble behavior in Bitcoin prices. The time interval was chosen between 2016 and 2018. Two distinct testing methodologies (PSY, LPPL) were used. The main problem of the study is what caused these episodes of bubble behavior. Many other reasons are not needed to explain Bitcoin price behavior. Reasons such as government restrictions and the use of other financial assets can impact Bitcoin price behavior. Kayral (2021) researched price bubbles in cryptocurrencies during the COVID-19 period and before. According to the results of the analysis, found that cryptocurrencies are speculative assets for new investments. When the entire analysis period is evaluated, the highest price bubble was detected in Chainlink with a total of 234 days. Also, Bitcoin showed the longest continuous price bubble with 131 days, followed by Theta and Ethereum.

Kyriazis *et al*. (2020) showed that several bubble stages occurred in Bitcoin prices between 2013 and 2017. They also mentioned that as of 2018, academic studies on the bitcoin price bubble have decreased. The price bubble can affect not only cryptocurrencies but also central bank currencies. Yildirim *et al*. (2022) found that the GSADF test results have concluded that there are price bubbles in the dollar exchange rate of countries other than the US Dollar (USD)/Indian Rupee (INR). Wang *et al*. (2022) have studied price bubbles in the NFT and DeFi markets. They used SADF and GSADF tests as methods. As a result of the study, they found periods when bubbles could not be detected, and they said that these markets have some intrinsic value and that bubbles can be ignored.

Li *et al*. (2021) examined Bitcoin price bubbles with the GASDF test. As a result of the study, they encountered too many speculative bubbles. The main reason for the emergence of bubbles was found to be global events or policies. They revealed that speculative behavior can be exhibited in an environment with policy risk.

3. METHODOLOGY

In the analysis phase, we used the SADF unit root test, which is based on the supremum statistics Augmented Dickey–Fuller-type regressions estimated using recursive windows from the right-tail tests (Phillips *et al.*, 2011), to detect the price bubbles of cryptocurrencies. It can be said that the right-tailed unit root test like SADF, GSADF, and, BSADF provide a great advantage in analyzing and detecting speculative price bubble dates. We have witnessed there have been many studies using this test procedure. For instance, Sharma and Escobari (2018) have used this test procedure to analyze price bubbles in the energy sector index, while Li *et al*. (2021) have analyzed stock price bubbles in medical masks. In another study, Pan (2019) investigated housing price bubbles in China, while Etienne *et al*. (2014) tested food product price bubbles. This test is based on the recurring estimation of the ADF model on a forward-widening set of samples. It reaches the sup value of the ADF statistical display harmonizing with the test.

Under this condition, the window size (fraction) (r_w) extends from (r_0) to 1. While r_0 states the smallest sample window width fraction, 1 indicates the total simple size. 0 is fixed as the starting point (r_1) of the sample sequence. Thereby the endpoint of each sample (r_2) is equal to (r_w) but varies from (r_0) to 1. ADF_0^2 represents the ADF test statistic for a sample running from 0 to r_2. The SADF test procedure is obviously described as (Phillips *et al.*, 2015):

$$SADF(r_0) = \sup ADF_0^2;\ r_2 \in [r_0, 1] \tag{1}$$

Following that, we also applied the asymmetric causality test developed by Hatemi-J (2012), which focuses on the causality relationship between positive and negative shocks between variables. Asymmetric causality test analyses the presence of asymmetric information by separating the negative and positive shocks in the variables. In this respect, it is seen that it makes an important contribution to the literature. The methodological background of the relevant test should be briefly examined. The causality relationship between two integrated variables, y_{1t} and,y_{2t} are described as a subsequent random walk process (Hatemi-J, 2012, p. 449):

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{1,0} + \sum_{i=1}^{t} \varepsilon_{1i} \tag{2}$$

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{2,0} + \sum_{i=1}^{t} \varepsilon_{2i} \tag{3}$$

where t = 1, 2, …,T; $y_{1,0}$ and $y_{2,0}$ represent the initial values of the constant terms, ε_{1i} and ε_{2i} the white noise error term. Positive shocks are stated as ε_{1i}^{+} = max $(\varepsilon_{1i}, 0)$, ε_{2i}^{+} = max $(\varepsilon_{2i}, 0)$, while negative shocks are defined as ε_{1i}^{-} = min $(\varepsilon_{1i}, 0)$, ε_{2i}^{-} = min $(\varepsilon_{2i}, 0)$. Therefore, it can be explained as $\varepsilon_{1i} = \varepsilon_{1i}^{+} + \varepsilon_{1i}^{-}$ whereas $\varepsilon_{2i} = \varepsilon_{2i}^{+} + \varepsilon_{2i}^{-}$.

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{1,0} + \sum_{i=1}^{t} \varepsilon_{1i}^{+} + \sum_{i=1}^{t} \varepsilon_{1i}^{-} \tag{4}$$

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{2,0} + \sum_{i=1}^{t} \varepsilon_{2i}^{+} + \sum_{i=1}^{t} \varepsilon_{2i}^{-} \tag{5}$$

Finally, the cumulative sum of the positive and negative shocks of each variable is $y_{1t}^{+} = \sum_{i=1}^{t} \varepsilon_{1i}^{+}$, $y_{1t}^{-} = \sum_{i=1}^{t} \varepsilon_{1i}^{-}$, is expressed as $y_{2t}^{+} = \sum_{i=1}^{t} \varepsilon_{2i}^{+}$.$y_{2t}^{-} = \sum_{i=1}^{t} \varepsilon_{2i}^{-}$ Next, the causality aspect of positive and negative shocks can be employed (Hatemi-J, 2012, p. 449).

For this test, the information criterion is as follows (Hatemi-J, 2012, p. 450):

$$\text{HJC} = \ln(|\widehat{\Omega}_j|) + j\left(\frac{n^2 lnT + 2n^2 \ln(lnT)}{2T}\right) \tag{6}$$

In Equation 6, the $\widehat{\Omega}_j$ symbol in the equation is the determinant of the predicted variance-covariance matrix of the error terms in the VAR model based on the j lags level; the n represents the number of equations in the VAR model, and T represents the number of observations. Additionally, the hypothesis of this test is as follows:

The null hypothesis (H_0) indicates that there is no causality relationship between variables, while the alternative hypothesis (H_1)states that there is causality relationship between variables. Accordingly, if the estimated WALD test statistic is greater than the critical value, the null hypothesis can be rejected. Additionally, when the estimated WALD test statistic is less than the critical value, the null hypothesis is not rejected.

4. DATA AND ECONOMETRIC ANALYSIS

Bubbles, collapses and financial crises have been the recurring phenomena of the markets in certain periods, from the initial establishment phase to the modern age, for the financial side (Brunnermeier & Oehmke, 2013) as well as in the economy in general. In our study, we examined the price bubbles for cryptocurrencies. It attracts the attention of economists as price bubbles also affect real sector activities. In the simplest terms, bubbles refer to a situation where asset prices are much higher than their real price. After a stage, the bubble bursts when investors encounter a sudden and excessive sales wave. This situation affects both the investors and the economy at a significant level. In our study, the price bubbles of cryptocurrencies, which are the new instruments of financial markets, were examined. For this purpose, we analyzed the potential price bubbles of the three selected cryptocurrencies (Bitcoin, Ethereum, Binance Coin) for daily data between 16.01.2018 and 31.12.2021. In this context, 1446 observations, 723 of which were before COVID-19 and 723 after COVID-19, were employed in the study. Note that we have split these 1446 observations into two parts based on the date the first case of COVID-19 in the USA was seen. In addition, we then examined the causality relationship between the negative and positive shocks these cryptocurrencies were exposed to. Table no. 1 presents the SADF test results used for detecting price bubbles.

Table no. 1- SADF Test Results

Cryptocurrency	Window Size	Include in test equation		
		None	Constant	Constant and Trend
Bitcoin	83	6.04*	7.99*	6.48*
Ethereum	83	7.11*	7.42*	5.84*
Binance Coin	83	12.21*	18.64*	19.80*
Test Critical Values	1%	3.44	2.02	1.13
	5%	2.87	1.62	0.69
	10%	2.54	1.35	0.45

Note: *sign illustrates that the series is statistically significant at 1%. It means that there is a price bubbles. In addition, test critical values are based on Monte Carlo simulation.

Table no. 1 indicates that SADF test statistics for cryptocurrencies examined in the study are above critical values for Bitcoin, Ethereum, and Binance Coin cryptocurrencies. In other words, the results indicate that these cryptocurrencies have a bubble formation. Table no. 2 presents the price bubble dates and price bubble times of each cryptocurrency. It has been determined that price bubble dates have increased, especially in the post- COVID-19 period.

Table no. 2- Price Bubbles for Bitcoin, Ethereum and Binance Coins

Price Bubbles	Bitcoin	Ethereum	Binance Coin
Panel A. None			
Bubble 1	22.12.2020-15.05.2021	07.02.2021-22.02.2021	17.05.2019-07.06.2019
Bubble 2	14.10.2021-31.10.2021	09.03.2021-10.03.2021	17.06.2019-02.07.2019
Bubble 3	01.11.2021-17.11.2021	04.04.2021-17.05.2021	04.02.2021-02.03.2021
Bubble 4	-	03.09.2021-12.09.2021	07.03.2021-16.03.2021
Bubble 5	-	23.10.2021-18.11.2021	27.03.2021-23.05.2021
Panel B. Constant			
Bubble 1	29.11.2020-30.11.2020	07.02.2021-22.02.2021	21.04.2019-22.04.2019
Bubble 2	19.12.2020-20.05.2021	09.03.2021-10.03.2021	17.05.2019-06.07.2019
Bubble 3	08.08.2021-19.09.2021	04.04.2021-17.05.2021	01.02.2021-18.05.2021
Bubble 4	05.10.2021-02.12.2021	03.09.2021-12.09.2021	24.08.2021-05.09.2021
Bubble 5	-	23.10.2021-18.11.2021	03.11.2021-20.11.2021
Bubble 6	-	-	02.12.2021-08.12.2021
Panel C. Constant and Trend			
Bubble 1	17.06.2019-13.07.2019	29.12.2020-25.05.2021	16.04.2019-04.05.2019
Bubble 2	09.08.2019-10.08.2019	15.08.2021-16.08.2021	14.05.2019-06.07.2019
Bubble 3	16.12.2020-15.05.2021	29.08.2021-12.09.2021	03.02.2021-20.05.2021
Bubble 4	19.10.2021-20.10.2021	22.10.2021-18.11.2021	11.11.2021-12.11.2021
Bubble 5	13.11.2021-14.11.2021	25.11.2021-26.11.2021	-
Bubble 6	-	30.11.2021-31.11.2021	-

Note: The dates given in the table reflect the price bubbles.

Table no. 2 indicates that there are serious differences when the price bubbles of cryptocurrencies are compared with those two-years before COVID-19. It has been proven that the speculation created by the post- COVID-19 uncertainty environment and the extreme volatility in asset prices also contributed to the formation of serious price bubbles for cryptocurrencies. In this context, Table 3 presents the number of price bubbles before and after COVID-19.

Table no. 3- Number of Price Bubbles before and after COVID-19

Cryptocurrency	Before COVID-19	After COVID-19
Bitcoin	33	270
Ethereum	-	190
Binance Coin	70	139
Total	103	599

Table no. 3 indicates that there is a significant difference in the number of price bubbles between pre- and post- COVID-19. Accordingly, while 103 price bubbles were detected before COVID-19 for the three cryptocurrencies, the existence of 599 price bubbles was determined after COVID-19 as a whole. The number of price balloons for Bitcoin, which we examined separately, reached 33 before COVID-19 and 270 after COVID-19. While no price bubble was detected for Ethereum before COVID-19, 190 price bubbles were detected after COVID-19. Finally, while 70 price bubbles were detected for Binance Coin before COVID-19, 139 price bubbles were detected after COVID-19. At this point we differ with the study of Güleç and Aktaş (2019). Additionally, this result have demonstrated that cryptocurrencies are an asset with high risks and are highly sensitive to speculative movements. Our findings are similar to Özdemir (2021) findings on these points. As a result of his work, due to the increasing financial instability, a potential crisis has emerged in the digital asset market, apart from Tether prices. A recurring and common bubble behavior is observed in Bitcoin, Ethereum, Ripple and Stellar prices. These results are also consistent with the study of Mete *et al*. (2019). As a result, it can be said that the post- COVID-19 process has caused many price bubbles in cryptocurrencies. Additionally, this result demonstrates that cryptocurrencies are an asset with high risks and are highly sensitive to speculative movements. The price bubbles for Bitcoin, Ethereum and Binance Coin can be shown in Figures no. 1-9.

Table no. 4 indicates the asymmetric causality test results between variables. In this framework, the causality relationship results between cryptocurrency prices are explained in three ways. First, the findings indicate a causality relationship from positive shocks in Bitcoin price to positive shocks in Binance Coin price. This result means that positive changes in Bitcoin prices have a positive impact on Binance Coin prices. Additionally, it was found that there is a casual relationship from negative shocks in Bitcoin prices to positive shocks in Binance Coin price. Accordingly, negative changes in Bitcoin prices have a positive impact on Binance Coin price. Similarly, a causal relationship is detected between negative shocks in Binance Coin price and positive shocks in Bitcoin price. The second result is related to the relationship between Bitcoin and Ethereum prices. As can be seen, there is a causality relationship between positive shocks in Bitcoin prices and positive shocks in Ethereum prices. However, a causality relationship is determined from positive shocks in Bitcoin prices to negative shocks in Ethereum prices. This result can be interpreted as the demand for Bitcoin negatively affecting Ethereum prices in terms of the substitution effect. Furthermore, a similar causality relationship is valid from Ethereum to Bitcoin. Additionally, it can be mentioned that there is a causality relationship from negative shocks in Ethereum prices to positive shocks in Bitcoin prices.

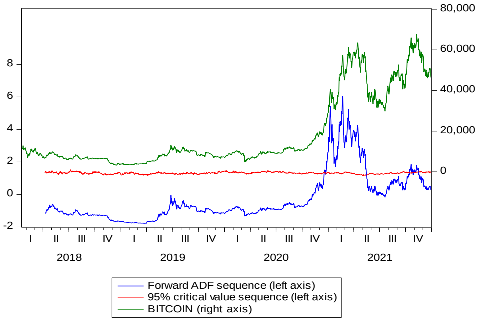

Figure no. 1 - SADF test results with no constant term and no trend for Bitcoin

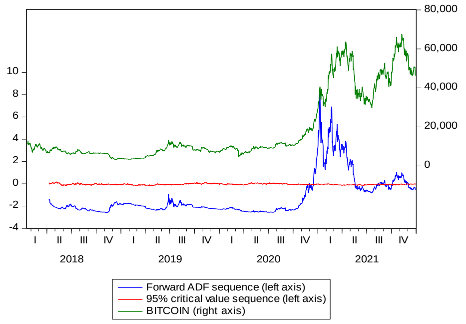

Figure no. 2 – SADF test results with constant term for Bitcoin

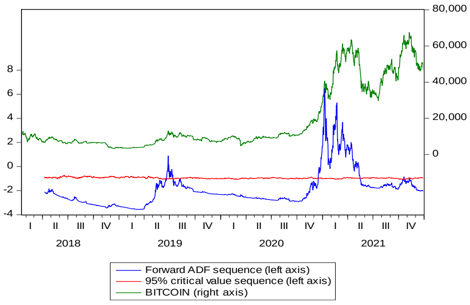

Figure no. 3 – SADF test results with constant term and trend for Bitcoin

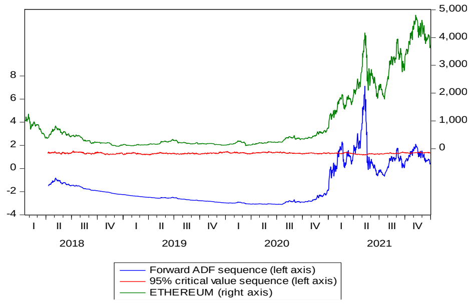

Figure no. 4 – SADF test results with no constant term and no trend for Ethereum

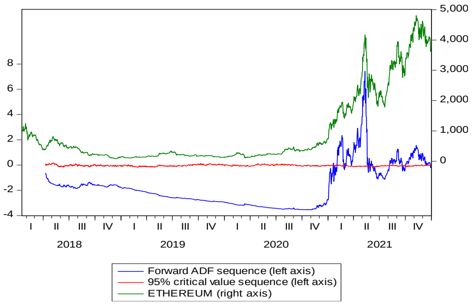

Figure no. 5 - SADF test results with constant term for Ethereum

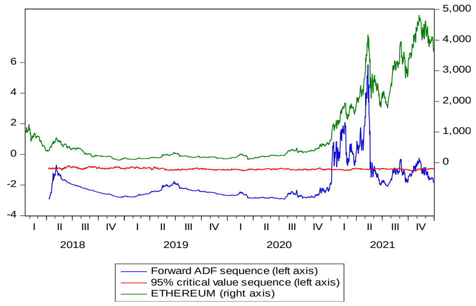

Figure no. 6 - SADF test results with constant term and trend for Ethereum

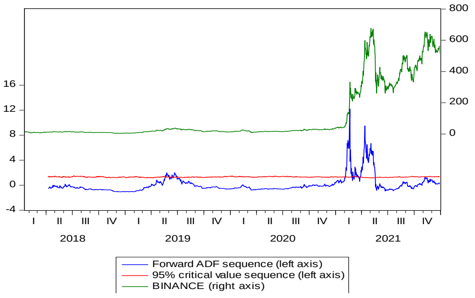

Figure no. 7 - SADF test results with no constant term and no trend for Binance

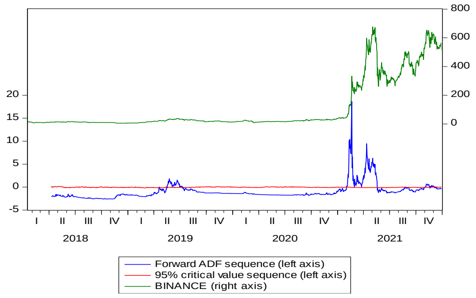

Figure no. 8 - SADF test results with constant term for Binance

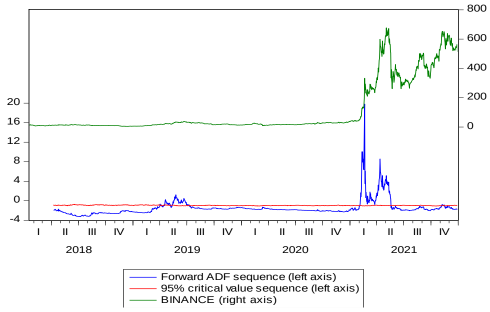

Figure no. 9 - SADF test results with constant term and trend for Binance

Note: The blue line on the figures represents the Forward ADF sequence, the red line represents the 95% confidence interval, and the green lines represent cryptocurrencies. In addition, we used the Eviews 12 to generate the figure.

Table no. 4 - Hatemi-J (2012) Asymmetric Causality Test Results

Null Hypothesis (H_0)	MWALD	Critical Values 1%	5%	10%	Optimal Lags
$BTC^{+} \nRightarrow BNC^{+}$	4.317**	6.903	3.808	2.686	1
$BTC^{+} \nRightarrow BNC^{-}$	2.046	9.328	6.125	4.660	2
$BTC^{-} \nRightarrow BNC^{-}$	0.410	6.608	3.768	2.637	1
$BTC^{-} \nRightarrow BNC^{+}$	22.272***	10.152	5.995	4.528	2
$BNC^{+} \nRightarrow BTC^{+}$	1.254	6.911	3.847	2.703	1
$BNC^{+} \nRightarrow BTC^{-}$	2.215	6.899	3.828	2.630	1
$BNC^{-} \nRightarrow BTC^{-}$	0.148	6.905	3.860	2.654	1
$BNC^{-} \nRightarrow BTC^{+}$	3.675*	6.925	3.857	2.679	1
$BTC^{+} \nRightarrow ETH^{+}$	2.934*	6.582	3.816	2.664	1
$BTC^{+} \nRightarrow ETH^{-}$	4.459**	6.501	3.760	2.707	1
$BTC^{-} \nRightarrow ETH^{-}$	0.449	6.685	3.746	2.603	1
$BTC^{-} \nRightarrow ETH^{+}$	4.875**	6.765	3.813	2.666	1
$ETH^{+} \nRightarrow BTC^{+}$	4.612**	6.763	3.803	2.629	1
$ETH^{+} \nRightarrow BTC^{-}$	5.036**	7.180	3.768	2.635	1
$ETH^{-} \nRightarrow BTC^{-}$	0.149	6.696	3.826	2.599	1
$ETH^{-} \nRightarrow BTC^{+}$	7.659***	6.682	3.742	2.630	1
$BNC^{+} \nRightarrow ETH^{+}$	1.044	7.127	3.802	2.613	1
$BNC^{+} \nRightarrow ETH^{-}$	1.884	6.644	3.841	2.657	1
$BNC^{-} \nRightarrow ETH^{-}$	0.112	6.839	3.867	2.670	1
$BNC^{-} \nRightarrow ETH^{+}$	4.311**	6.674	3.854	2.664	1
$ETH^{+} \nRightarrow BNC^{+}$	3.316*	6.692	3.683	2.681	1
$ETH^{+} \nRightarrow BNC^{-}$	1.277	6.637	3.844	2.651	1
$ETH^{-} \nRightarrow BNC^{-}$	0.943	6.865	3.738	2.603	1
$ETH^{-} \nRightarrow BNC^{+}$	15.630***	7.286	3.959	2.643	1

Note: $^{-}$, $^{+}$ state the positive and negative shocks, respectively. In addition *, ** and, *** display significance at and 10%, 5%, 1% level, respectively.

Looking at the asymmetric causality relationship between Binance Coin and Ethereum, a causality relationship is found from negative shocks in Binance Coin prices to positive shocks in Ethereum prices, while a causality relationship is also detected between positive shocks in the price movements of both cryptocurrencies. Finally, we found a causality relationship from negative shocks in Ethereum prices to positive shocks in Binance Coin prices. Note that all interpreted results are statistically significant. In addition, analyzing cryptocurrencies, positive and negative shocks are also encountered in other studies. As Şak (2021) mentioned, it was determined that investors shifted their investments to Ripple, Binance coin, Bitcoin cash and Monero, which they saw less risky among cryptocurrencies during negative shock periods. It has been observed that different types of cryptocurrencies are used when investing in cryptocurrencies during periods of positive shocks, and investments are mostly directed towards Bitcoin, Ripple, Binance coin, Dash and Bitcoin cash.

5. CONCLUSION

Price bubbles in the market are a crucial indicator in terms of being a harbinger of crisis conditions. The formation of speculative price bubbles and the subsequent bursting of these bubbles can cause serious fluctuations in the economy, and if these fluctuations are exorbitant high, eventually it may create a crisis condition. For instance, especially the sharp decline in the crypto money market in 2022 has economically harmed many crypto money investors.

Analysis results show that the number of price bubbles that emerged in the post-COVID-19 period is much higher than before COVID-19. Expansionary monetary and fiscal policies implemented by countries, especially in the post-COVID-19 period, have created a significant demand for cryptocurrencies. These implementations also led to the emergence of price bubbles. In addition, a causal relationship is determined between the negative and positive external shocks to which the variables are exposed. It is expressed as a policy proposal that mechanisms that can protect crypto money investors must be developed to prevent sharp price movements and high-level volatility. In this direction, it should be demonstrated that the detection of cryptocurrency price bubbles can also support precautionary policies that economic decision-makers can develop.

For future studies, the volatility levels of the cryptocurrency market and other financial instruments can be analyzed and compared, simultaneous analysis of many cryptocurrencies based on various features can be made for price bubble analysis, and it can be researched whether cryptocurrencies will be an alternative investment tool to centralized and more controllable world stock markets, gold and foreign exchange markets.

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