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AN EMPIRICAL ANALYSIS OF SPECULATIVE BEHAVIOR AND THE SPILLOVER EFFECT IN CRYPTOCURRENCY MARKETS

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Abstract

For risk management and stable pricing in the cryptocurrency market, it is necessary to determine the interdependence of speculative behaviour and crypto assets. The correlation and high volatility caused by the interdependence of financial assets in the cryptocurrency market can lead to spreading risks. The study aims to measure the speculative behaviour and spillover effect in the prices of financial assets in the cryptocurrency market. The study used the SADF test, the generalized Dickey-Fuller test (GSADF), and the frequency domain causality test of Breitung and Candelon (2006) to determine the speculative behaviour and spillover effect in the prices of financial assets in the cryptocurrency market. Empirical evidence of speculative bubble formation between January 1, 2018, and December 2021 for the cryptocurrency assets covered in the study (ADA, BNB, BTC, DOGE, ETH, XLM, and XRP) is presented. Moreover, the frequency domain causality results obtained in the study show a contagion and spillover effect between crypto assets. The results provide essential information on the development of speculative behaviour and spread risk in the formation of financial asset prices in the cryptocurrency market.

Keywords: Cryptocurrency Markets; Bubbles; Spread Risks; Right-tailed Unit Root Tests, Frequency Domain Causality
JEL Classification: D53, F38, G00

1. Introduction

Developed financial markets have positive effects on economic growth and development. One of the most studied factors among the determinants of a well-developed financial system is the interdependence among financial assets. The main reason is the integration of financial markets and assets as part of globalization. Globalization causes a shock in one country's financial system to spread rapidly to the rest of the world (Polat and Eş-Polat, 2022). A similar situation applies to the cryptocurrency market. The lack of a regulatory and supervisory mechanism in

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the cryptocurrency market and the still developing and immature technology of blockchain technology increases the volatility in the relevant market, increasing the correlation and cooperation relationship between the assets in the cryptocurrency market.

The high correlation relationship between assets in the cryptocurrency market is one factor that is also effective in financial decision-making. This is because, as Huynh (2019) states, determining the degree of interdependence between financial instruments is essential for developing portfolio management and hedging strategies. Therefore, in assessing the degree of cooperation in the cryptocurrency market, the management of financial assets is critical to the forecasting and pricing process. Another important topic is the interdependence between financial markets, the development of the movement and volatility of financial instruments, and asset prices. In particular, unstable pricing in financial markets can have substantial effects that can lead to a global financial crisis, as was the case in the 2008 global crisis. In this context, it can be assumed that one factor that triggers these strong effects on modern financial markets and instruments is the increasing correlation and volatility in the cryptocurrency market.

Research on the causes of high correlation and volatility in the cryptocurrency market is gaining momentum in two different areas (Moratis, 2021). One is that fundamental external factors such as economic, financial, and geopolitical uncertainty cause high correlation and volatility in the cryptocurrency market (Giudici and Abu-Hashish, 2019; Smales, 2019; Panagiotidis et al., 2018; Moratis, 2021). The other is intrinsic fundamentals, such as increased volatility in the cryptocurrency market and the high correlation between crypto assets (Francés et al., 2018; Ji et al., 2019). As these internal and external factors prevent investors from reducing risk, they inhibit market dynamics in cryptocurrency and all financial markets.

The primary motivation of this study is to determine the speculative behaviours and the spillover effect in the prices of seven crypto assets (ADA, BNB, BTC, DOGE, ETH, XLM, and XRP) are dominant in terms of market value in the crypto money market. Compared to other related studies examining speculative price behaviour and spillover effects in cryptocurrencies, it differs from similar studies regarding subject and method. First, the study differs from other studies in analyzing the interconnectedness and persistence of seven significant cryptocurrencies. Secondly, the study provides an essential guide, especially in shaping the markets and investor decisions, by revealing the spread of speculative price behaviours and causality effects among cryptocurrencies. Third, the fact that the selected period of the study covers the period between January 1, 2018, and December 2021 contributes to the observation of the possible effects of investors' tendency to invest in different cryptocurrencies following the rapid increase in Bitcoin prices in the last quarter of 2017. Fourth, SADF and GSADF tests, which detect price bubbles, allow better inferences than the methods in the literature, thanks to their dynamic structure, unlike indirect methods. The frequency domain causality test, another technique used, makes a significant difference in determining whether there is a connection between cryptocurrencies in the short, medium, and long term, as it allows investigation of the causality dynamics at different frequencies. Therefore, the study may provide more compelling evidence than similar studies in the literature.

This paper is organized as follows. After this introductory section, Section 2 presents an overview of previous research on the issue. Section 3 presents this study's model, dataset, and method. Section 4 introduces the empirical results of the analysis. Finally, Section 5 concludes the research undertaken in this study.

2. Literature

According to the scope of the study, the literature, bubble formation, spillover effects, and causality are examined. If the bubble concept is evaluated from an economic perspective, it is characterized as a deviation from the fundamental value of the current asset. However, it isn't straightforward to determine this fundamental value, especially in the cryptocurrency market. For this reason, bubbles in cryptocurrencies are defined as price breakouts and provide an opportunity to do more reliable valuations (Enoksen et al., 2020).

The various dynamics behind the price increase in the cryptocurrency market can be grouped under two headings in general; i) the price increase experienced as a result of the introduction of various macroeconomic dynamics that will affect the returns of traditional investment instruments, as market participants turn to digital investment instruments to compensate for their potential losses ii) price increase through speculative effects. In the literature, it is seen that the studies on the values of crypto assets primarily focus on speculative effects. It is widely believed that difficulties in determining the fundamental importance of digital currencies set the stage for speculative behaviour. Market price formation is shaped around these relationships (Kristoufek, 2013; Shahzad et al., 2022). This view is supported by the assumption that the factors that play a role in price formation in cryptocurrency markets are not based on the same dynamics as the determinants of traditional asset markets. The difference between crypto money markets from traditional financial markets is that their supply is fixed, and the investor expectations on the demand side have a critical role. Therefore, the active part of the participants in the price formations in the crypto market makes the market dynamics open to speculative behaviours. Evlimoğlu and Güder's (2021) studies support this view. The main points, how and where the determinants of potential bubbles that may occur in crypto markets and the economic bubbles experienced in the past differ, were stated in their studies. These factors are listed as the fact that the fundamental value has not been determined in the crypto markets, the supply is limited, and blockchain technology is still developing. Therefore, it is argued that the decision-making processes of market actors are determined not on a rational basis, that is, on complete information, but on asymmetric information and irrational expectations (Yanık and Aytürk, 2011). The fact that the value of crypto assets is shaped in line with the perception of market actors triggers unstable price formation, preparing the ground for speculative bubbles. Due to the price movements in cryptocurrency markets in recent years, studies focusing on bubbles in this area have come to the forefront Yermarck (2015) argues that Bitcoin, which has the most significant value in the cryptocurrency market, is a speculative asset, while Cheah and Fry (2015) argue that Bitcoin has speculative bubbles. In another study that comes to similar conclusions, cryptocurrency markets are found to be highly volatile and subject to speculative effects (Fry and Cheah, 2016). In this context, the supremum-augmented Dickey-Fuller tests (SADF) of Phillips et al. (2011) and the generalized supremum-augmented Dickey-Fuller tests (GSADF) of Philips et al. (2015) are widely used. Several studies using the method have found evidence of cryptocurrency bubble formation (Cheung et al., 2015; Su et al., 2018; Bouri et al., 2019; Waters and Bui, 2021). The empirical studies by Souza et al. (2017) using RADF, SADF, and GSADF tests prove that speculative bubbles are common in cryptocurrency. On the other hand, the study by Buğan (2021), which investigated the formation of bubbles in cryptocurrencies, found that the bubbles detected in Litecoin and Cardano were not statistically significant as a result of the GSADF test, while the existence of bubbles was accepted for Bitcoin, Ethereum, Ripple, and Chainlink. In Şahin (2020) study, the bubbles in cryptocurrencies Bitcoin, IOTA, and Ripple were tested by the GSADF test, and the bubble formation in cryptocurrencies was confirmed again. In addition, the study drew attention to the impact of news manipulation on explaining the periods when bubbles were formed.

The literature also contains studies that examine the formation of bubbles in different types of markets. Maouchi et al. (2022), using the real-time bubble detection method proposed by Phillips and Shi (2020), investigated the existence of digital financial bubbles and detected bubble formation in 3 NFT, 9 DeFi tokens, Bitcoin and Ethereum. The study's findings covering the Covid-19 period are that the bubbles in DeFi and NFTs are more giant than those in Bitcoin and Ethereum but occur less frequently. Using the PSY test (GSADF), Gharib et al. (2021) point to boom periods in the crude oil and gold markets between 2010 and 2020. In particular, the Covid-19 period has shown the contagion effect in the bubbles in the two markets. When crypto asset prices are volatile, markets give signals of uncertainty and instability. The seizure of these factors in the markets raises financial concerns for crypto assets. Therefore, it is essential to measure the interdependence and volatility spreads of cryptocurrencies in shaping the risk management mechanism within the scope of the decision processes of investors. For this reason, in addition to detecting bubbles, evaluating the contagion effect of bubbles is essential in deepening the discussion of cryptocurrencies. Uncovering the spillover and causality effects between cryptocurrencies is crucial, especially in shaping markets and investors' decisions.

Various studies have been conducted in the literature on whether there are causality and volatility spillovers between cryptocurrencies. The logistic regression results in the study by Bouri et al. (2019) show that the probability of an explosion period in cryptocurrencies is shaped by the presence of explosions in other cryptocurrencies. Huynh (2019) investigates the spillover effects between five cryptocurrencies (bitcoin, Ethereum, XRP, Litecoin, Stellar) through VAR – SVAR Granger causality and the Copulas method. The research results show that Ethereum is independently compared to other cryptocurrencies, while the validity of the spillover effect between the different cryptocurrencies is questioned. On the other hand, the Student's t-Copulas test suggests a contamination risk when cryptocurrencies contain extreme values. When examining the competition between cryptocurrencies, one study's empirical results indicate a spread from Ripple to Bitcoin (Fry and Cheah, 2016). In another study, they pointed out the presence of structural breaks in the cryptocurrency market. They concluded that systematic price fluctuations spread from currencies with low market values to those with high market values (Canh et al., 2019). Yi et al. (2018), according to the results of their studies, the existence of a spillover effect is assumed in cryptocurrencies. Global finance, uncertainty effects, and trading volume are the variables that trigger the spillover effect. Ji et al. (2019) studied the return and volatility spreads of six cryptocurrencies and found that Bitcoin and Litecoin are at the centre of returns. In addition, positive returns were shown to be weaker than negative returns.

In their study, Enoksen et al. (2020) investigated the dynamics associated with the presence of bubbles. They used the PSY (GSADF) method to detect bubbles in cryptocurrency markets, and it was found that the variables that predict bubble formation are trading volume, transactions, and volatility. Cryptocurrency bubbles show a positive relationship with EPU (economic policy uncertainty index) and a negative relationship with VIX (fear index).

Canh et al. (2019) used data from seven cryptocurrencies (Bitcoin, Litecoin, Ripple, Stellar, Monero, Dash, and Bytecoin); the Granger causality test, the LM test for ARCH, and the DCC-MGARCH method were preferred. The results of the study show that there are structural breaks and volatility spillovers in the cryptocurrency market. It is found that the spillover effect is from more minor market cap currencies to more significant coins. Empirical evidence shows that cryptocurrencies exhibit strong and positively correlated volatility spillovers. Kirikkaleli et al. (2020) present empirical evidence of bubbles in Bitcoin and Ethereum, Litecoin, and Ripple between 2016 and 2019 and accept a positive relationship between Bitcoin and three other cryptocurrencies in the short run. In their studies using the quantile Granger non-causality test, Kim et al. (2021) conclude that coins with a high market value do not exhibit a strong bidirectional relationship with other currencies. While XRP has bidirectional causality with other coins, EOS has the weakest causal relationship with all coins. On the other hand, BNC has bidirectional causality with all coins except EOS. Katsiampa et al. (2019) studied the relationship between Bitcoin-Ethereum, bitcoin-litecoin, and etherium-litecoin between August 7, 2015, and July 10, 2018, using the BEKK model. The results show that cryptocurrency price volatility relates to prior volatility and currency shocks. While there is a bidirectional spread between Bitcoin and the other two cryptocurrencies, the spread between Ethereum and Litecoin is one-way. In addition, studies examining the relationship and spillover effect between cryptocurrencies and other financial assets are also prominent. Using the VAR GARCH model, Bouri et al. (2018) found that bitcoin returns are associated with traditional assets such as stocks, commodities, currencies, and bonds. The study also found that Bitcoin is a receiver rather than a transmitter of volatility. The volatility spillover index was created using the TVP-VAR model of Cao and Xie (2022). It was found that there is an asymmetric and time-varying volatility spillover effect between cryptocurrency and the Chinese financial market. At the same time, it has been determined that the risk spread of the financial market has a feeble impact on cryptocurrency. In contrast, the risk spread of cryptocurrency on the financial market is substantial. In the study by Elsayed et al. (2020), which investigated the spillover effects between three cryptocurrencies and nine foreign currencies using the Diebold-Yılmaz method, the return spillover effect for Bitcoin and Litecoin in the first three quarters of 2017 was determined. As a result of the Bayesian chart structure model VAR (BGSVAR), it was found that the level of bitcoin to the Chinese yuan, the bitcoin and litecoin values of Ripple, and the level of litecoin are dependent on Ripple and the Chinese yuan. The result of the study is causality between cryptocurrencies; among foreign currencies, only the Chinese yuan influences cryptocurrencies.

When considered as a whole, external dynamics, such as the fact that the cryptocurrency market is an unregulated market and the technological infrastructure development process, have not yet been completed. The increase in economic and geopolitical uncertainty leads to a rise in the vulnerability of cryptocurrencies to speculative behaviours in the market and triggers the formation of a bubble. By encouraging the spread of interdependence and volatility among cryptocurrencies, these developments pave the way for market efficiency deterioration.

3. Data Set and Method

3.1. Dataset

The study empirically investigates the existence of asset price bubbles in cryptocurrency markets, asset interdependence, and the spillover effect. In this regard, the variables used in the study were ADA, BNB, BTC, DOGE, ETH, XLM, and XRP, depending on the availability of data and the volume of transactions in the cryptocurrency market. The descriptive test statistics for the above variables are shown in Table 1. Accordingly, daily data was used for the selected variables between January 1, 2018, and December 2021, obtained from the Yahoo Finance database. On December 31, 2021, the cryptocurrency market cap was approximately 92 billion USD. On the same date, the share of cryptocurrencies selected as the study's sample in the market volume was approximately 65% (https://www.coinecko.com/en/global-charts, Access Date: 15.01.2023). Another factor affecting the period selection in the study is that, following the rapid increase in Bitcoin prices in the last quarter of 2017, investors tended to invest in different cryptocurrencies.

According to the results of the descriptive statistics given in Table 1, it is seen that the cryptocurrencies with the highest standard deviation are BTC and BNB. The lowest standard deviation is seen in DOGE. On the other hand, all variables used in the study are skewed to the right. Jarque-Bera test results, which indicate whether the variables show a normal distribution or not, suggest that the variables do not comply with the normal distribution.

Table 1: Descriptive Statistics

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	J-B	Obs.
ADA	0.46	0.10	2.96	0.02	0.68	1.689	4.737	878.75(0.00)***	1461
BNB	107.67	19.69	675.68	4.52	177.68	1.723	4.491	858.83(0.00)***	1461
BTC	18375	9475	67566	3236	17760	1.303	3.153	415.30(0.00)***	1461
DOGE	0.053	0.003	0.684	0.001	0.107	2.256	7.934	2722(0.00)***	1461
ETH	937.36	346.52	4812	84.308	1196	1.646	4.490	795(0.00)***	1461
XLM	0.20	0.144	0.896	0.033	0.148	1.022	3.598	276(0.00)***	1461
XRP	0.52	0.363	3.377	0.139	0.389	2.272	11.377	5529(0.00)***	1461

Note: Values in parentheses are probability values. In addition, * indicates the significance levels of 0.10, **0.05, and *** 0.01.

3.2. Research Methodology

In the study, first, whether there are speculative bubbles in the cryptocurrency market, Phillips et al. (2011) ekus ADF (SADF) and Phillips et al. (2015) generalized Dickey-Fuller (GSADF) test. The methods in question are recursive and right-justified unit root tests that have been widely used recently due to their excellent performance in detecting speculative bubbles and their occurrence.

The Exus-ADF test (SADF), one of the most commonly used right-tailed unit root tests among these methods, was developed by Phillips et al. (2011), and the extended standard Dickey-Fuller test (ADF) was developed to detect speculative bubbles and when they occur. As Homm and Breitung (2012) found, this test performs as well as other tests using similar procedures. The SADF test is essentially based on an iterative estimation of the standard ADF test. The SADF test is obtained as the lower value corresponding to the statistical ADF sequence and is obtained by estimating the values given in Equation 1 using least squares (Philips et al., 2015).

$$x_t=\mu_x+\delta x_{t-1}+\sum_{j=1}^{j} \emptyset j_j \Delta x_{t-j}+\varepsilon_{x,},\varepsilon_{x,t}\sim NID(0,\sigma_x^2) \tag{1}$$

For some values of J given in equation 1, the null hypothesis H0: δ=1 and the alternative hypothesis H1: $\delta > 1$ are formed in the right-tailed SADF unit root test so that the NID is independent and normally distributed. Iterative regressions on the sample data then increase one observation at each run. The result is repeatedly estimated using subsets.

$$sup_{r\epsilon[r_0,1]}\, ADF_r \rightarrow sup_{r\epsilon[r_0,1]} \frac{\int_0^r \widetilde{W} dW}{\left(\int_0^r \widetilde{W}^2\right)^{1/2}} \tag{2}$$

Equation 2 shows standard Brownian motion W and reduced Brownian motion $\widetilde{W}(r) = W(r) - \frac{1}{r}\int_0^1 W$ (Philips et al., 2011: 206-207). Considering the criticism in the literature that the statistical power of the SADF test decreases in the case of multiple bubbles, Phillips et al. (2015) developed the generalized GSADF unit root test to address the shortcomings of the SADF test in this direction. Although the GSADF test has similar features to the SADF test, it differs because the standard ADF test uses an iterative soft estimate of the regression obtained from the standard ADF test in computing the test, allowing for long-term nonlinear structures and structural breaks. In this regard, the GSADF test outperforms the SADF and standard ADF unit root tests by providing more consistent and accurate results in the case of multiple bubbles (Phillips et al., 2015). Although the GSADF test is based on the recursive operation of the ADF test in subsamples, similar to the SADF test, it is referred to as the most significant ADF test because it is much broader than the SADF test.

To calculate the GSADF test statistic, we first estimate the iterative regression equation 3. Here, k is the lag length, and r1 and r2 are included in the equation to represent the start and end points of the subsample so that iterative regression estimates can be performed (Çağlı and Mandacı, 2017: 66).

$$\Delta y_t = \hat{\alpha}_{r_1,r_2} + \hat{\beta}_{r_1,r_2} y_{t-1} + \sum_{i=1} \hat{\psi}^{i}_{r_1,r_2} \Delta y_{t-i} + \hat{\varepsilon}_t \tag{3}$$

The GSADF test Equation 3 is repeatedly estimated for multiple subsamples using subsets with a future date. Unlike the SADF test, subsamples are created where the initial points of the subsamples in r1 change dynamically instead of the final moments in r2 and deviate from zero (Çağlı and Mandacı, 2008). 2017:66). From this point of view, the GADF test is calculated using the formula given in equation 4 (Philips, Shi, and Yu, 2015: 1049)

$$GSADF(r_0) = sup_{r_2 \in r_1 \in [0, r_2 - r_1][r_0, 1]} \{ADF_{r_1}^{r_2}\} \tag{4}$$

The frequency domain causality test, another method used in the study, allows for investigating the causality relationship of the variables under study at multiple time points. Since traditional causality tests generate test statistics for a single t-period, they ignore the possibility that the causality relationship changes at different frequencies and periods (Bozoklu & Yılancı, 2013). On the other hand, traditional causality methods perform a linear causality analysis between the variables included in the study. Geweke (1982) and Hosoya (1991) proposed a causality analysis method based on spectral density decomposition at a specific frequency to address this shortcoming of traditional causality analysis. Subsequently, Breitung and Candelon (2006) developed a computational method that simplifies the complex structure of frequency-based causality analysis. This calculation method has created a procedure based on the autoregressive parameters based on the VAR model (Başarır, 2018). Due to its structure, the method also has the advantage of performing a nonlinear causality analysis between the variables included in the study. In this context, the causality analysis can be performed for different frequencies as follows:

$$M_{y \to x}(\omega) = log\left[\frac{2\pi f_x(\omega)}{|\Psi_{11}(e^{-i\omega})|^2}\right] = log\left[1 + \frac{|\Psi_{12}(e^{-i\omega})|^2}{|\Psi_{11}(e^{-i\omega})|^2}\right] \tag{5}$$

According to equation 5, in the case of $|\Psi 12(e^{-i\omega})|= 0$ above a certain w frequency, there is no causality relationship from the y variable to the x variable (Ciner, 2011:500). Breitung and Candelon (2006) change the hypothesis to equation #5, according to which if $My\rightarrow x(\omega)=0$. $|\Psi 12(e^{-i\omega})|=0$ then ,

$$\Psi(L) = \Theta(L)^{-1}G^{-1} \text{ ve } \Psi_{12}(L) = -\frac{g^{22}\Theta_{12}(L)}{|\Theta(L)|} \tag{6}$$

In equation 6, g^{22} represents the common diagonal elements of the G^{-1} matrix, $|\Theta(L)|$ represents the determinant of $\Theta(L)$. In this case, causality in the frequency domain can be tested with the following equation. (Bodart and Candelon, 2009: 143).

$$|\Theta_{12}(e^{-i\omega})| = \left|\sum_{k=1}^{p} \Theta_{12,k}\cos(k\omega) - \sum_{k=1}^{p} \Theta_{12,k}\sin(k\omega)\, i\right| = 0 \tag{7}$$

Since $\Theta_{12,}$ indicates the element of Θ_k and Θ_k in equation 7, the expression $|\Theta_{12}(e{-}i\omega)|=0$ can be expressed such that "y" is not the cause of "x" at "w" (Tarı et al., 2012: 10) . Breitung and Candelon (2006) model the method as a function of linear constraints, as shown in equation 8. In this case, the equation VAR can be formed with 9 for x_t.

$$\sum_{k=1}^{p} \Theta_{12,k}\cos(k\omega) = 0$$
$$\sum_{k=1}^{p} \Theta_{12,k}\sin(\mathrm{k}\omega) = 0 \tag{8}$$

$$x_t = \alpha_1 x_{t-1} + \cdots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \varepsilon_{1t} \tag{9}$$

Since the hypothesis $My\rightarrow x(\omega)=0$ is equivalent using equations 8 and 9 with linear constraints, the H0 hypothesis can be stated in equation 10.

$$R(\omega) = \begin{bmatrix} \cos(\omega) & \cos(2\omega) & \cdots & \cos(p\omega) \\ \sin(\omega) & \sin(2\omega) & \cdots & \sin(p\omega) \end{bmatrix} \tag{10}$$

Thus, H0: $(\omega)\beta=0$ $(\beta=[\beta 1,\ldots,\beta p]')$ $R(\omega)$ is calculated using the following equation. On the other hand, it is possible to separate the causal dynamics between the variables studied in the frequency domain causality analysis temporarily and permanently. Accordingly, a short-term (temporary) causality analysis is performed when the ω-frequency value is calculated for a high frequency (ω =2.5). When the value of ω=1.5, a medium-term causality analysis is performed, while when the value of ω=0.5 (low frequency), a permanent causality analysis is possible. Therefore, causality analysis in the frequency domain allows the decomposition of causality into more than one time period.

4. Empirical Results

In this part of the study, the hypothesis formulated as H1 is first tested using the prices of 7 financial assets in the cryptocurrency market. The hypothesis states that increasing financial interconnectedness with globalization will cause a shock in the financial system to spread quickly to the rest of the world. In the case of a spillover effect, bubbles can occur when investors continue to hold assets because they believe they can sell them at a higher price than other investors, even though the financial asset's price exceeds its fundamental value. This situation, which also applies to the cryptocurrency market, leads to the unstable pricing of cryptocurrency market assets. In other words, bubbles can occur in the prices of crypto assets.

H1: External factors affecting the cryptocurrency market make for unstable pricing.

The SADF and GSADF tests were used to determine the presence of bubbles by testing the hypothesis expressed as H1 and to determine when bubbles occur. In applying the above tests, 2000 replicate Monte Carlo simulations were used for each observation. The results of the estimations are reported in Table 1.

Table 2: The SADF and GSADF Test Statistics

	SADF Test Statistic	*GSADF* Test Statistic
ADA	3.00***	12.52***
BNB	19.72***	19.81***
BTC	5.86***	8.04***
DOGE	15.99***	16.01***
ETH	5.79***	6.68***
XLM	-1.00	6.139***
XRP	-1.72	6.128***

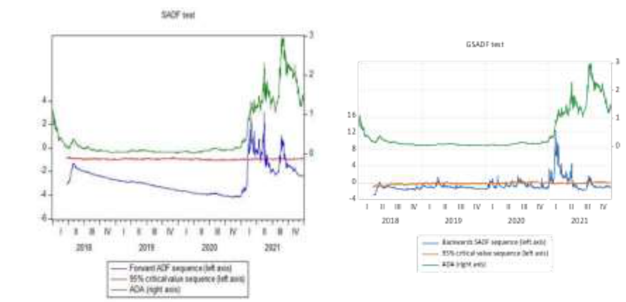
Note: Critical values for SADF statistics are 0.43, 0.69, and 1.15 for 10%, 5%, and 1% significance levels, respectively. Critical values for GSADF statistics are 1.28, 1.46, and 1.91 for 10%, 5%, and 1% significance levels, respectively. In addition, the significance levels * 0.10, ** 0.05, and *** 0.01 are given. These critical values were obtained by Monte Carlo simulation with 2,000 replicates.

Examination of the SADF and GSADF test statistics in Table 2 shows that the estimated test statistics for the cryptocurrencies ADA, BNB, BTC, DOGE, and ETH are more significant than the critical values. Therefore, a speculative bubble in these currencies was established for the analyzed periods. On the other hand, when examining the SADF and GSADF test statistics obtained for the XLM and XRP currencies from the selected assets in the cryptocurrency market, it can be seen that the estimated SADF test statistics are smaller than the critical values. In other words, the H0 hypothesis is accepted. However, the estimated GSADF test statistics are shown to be larger than the critical values, so the H0 hypothesis is rejected. Phillips et al. (2015) found that the GSADF test is more consistent and gives better results than the SADF and standard ADF tests. Based on this view, it can be said that a speculative bubble occurred for the XLM and XRP currencies during the analyzed periods.

In summary, the test results show that although the prices of all currencies exceed the fundamental value of the prices of the analyzed period, they continue to hold assets because they believe they can sell them at a higher price than other investors. In other words, it can be said that bubbles were created in the cryptocurrency market during the studied period. Thus, the obtained results confirm the hypothesis that external factors affecting the cryptocurrency market make the pricing unstable and lead to the formation of bubbles.

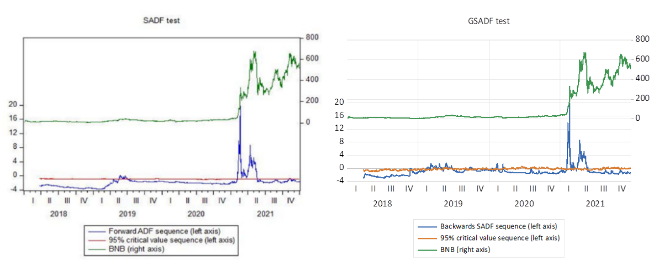
Having established the presence of bubbles in the selected cryptocurrencies, the second phase began to identify the periods in which bubbles occurred. In this way, it is possible to determine which factors cause instability in price formation and lead to the formation of bubbles.

Figure 1: ADA Cryptocurrency Test Results Charts



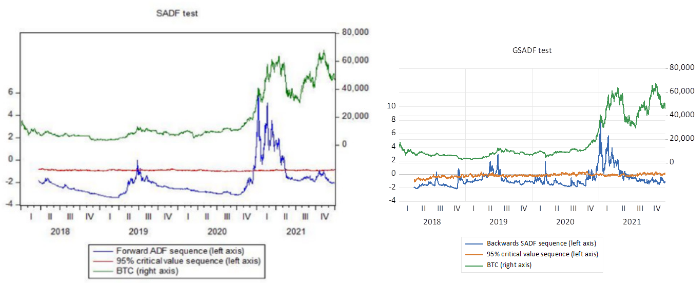
From the SADF and GSADF test charts shown in Figure 1, it can be seen that a bubble formed during the period from late January 2021 to early June 2021. During the period in question, the technological upgrade of the cryptocurrency ADA led to excessive demand for the cryptocurrency ADA by many investors, creating a bubble.

Figure 2: BNB Cryptocurrency Test Results Charts



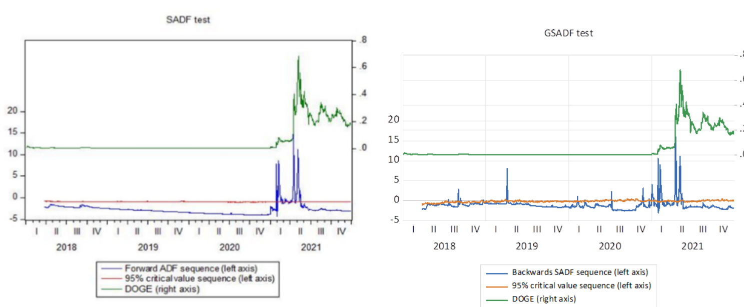
Based on the SADF and GSADF test charts of the cryptocurrency BNB shown in Figure 2, it was determined that a bubble formed from the beginning of 2021 to the end of May 2021. In the studied period, it can be said that the interventions of the cryptocurrency exchange Binance to reduce the total supply of BNB cryptocurrency and the excessive demand for BNB due to the increase in transaction costs in Ethereum drive up prices and cause the formation of a bubble.

Figure 3: BTC Cryptocurrency Test Results Charts



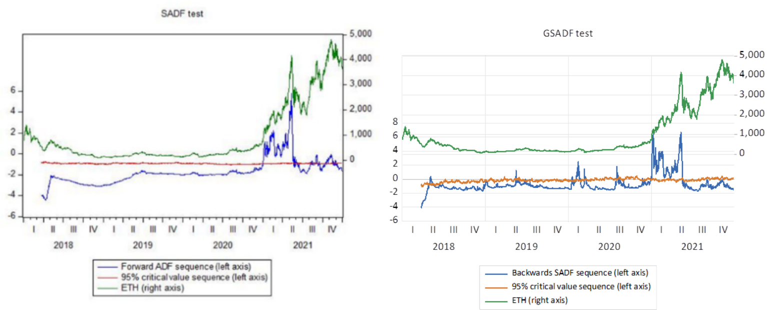
According to the SADF and GSADF charts for bitcoin in Figure 3, a bubble in the bitcoin price was observed in the last quarter of 2018, the middle of 2019, and between the last quarter of 2020 and the second quarter of 2021. During the earlier periods, the improvements in the system's functioning with the blockchain system's updates have increased the demand for bitcoin and pushed the prices. This has led to a bubble in BTC prices. On the other hand, it can be said that the big rally in BTC price was effective in the bubble formation observed between the last quarter of 2020 and the second quarter of 2021.

Figure 4: DOGE Cryptocurrency Test Results Charts



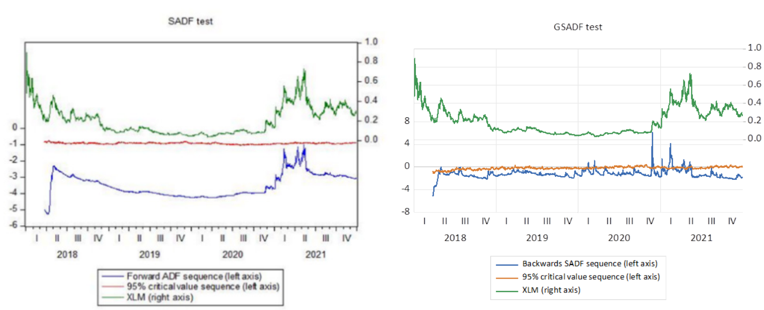
The SADF and GSADF test charts of the cryptocurrency DOGE, shown in Figure 4, indicate that there have been several bubble formations between the last quarter of 2020 and mid-2021. In the mentioned period, it can be observed that external factors are particularly effective in bubble formation in DOGE cryptocurrency prices. In particular, social media posts for the cryptocurrency DOGE created excessive demand by directing investors to this cryptocurrency during the period in question. The high demand for the stocks in question led to a large price rally. As a result, the sharp rise in prices led to a bubble.

Figure 5: ETH Cryptocurrency Test Results Charts



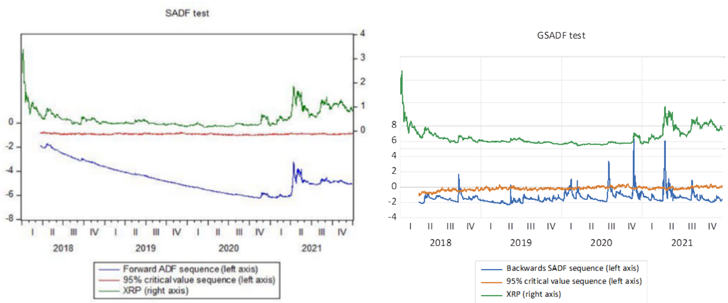
According to the SADF and GSADF charts for Ethereum in Figure 5, a price bubble can be observed from early 2021 to mid-2021. The reason for the bubble formation in the mentioned period is the announcement by the financial institutions that the Ethereum Trust will be reopened for public trading in the mentioned period. Also, in the mentioned period, the tendency of retail investors to engage in decentralized trading of virtual currencies increased the demand for Ethereum, one of the currencies with the largest market volume in the cryptocurrency markets. It contributed to the formation of speculative price bubbles.

Figure 6: XLM Cryptocurrency Test Results Charts



The SADF chart for Stellar (XLM) in Figure 6 shows no speculative price bubble during the period in question. However, the graphs of the GSADF test, which gives more accurate results than the SADF test, indicate the existence of several different bubbles during the period in question. The main reason for this difference is that while the SADF test is a powerful method for detecting bubbles, it can be weak, especially in more than one price bubble. As confirmed by the GSADF graphs, price bubbles occurred in three different periods during the relevant period: the last quarter of 2020, the first quarter of 2021, and the second quarter. It can be said that regulatory decisions made in developed countries regarding the blockchain system and cryptocurrencies were effective in forming these bubbles. In the same period, developments such as the partnership of major banks with Stellar in Europe led to an increase in demand. They became one of the factors contributing to the inflation of the Stellar price.

Figure 7: XRP Cryptocurrency Test Results Charts



The SADF chart of Ripple (XRP) in Figure 7 shows no speculative price bubble during the period. However, the charts from the GSADF test, which provides more accurate results than the SADF test, provide empirical evidence of the existence of several different bubbles during the relevant period. As shown in the GSADF charts, price bubbles are observed in the third quarter of 2018, the first and fourth quarters of 2020, and the first and third quarters of 2021. In the formation of price bubbles, banks in Japan and South Korea announced their intention to test Ripple's blockchain technology in 2018. In late 2019, Japan and South Korea will begin testing blockchain technology to reduce the time and costs of international money transfers between the two countries. In 2021, price increases in other cryptocurrencies drove up Ripple's prices and contributed to the formation of a bubble.

In this part of the study, the hypothesis formulated as H2 is tested using the prices of 7 financial assets in the cryptocurrency market.

H2: Assets in the cryptocurrency market have the power to affect each other directly

The said hypothesis, Frequency Domain Causality Test, was used to determine whether the assets in the cryptocurrency market have the power to influence each other.

The Frequency Domain Causality Test used to test the hypothesis formulated as H2, can distinguish between temporary or permanent causal dynamics between crypto assets. For this purpose, test statistics with high (ω=2.5) frequency were used when examining short-term causality, while test statistics with medium frequency (ω=1.5) were utilized for medium-term causality. Test statistics with low (ω=0.5) frequency were used to study long-term permanent causality. The test results are presented in Table 2, Table 3, and Table 4.

Table 2: Short-term (ω=2.5) Frequency Domain Causality Test Results

Causality Direction	ADA	BNB	BTC	DOGE	ETH	XLM	XRP
ADA ➟	-	6.00**	2.83	6.53**	9.81***	10.81***	6.15**
BNB ➟	17.68***	-	31.82***	51.25***	6.92**	23.20***	18.65***
BTC ➟	5.02*	10.00***	-	19.50***	17.23***	3.48	4.97*
DOGE ➟	24.88***	18.13***	2.33	-	3.64	21.18***	10.99***
ETH ➟	11.83***	1.51	20.48***	27.79***	-	16.40***	15.73***
XLM ➟	1.27	1.56	11.59***	7.21**	0.008	-	1.29
XRP ➟	0.54	1.33	7.39**	13.86***	2.02	1.68	-

Note: the significance levels * 0.10, ** 0.05, and *** 0.01 are given.

According to the results of the short-term frequency domain causality test in Table 2, a bidirectional causality relationship was found between ADA cryptocurrency and BNB, DOGE, and ETH. A bidirectional causality relationship was found between BNB cryptocurrency and ADA, BTC, and DOGE cryptocurrencies. A short-term and bidirectional causality relationship was found between the cryptocurrency BTC and the cryptocurrencies BNB, ETH, and XRP. A statistically significant and bidirectional causality relationship was found between the cryptocurrency DOGE and the cryptocurrencies ADA, BNB, XLM, and XRP. It is found that there is a transitory and bidirectional causality relationship between the cryptocurrency ETH and the cryptocurrency values ADA and BTC. Finally, a bidirectional causality relationship existed between XRP and BTC, DOGE.

On the other hand, a one-way causality relationship was found from cryptocurrency ADA to cryptocurrencies XLM and XRP. A one-way causality relationship was found between BNB and ETH. Similarly, a one-way causality relationship was found to exist from BTC to ADA. A unidirectional and statistically significant causality relationship exists between ETH to DOGE, XLM, and XRP. A unidirectional causality relationship was found to exist between XLM cryptocurrency and BTC.

Table 3: Mid-term (ω=1.5) Frequency Domain Causality Test Results

Causality Direction	ADA	BNB	BTC	DOGE	ETH	XLM	XRP
ADA ➟	-	5.80*	2.63	7.19**	9.53***	10.99***	7.02**
BNB ➟	18.74***	-	28.93***	56.03***	7.59**	23.79***	20.22***
BTC ➟	5.22*	8.62**	-	20.34***	15.99***	3.63	5.59*
DOGE ➟	26.57***	20.33***	1.65	-	3.60	21.55***	12.18***
ETH ➟	12.47***	1.36	19.46***	29.18***	-	16.91***	16.95***
XLM ➟	1.24	1.53	10.40***	7.98**	0.01	-	0.79
XRP ➟	0.40	1.29	6.37**	15.33***	2.04	1.11	-

Note: the significance levels * 0.10, ** 0.05, and *** 0.01 are given.

According to the medium-term frequency domain causality test results listed in Table 3, a bidirectional causality relationship was found between ADA cryptocurrency and BNB, DOGE, and ETH. A bidirectional causality relationship was found between BNB cryptocurrency and ADA, BTC, and DOGE cryptocurrencies. A medium-term and bidirectional causality relationship was found between the cryptocurrency BTC and the cryptocurrencies BNB, ETH, and XRP. A statistically significant and bidirectional causality relationship was found between the cryptocurrency DOGE and the cryptocurrencies ADA, BNB, XLM, and XRP. A bidirectional causality relationship existed between the cryptocurrency ETH and the cryptocurrency assets ADA and BTC. Finally, a bidirectional causality relationship existed between XRP and BTC, DOGE.

It was found that there is a one-way causality relationship between the cryptocurrency XLM and BTC. On the other hand, a one-way causality relationship existed between the cryptocurrency ADA and the cryptocurrencies XLM and XRP. It was found that there is a one-way causality from BNB to ETH, XLM and XRP. Similarly, it was found that there is a one-way causality relationship between BTC to ADA and DOGE. A unidirectional and statistically significant causality relationship exists between ETH to DOGE, XLM, and XRP.

Table 4: Long-term (ω=0.5) Frequency Domain Causality Test Results

Causality Direction	ADA	BNB	BTC	DOGE	ETH	XLM	XRP
ADA ➟	-	3.22	1.30	12.27***	5.71*	12.96***	21.42***
BNB ➟	22.03***	-	2.33	88.73***	10.14***	29.38***	41.89***
BTC ➟	10.21***	1.15	-	31.54***	3.19	7.40**	16.05***
DOGE ➟	26.43***	28.70***	4.91*	-	1.29	22.12***	25.77***
ETH ➟	14.36***	0.28	8.25**	36.93***	-	22.12***	34.05***
XLM ➟	0.93	1.21	0.32	12.98***	0.13	-	4.59
XRP ➟	1.62	0.94	0.40	22.74***	1.66	3.14	-

Note: the significance levels * 0.10, ** 0.05, and *** 0.01 are given.

According to the long-term frequency domain causality test results in Table 4, a bidirectional causality relationship was found between ADA cryptocurrency and DOGE and ETH. A bidirectional causality relationship was found between BNB cryptocurrencies and DOGE cryptocurrencies. A bidirectional causality relationship was found between BTC and DOGE. A statistically significant and bidirectional causality relationship was found between DOGE cryptocurrency and ADA, BNB, BTC, XLM, and XRP cryptocurrencies. It was found that there is an ongoing and bidirectional causality relationship between the cryptocurrency ETH, the cryptocurrency assets ADA, and BTC. It was found that there is a bidirectional causality relationship between XLM and DOGE cryptocurrencies. Finally, a bidirectional causality relationship existed between XRP and DOGE.

On the other hand, a one-way causality relationship existed between ADA cryptocurrency and XLM and XRP cryptocurrencies. It was found that there is a one-way causality from BNB cryptocurrencies to the cryptocurrencies ADA, ETH, XLM, and XRP. Similarly, it was found that there is a one-way causality relationship between BTC to ADA, XLM, and XRP. A unilateral and persistent causality relationship exists between ETH to BTC, DOGE, XLM, and XRP.

When the results of the frequency domain causality test in Table 2, Table 3, and Table 4 are evaluated together, it can be concluded that there are spillover and contagion effects between cryptocurrency markets. It can be observed that the cryptocurrency with the strongest contagion and spillover effect in the short and medium term is Binance Coin (BNB). Also, a contagion and spreading effect can be seen in Binance Coin and other cryptocurrency assets in the long term. Moreover, another conclusion is that the said effect is permanent. On the other hand, although Stellar (XLM) and Ripple (XRP) cryptocurrencies have a contagion and spread effect from other cryptocurrencies in the short, medium, and long term, the contagion and spread impact of these cryptocurrencies to other cryptocurrencies is weak. Therefore, it can be observed that the risk of Stellar (XLM) and Ripple (XRP) spreading to other cryptocurrencies is low. Another result of the frequency domain causality test is that the cryptocurrency DOGE has the highest contagion and propagation effects among other cryptocurrencies. In other words, the cryptocurrency DOGE has a very high degree of dependence on other cryptocurrencies and has the highest risk of propagation. Finally, Bitcoin (BTC) and Ethereum (ETH) have a contagion and spillover effect that causes the prices of other cryptocurrencies to change.

In contrast, the degree of influence of other cryptocurrencies is low. Bitcoin (BTC) and Ethereum (ETH) are independent cryptocurrencies with spillover effects but low impact. In conclusion, the obtained results confirm the correctness of the H2 hypothesis, which states that assets in the cryptocurrency market can directly influence each other.

5. Conclusion

The globalization process that has taken place in the financial markets in recent years has put on the agenda the need for alternative currency systems and new financial instruments. This situation has led to the emergence of cryptocurrencies, especially following the 2008 crisis. Cryptocurrencies have started to attract attention in the financial system with their advantages, such as the alternative monetary system they offer and the potential to generate high returns. Moreover, the existing regulations in the cryptocurrency market are still in their infancy, which makes the financial assets in the cryptocurrency market vulnerable to high volatility and speculative developments. In this context, the speculative behaviours observed in the cryptocurrency market may lead to price bubbles. Moreover, the correlation and high volatility caused by the interdependence of financial assets in the cryptocurrency market can lead to spreading risks. Therefore, determining the interdependence of speculative behaviour and crypto assets is necessary for risk management and stable pricing in the cryptocurrency market.

In the study, Phillips et al. (2011) (SADF) and Phillips et al. (2015) generalized the Dickey-Fuller test (GSADF) used to determine whether the external factors affecting the cryptocurrency market cause instability in price formation. In other words, it aims to determine whether the speculative behaviour of the assets in the cryptocurrency market creates a price bubble and to measure the interdependence and spillover effect of the assets in the cryptocurrency market using the frequency domain causality test. Therefore, the study estimates the speculative behaviour and spread risk in the cryptocurrency market in two dimensions. The study results show that it is statistically significant for cryptocurrencies ADA, BNB, BTC, DOGE, ETH, XLM, and XRP. Therefore, there is empirical evidence of the formation of speculative bubbles between January 1, 2018, and December 2021, which is discussed in the study. On the other hand, when examining the SADF and GSADF test statistics obtained for the XLM and XRP currencies from the selected assets in the cryptocurrency market, it was found that the SADF test is not, while the GSADF test is statistically significant. Based on the view that the GSADF test is more consistent and provides better results than the SADF test, it can be said that empirically a speculative bubble occurred within the XLM and XRP currencies for the analyzed periods.

On the other hand, the results of the frequency domain causality test in the study provide empirical evidence that there is a spillover and contagion effect between financial assets in the cryptocurrency market. In other words, price changes between selected currencies in the cryptocurrency market cause increased correlation and volatility. In particular, the degree of pegging the cryptocurrency DOGE to other cryptocurrencies was relatively high. Stellar (XLM) and Ripple (XRP) cryptocurrencies also have a high degree of pegging to other cryptocurrencies in the short, medium, and long term. However, the price changes observed in Stellar (XLM) and Ripple (XRP) cryptocurrencies do not affect other crypto assets. In other words, when a market event occurs in the Stellar (XLM) and Ripple (XRP) cryptocurrencies, it has little potential to cause an upward or downward trend in the prices of other cryptocurrencies. Therefore, sudden changes in other cryptocurrencies can be expected to simultaneously affect DOGE, Stellar (XLM), and Ripple (XRP) and increase the risk of a spread. Another important finding of the study is that Bitcoin (BTC) and Ethereum (ETH) have a contagion and spillover effect that causes the prices of other cryptocurrencies to change. In contrast, the degree of influence by other cryptocurrencies is low. Bitcoin (BTC) and Ethereum (ETH) are cryptocurrencies in their own right that pose spillover risks but are only affected by spillover and volatility risks to a small extent.

In the context of the results obtained in the study, assets in the cryptocurrency market have a spillover effect in the form of overvaluation with the impact of internal and external factors. In other words, the high interdependence of crypto assets in the crypto money market is a significant obstacle to stable price formation when supported by speculative pricing behaviour. Therefore, the study results provide a better understanding of the interconnectedness of assets in the cryptocurrency market and the transmission of contagion effects. In addition, the study's findings indicate that investors should pay attention to the moving signals in the markets. This means that any current and past change in one cryptocurrency could have a negative impact on the movement of other cryptocurrencies. Therefore, the study's findings to establish a dynamic early warning mechanism for risk management and stable pricing in the cryptocurrency market will be an essential guide.

Future studies may expand the scope of work with other currencies in the cryptocurrency market. In addition, the studies on this topic can use quantitative methods to investigate the macroeconomic and socioeconomic factors determining the cryptocurrency market's spread risk.

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