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# CAUSALITY AND COINTEGRATION IN CRYPTOCURRENCY MARKETS

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## Abstract

This paper investigates the causality and cointegration relationships between seven major cryptocurrencies, namely Bitcoin (BTC), Binance Coin (BNB), Cardano (ADA), Dogecoin (DOGE), Ethereum (ETH), Polkadot (DOT) and Ripple (XRP), using Johansen Cointegration and Granger Causality tests over the period from August 21, 2020 to April 19, 2021. Results indicate that there exists cointegration among cryptocurrencies in the long run. Findings also show that there is a bi-directional causal relationship between BNB and ETH. Additionally, BNB appears to be Granger cause of ADA, DOGE and DOT. On the other hand, analyses provide evidence of one-way causality running from XRP to both DOGE and DOT. These results might have some important implications for investors in terms of portfolio management.

***Keywords:*** *Cryptocurrencies, Cointegration, Causality.*
***JEL Classification:*** *C58, G11, G23.*

# KRİPTO PARA PİYASALARINDA NEDENSELLİK VE EŞBÜTÜNLEŞME

## Öz

Bu makalede, Johansen Eşbütünleşme ve Granger Nedensellik testleri kullanılarak Bitcoin (BTC), Binance Coin (BNB), Cardano (ADA), Dogecoin (DOGE), Ethereum (ETH), Polkadot (DOT) ve Ripple (XRP) olmak üzere yedi kripto paranın arasındaki nedensellik ve eşbütünleşme ilişkileri araştırılmaktadır. Çalışma dönemi 21 Ağustos 2020 – 19 Nisan 2021 tarihleri arasını kapsamaktadır. Sonuçlar, kripto paralar arasında uzun dönemde eşbütünleşme olduğunu işaret etmektedir. Bulgular ayrıca BNB ve ETH arasında çift yönlü nedensellik ilişkisi bulunduğunu göstermektedir. Bunlarla birlikte BNB'nin, ADA'nın, DOGE'nin ve DOT'un Granger nedeni olduğu görünmektedir. Diğer yandan analizler, XRP'den, hem DOGE'ye hem DOT'a doğru tek yönlü nedensellik bulunduğuna dair kanıtlar sunmaktadır. Bu sonuçlar yatırımcıların portföy yönetimi açısından bazı önemli çıkarımlar yapmasını sağlayabilir.

***Anahtar Kelimeler:*** *Kripto Paralar, Eşbütünleşme, Nedensellik.*
***JEL Sınıflandırması:*** *C58, G11, G23.*

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## 1. Introduction

Cryptocurrencies, which use cryptography for security purposes and known as virtual or digital currencies, began to emerge with the launch of Bitcoin in 2009 (Adebola et al., 2019:1227) and to become more popular day by day. Today, thousands of cryptocurrencies are traded in cryptocurreny markets and the number of participants and trading volumes of these markets are rapidly increasing. Bitcoin is the most popular cryptocurrency and pioneer of all cryptocurrencies. It also has the highest market cap among cryptocurrencies. Apart from Bitcoin, there are many cryptocurrencies such as Ethereum, Ripple, Cardano, which are called "altcoin". Despite the volatile and extremely risky nature of these currencies, almost everyone in every profession desires to own a cryptocurrency and engages in trading activities in cryptocurrency markets. In addition, investors may prefer to include cryptocurrencies in their portfolios for diversification and risk distribution.

The most important characteristics of cryptocurrencies are decentralization, elimination of third parties and not being subject to any control mechanism or regulations. Besides, the blockchain technology, on which cryptocurrencies are based on, helps the transactions done with these currencies to gain an anonymity. While these characteristics increase the attractiveness of cryptocurrencies, they can also cause cryptocurrencies to be used for illicit activities such as money laundering, drug and arms trafficking.

Cryptocurrencies have a different nature than traditional currencies. It is relatively possible to predict the future prices of traditional currencies based on the factors that affect them, but the prices of cryptocurrencies are mainly determined by supply and demand. It can be claimed that various news, rumors and psychological factors (such as herding behavior) play significant role in the formation of this supply and demand equilibrium. Therefore, it is difficult to predict the future prices of cryptocurrencies and to detect possible fluctuations in prices. Considering the speculative nature of cryptocurrencies, it becomes even more difficult to find the right strategy in these markets. This situation raises the need for more detailed analyses on cryptocurrencies.

The rising popularity and use of cryptocurrencies has attracted the attention of governments as well as people. While some governments may make various regulations and take some actions regarding cryptocurrencies, some may choose to adopt a neutral attitude.

Whether cryptocurrencies have the characteristics required for an asset to be considered as ‘’money’’ is one of the issues that are heavily debated. While some say that cryptocurrencies are a "currency", others claim that they are "payment method". Today, the fact that cryptocurrencies have become a part of the natural flow of life has attracted the attention of researchers (especially in the field of finance) and the number of academic researches and analyses addressing cryptocurrencies has increased.

As of April 16, 2021, the total market cap of cryptocurrencies has exceeded $ 2 trillion. Top ten cryptocurrencies by market cap are presented in Table 1.

Table 1: **Overview of Top Ten Cryptocurrencies**

| Cryptocurrencies | Symbol | Market Cap ($) | Circulating Supply | Market Dominance |
|---|---|---|---|---|
| Bitcoin | BTC | 1.057.350.198.527 | 18.685.818 | %51.26 |
| Ethereum | ETH | 259.047.260.748 | 115.524.748 | %12.55 |
| Binance Coin | BNB | 73.748.803.638 | 153.432.897 | %3.57 |
| Ripple | XRP | 65.109.009.904 | 45.404.028.640 | %3.15 |
| Tether | USDT | 48.070.464.990 | 48.075.190.515 | %2.33 |
| Dogecoin | DOGE | 41.542.604.746 | 129.237.971.710 | %2.01 |
| Cardano | ADA | 40.832.963.031 | 31.948.309.441 | %1.97 |
| Polkadot | DOT | 35.090.619.431 | 930.989.386 | %1.70 |
| Litecoin | LTC | 18.386.485.709 | 66.752.415 | %0.89 |
| Bitcoin Cash | BCH | 17.958.680.699 | 18.712.513 | %0.87 |

**Source:** coinmarketcap.com

In recent years it is one of the debates whether cryptocurrencies can be seen as a financial instrument and included in portfolios for diversification and risk distribution benefits, and there are various studies on this subject. Wu and Pandey (2014), Carpenter (2016), Gangwal (2016), Feng et al. (2018), Lee et al. (2018), Guesmi et al. (2019), Gül (2020) and Trimborn et al. (2020) are some of these studies. When viewed from this aspect, it is important to investigate relationships such as correlation, cointegration, and causality between cryptocurrencies. In this regard, the main purpose of the study is to analyze the causality and cointegration relationships among cryptocurrencies and to shed light on the interactions between these assets.

The rest of the paper is organized as follows. Section two presents the literature review. Third part of the paper covers the dataset and description of the data used for the analyses. Section four outlines the empirical methodology. Section five discusses the empirical results and the final section provides concluding remarks.

## 2. Literature Review

The number of academic studies in the field of finance on the cryptocurrencies are gradually increasing. There are many researches which discuss the relationships between cryptocurrencies, stock markets, exchange rates or commodities (such as gold). Some of these studies are presented below.

Dirican and Canoz (2017) examined the relationship between Bitcoin prices and various stock market indices. As a result, they stated that there is a cointegration between Bitcoin prices and the leading indices of the US and Chinese stock markets.

Corelli (2018) examined the relationship between six cryptocurrencies and eleven exchange rates and stated that Thai Baht, Taiwan Dollar and Yuan have a strong and statistically significant effect on cryptocurrencies.

Adebola et al. (2019) discussed the relationship between cryptocurrencies and gold prices and found very small degree of cointegration between Bitcoin and gold prices.

Dastgir et al. (2019) investigated the relationship between Bitcoin returns and investor attention on Bitcoin, and suggested that there is a bidirectional causal relationship between Bitcoin returns and attention of Bitcoin.

Aksoy et al. (2020) focused on the relationships between the top five cryptocurrencies by market capitalization using the Toda-Yamamoto causality test. As a result, they determined that Bitcoin, Ethereum, Ripple and Bitcoin Cash affect Litecoin and also Ethereum affects all cryptocurrencies.

Bedowska-Sójka et al. (2020) investigated the relationship between volatility and liquidity in cryptocurrency markets and declared that high volatility causes to high liquidity and also increases investors' interest to cryptocurrency markets.

Gil-Alana et al. (2020) analyzed the relationship between six cryptocurrencies and six stock markets and determined that there is no cointegration relationship among cryptocurrencies and also between cryptocurrencies and stock markets.

Kayral (2020) tried to predict the volatility of Bitcoin, Ethereum and Ripple and found that the best model to predict the volatility of Bitcoin and Ethereum is EGARCH (1.1) and Ripple is APARCH (1.1).

Keskin and Aste (2020) examined the relationship between social media sentiment and cryptocurrency prices. As a result, they detected that there is a causal relationship running from sentiment to prices of Ripple and Litecoin, and from prices of Bitcoin and Ethereum to sentiment changes.

Subramaniam and Chakraborty (2020) investigated the relationship between cryptocurrency returns and investor attention. Researchers stated that investors show more interest in better known cryptocurrencies such as Bitcoin and Ethereum. They also discovered that spike in investor attention has increased cryptocurrency returns.

Zhang and Wang (2020) analyzed the relationship between twenty cryptocurrencies and investor attention and stated that they observed a bidirectional causal relationship between cryptocurrency returns and investors' attention.

Gemici and Polat (2021) examined the volatility spillovers between Bitcoin, Litecoin and Ethereum and reported that they observed a one-way causality running from Bitcoin to both Litecoin and Ethereum.

Li et al. (2021) investigated the relationship between investor attention and cryptocurrency returns. As a result of their studies, they explored that there is a bidirectional causal relationship between investors' attention and the returns of Bitcoin, Ripple, Ethereum and Litecoin. They also showed that investor attention has a relatively stronger effect on the cryptocurrency returns in bearish market.

Lin (2021) examined the causal relationships between cryptocurrencies and investor attention and revealed that there is an interaction between investor attention and cryptocurrency returns. Also claimed that investors are more interested in cryptocurrencies that have generated higher returns in the past.

Mokni and Ajmi (2021) focused on the causality relationships between cryptocurrencies and the US dollar. As a result, they emphasized that there is a strong causal relationship between these two markets, especially during the COVID-19 period, and reported that COVID-19 significantly affects the relations between these markets.

Sahoo (2021) examined the impact of COVID-19 on the cryptocurency markets and found that there is a unidirectional causality running from the number of cases and deaths from COVID-19 to cryptocurrency returns.

Sami and Abdallah (2021) discussed the effects of cryptocurrencies on stock markets and stated that there is a statistically significant relationship between these two markets.

Elsayed et al. (in press) focused on the causality relationships and spillover effects between cryptocurrencies and exchange markets. As a result, they discovered that there are statistically significant causal relationships between cryptocurrencies, but exchange rates (excluding Yuan) do not significantly affect cryptocurrencies.

## 3. Data

The aim of this study is to investigate the cointegration and causality relationships between cryptocurrencies. In this context, it was planned to analyze eight cryptocurrencies with a market cap above $ 20 billion as of the date of the study carried out. Tether (USDT) was not included in the study because it is a "stable coin" whose price is indexed to the US dollar and therefore exhibits a different return and volatility characteristics than other cryptocurrencies. Thus, it was decided to perform analyses with seven cryptocurrencies. These are Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), Cardano (ADA), Dogecoin (DOGE) and Polkadot (DOT).

The daily closing prices from August 21, 2020 to April 19, 2021 were used in the study, a total of 242 observations for all cryptocurrencies (see Appendix which illustrates the graphics of the time series). The sample period starts from August 21, 2020, because Polkadot data is available after that day. Data were provided from Coinmarketcap (https://www.coinmarketcap.com) and Investing (https://www.investing.com). Eviews 10 and STATA 16 package programs were used for organizing and analyzing the data.

Descriptive statistics of the cryptocurrencies are presented in Table 2. Jarque-Bera and p-values show that the cryptocurrency series are not normally distributed. This can often be observed in time series and requires the use of Spearman correlation coefficients to examine correlations between variables.

Table 2: **Descriptive Statistics**

| | **Bitcoin** | **Binance Coin** | **Dogecoin** | **Ethereum** | **Cardano** | **Ripple** | **Polkadot** |
|---|---|---|---|---|---|---|---|
| **Mean** | 29733.33 | 108.1013 | 0.027303 | 995.2669 | 0.454959 | 0.431920 | 15.37803 |
| **Median** | 23192.90 | 32.34000 | 0.004099 | 631.7550 | 0.163763 | 0.303000 | 5.838000 |
| **Maximum** | 63540.90 | 598.6900 | 0.419809 | 2514.220 | 1.478656 | 1.836250 | 45.80680 |
| **Minimum** | 10092.20 | 19.47000 | 0.002514 | 319.9500 | 0.076593 | 0.211310 | 3.077600 |
| **Std. dev** | 18027.43 | 134.7081 | 0.050353 | 647.1017 | 0.460954 | 0.284036 | 13.84278 |
| **Skewness** | 0.468171 | 1.696801 | 4.762000 | 0.539167 | 0.904349 | 2.767869 | 0.822754 |
| **Kurtosis** | 1.668016 | 5.046701 | 31.97640 | 1.763835 | 2.071039 | 11.83825 | 2.002690 |
| **Jarque-Bera** | 26.73009 | 158.3640 | 9380.909 | 27.13333 | 41.68807 | 1096.653 | 37.33179 |
| **p- values** | 0.000002 | 0.000000 | 0.000000 | 0.000001 | 0.000000 | 0.000000 | 0.000000 |
| **Obs.** | 242 | 242 | 242 | 242 | 242 | 242 | 242 |

Methodology followed for this study is explained in the next section.

## 4. Methodology

When working with time series, the first thing to do is to determine whether the series are stationary or not. Because analyses made with non-stationary series can cause problems such as spurious regression and generate erroneous results. Therefore, it is necessary to ensure the stationarity of the series first. Stationarity means that the ''variances'', ''autovariations'' and ''means'' of the series do not change over time (Büyükakın et al., 2009:108). In order to test the stationarity of the series, unit root tests such as Augmented Dickey-Fuller (ADF), Philips-Perron (PP) and KPSS are generally used. Augmented Dickey-Fuller (ADF) test was adopted in this study. The equation to be predicted in this test is as follows (Büyükakın et al., 2009:108):

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + e_t \tag{1}$$

The null hypothesis stating that the series is not stationary and has unit root is $H_0$: $\delta = 0$. Accepting the null hypothesis shows that the series is not stationary, and its rejection denotes that the series is stationary. This decision is made by comparing the ADF test statistics with the MacKinnon critical values. If the series are non-stationary in their levels, then they are tried to be made stationary by performing log transformation and/or taking the difference (differencing).

The most popular tests to examine long-run relationships between variables are Engle-Granger Cointegration test (1987) and Johansen Cointegration test (1988). These tests help to determine whether the variables in the analysis move together over long-run. In other words, cointegration tests are applied to identify the long-run relationships between the time series integrated of the same order. This method enables the use of the level values of the series, which have a unit root at the level but become stationary when the differencing is done (Işık et al., 2004:332). Long-run relationships were investigated using Johansen Cointegration test (1988) in this paper.

Causality analyses are applied to investigate the presence and direction of short-run relationships between variables. The most well-known of these tests is the Granger (1969) Causality test. If it is determined that there is no cointegration relationship between the variables, then the traditional (VAR-based) Granger-Causality test should be used. However, if cointegration is found between variables, error correction term (ECT) should be included in the model and causality test should be performed based on Vector Error Correction Model (VECM) estimation. According to Engle and Granger (1987), cointegration, which shows the long-run relationship, enables the error correction model to be defined (Bilgin and Şahbaz, 2009:186). If the traditional Granger Causality test is used when there exists a cointegration relationship and the coefficient of the error correction term is statistically significant, then incorrect conclusion could be drawn by erroneously ignoring the causality when, in fact, it does exist (Güneş, 2013:82). Technically, the VECM to be established in the causality analysis between two variables such as X and Y is as follows (Taban, 2006:38):

$$\Delta Y_t = \alpha_1 + \sum_{i=1}^{m} \beta_{1i}\Delta X_{t-i} + \sum_{i=1}^{n} \Upsilon_{1i}\Delta Y_{t-i} + \sum_{i=1}^{r} \delta_{1i}\upsilon_{r,t-1} + \upsilon_t \quad (2)$$

$$\Delta X_t = \alpha_2 + \sum_{i=1}^{m} \beta_{2i}\Delta X_{t-i} + \sum_{i=1}^{n} \Upsilon_{2i}\Delta Y_{t-i} + \sum_{i=1}^{r} \delta_{2i}\upsilon_{r,t-1} + \upsilon_t \quad (3)$$

The tests mentioned above are sensitive to lag length selection. Therefore, it is crucial to determine the optimal lag lengths. Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Hannan-Quinn Information Criterion (HQIC) are mostly used in the determination of the lag lengths. Optimal lag lengths in this study were chosen by the Schwarz Information Criterion (SIC).

## 5. Findings

Before conducting cointegration and causality analyses, the correlation relations between cryptocurrencies were investigated and the results obtained are given in Table 3.

Table 3: **Correlation Matrix**

| | **Bitcoin** | **Binance Coin** | **Cardano** | **Dogecoin** | **Ethereum** | **Polkadot** | **Ripple** |
|---|---|---|---|---|---|---|---|
| **Bitcoin** | 1.000 | | | | | | |
| **Binance Coin** | 0.935*** | 1.000 | | | | | |
| **Cardano** | 0.957*** | 0.917*** | 1.000 | | | | |
| **Dogecoin** | 0.919*** | 0.860*** | 0.937*** | 1.000 | | | |
| **Ethereum** | 0.982*** | 0.920*** | 0.958*** | 0.949*** | 1.000 | | |
| **Polkadot** | 0.899*** | 0.864*** | 0.921*** | 0.927*** | 0.927*** | 1.000 | |
| **Ripple** | 0.719*** | 0.621*** | 0.738*** | 0.717*** | 0.746*** | 0.668*** | 1.000 |

**Note:** *** denotes significance at 1% level.

According to the table 3, there are strong correlations between cryptocurrencies and all correlations are statistically significant. This findings show that cryptocurrencies move together. When the price movements and graphics of cryptocurrencies are examined, it can be suggested that this is not surprising. Although Ripple has a relatively low correlations with other cryptocurrencies, it is still possible to talk about a strong relationship.

In order to reveal the relationships between time series, it is necessary to first test the stationarity of the series and determine whether they are stationary or not. The results of the Augmented Dickey-Fuller (ADF) test applied with this purpose in mind are given in Table 4.

Table 4: **Stationarity Results**

| | **Lags** | **Test Statistics** | | | **Result** |
|---|---|---|---|---|---|
| | | **Constant** | **Constant and Trend** | **No Constant** | |
| **Bitcoin** | 0 | -0.135 (0.9430) | -2.626 (0.2688) | 1.676 (0.9774) | Not stationary |
| **Ethereum** | 0 | 0.145 (0.9685) | -2.435 (0.3602) | 1.690 (0.9780) | Not stationary |
| **Binance Coin** | 2 | 1.315 (0.9987) | -0.542 (0.9809) | 2.179 (0.9932) | Not stationary |
| **Ripple** | 0 | 0.121 (0.9668) | -1.024 (0.9375) | 1.093 (0.9287) | Not stationary |
| **Cardano** | 0 | 0.093 (0.9647) | -1.884 (0.6595) | 1.245 (0.9457) | Not stationary |
| **Polkadot** | 0 | -0.237 (0.9303) | -1.776 (0.7134) | 1.075 (0.9264) | Not stationary |
| **Dogecoin** | 4 | 1.898 (0.9998) | 0.052 (0.9967) | 2.261 (0.9945) | Not stationary |

Table 4 (Continued): **Stationarity Results**

| | Lags | Test Statistics | | | Result |
|---|---|---|---|---|---|
| | | Constant | Constant and Trend | No Constant | |
| **ΔBitcoin** | 0 | -15.537** (0.0000) | -15.532** (0.0000) | -15.303** (0.0000) | Stationary |
| **ΔEthereum** | 0 | -15.861** (0.0000) | -15.908** (0.0000) | -15.648** (0.0000) | Stationary |
| **ΔBinance Coin** | 1 | -9.688** (0.0000) | -10.000** (0.0000) | -9.460** (0.0000) | Stationary |
| **ΔRipple** | 0 | -14.206** (0.0000) | -14.304** (0.0000) | -14.155** (0.0000) | Stationary |
| **ΔCardano** | 0 | -15.278** (0.0000) | -15.331** (0.0000) | -15.133** (0.0000) | Stationary |
| **ΔPolkadot** | 0 | -14.815** (0.0000) | -14.822** (0.0000) | -14.697** (0.0000) | Stationary |
| **ΔDogecoin** | 2 | -4.877** (0.0001) | -5.203** (0.0001) | -4.751** (0.0000) | Stationary |

**Note:** $H_0$: The series is not stationary (there exists unit root). $H_1$: The series is stationary (there is no unit root). p- values are in the parentheses. ** denotes significance at 5% level. Lag lengths were selected based on SIC. Δ represents the first differences.

Table 4 indicates that all cryptocurrencies have a unit root in their levels. Therefore, the null hypothesis cannot be rejected but they all become stationary after the first differencing, that is *I*(1), thus the null hypothesis was rejected. This finding made it necessary to perform cointegration tests to examine long-run relationships between series. In this regard, optimal lag lengths were selected. Table 5 shows that the lag length ‘’1’’ minimizes SIC and there is also an agreement between the selection criteria of SIC, AIC and HQIC. So the optimal lag length was determined as "1".

Table 5: **Lag Length Selection**

| Lags | AIC | SIC | HQIC |
|---|---|---|---|
| 0 | 0.521712 | 0.557435 | 0.61031 |
| **1** | **-16.8706** | **-16.6205** | **-16.2504** |
| 2 | -16.6986 | -16.2342 | -15.5468 |
| 3 | -16.6565 | -15.9777 | -14.9731 |
| 4 | -16.6328 | -15.7397 | -14.4178 |
| 5 | -16.5712 | -15.4638 | -13.8246 |
| 6 | -16.5967 | -15.2750 | -13.3186 |
| 7 | -16.5241 | -14.9880 | -12.7144 |
| 8 | -16.5522 | -14.8018 | -12.2109 |

**Note:** AIC stands for Akaike Information Criterion, SIC stands for Schwarz Information Criterion and HQIC stands for Hannan-Quinn Information Criterion.

After choosing the optimal lag length, Johansen Cointegration test was employed. According to the results from Table 6, the null hypothesis is rejected for r=0 and r≤1. However, p- values are greater than 0.05 for r≤2. This means that the null hypothesis is retained but the alternative hypothesis ($H_1$) is rejected and hence, there exists at most ‘’one’’ cointegration vector among cryptocurrencies. To be more specific, cryptocurrencies move together and there exists long-run equilibrium relationship between the cryptocurrencies.

Table 6: **Cointegration Test Result of Cryptocurrencies**

| | Eigenvalues | Trace Statistic | Critical Value (0.05) | p- values | Max Statistic | Critical Value (0.05) | p- values |
|---|---|---|---|---|---|---|---|
| **r=0** | 0.366636 | 238.4865 | 125.6154 | 0.0000 | 109.6104 | 46.23142 | 0.0000 |
| **r≤1** | 0.253849 | 128.8760 | 95.75366 | 0.0000 | 70.27868 | 40.07757 | 0.0000 |
| **r≤2** | 0.116161 | 58.59736 | 69.81889 | 0.2810 | 29.63536 | 33.87687 | 0.1477 |

Table 6 (Continued): **Cointegration Test Result of Cryptocurrencies**

| | Eigenvalues | Trace Statistic | Critical Value (0.05) | p- values | Max Statistic | Critical Value (0.05) | p- values |
|---|---|---|---|---|---|---|---|
| **r≤3** | 0.049192 | 28.96201 | 47.85613 | 0.7702 | 12.10637 | 27.58434 | 0.9283 |
| **r≤4** | 0.039278 | 16.85564 | 29.79707 | 0.6507 | 9.616859 | 21.13162 | 0.7798 |
| **r≤5** | 0.027020 | 7.238779 | 15.49471 | 0.5501 | 6.573969 | 14.26460 | 0.5407 |
| **r≤6** | 0.002766 | 0.664810 | 3.841466 | 0.4149 | 0.664810 | 3.841466 | 0.4149 |

**Note:** $H_0$: There is no cointegration vector between cryptocurrencies. $H_1$: There is cointegration vector between cryptocurrencies.

Following that coingtegration is detected, short-run dynamics between the cryptocurrencies is estimated using a Vector Error Correction Model (VECM) instead of a Vector Autoregression (VAR). VECM incorporates the error correction term into the model. Table 7 reports the results of the Granger Causality test.

Table 7: **VEC Granger Causality Test Results**

| Null Hypothesis | Chi- sq (χ2) | p- values | Decision |
|---|---|---|---|
| BTC does not Granger cause BNB | 0.382503 | 0.5363 | Do not reject |
| **BTC does not Granger cause ETH** | **3.395295** | **0.0654*** | **Reject** |
| BTC does not Granger cause XRP | 0.098872 | 0.7532 | Do not reject |
| BTC does not Granger cause ADA | 1.935748 | 0.1641 | Do not reject |
| BTC does not Granger cause DOGE | 0.105191 | 0.7457 | Do not reject |
| BTC does not Granger cause DOT | 0.021223 | 0.8842 | Do not reject |
| BNB does not Granger cause BTC | 0.017313 | 0.8953 | Do not reject |
| **BNB does not Granger cause ADA** | **7.967852** | **0.0048***** | **Reject** |
| **BNB does not Granger cause DOGE** | **14.97955** | **0.0001***** | **Reject** |
| **BNB does not Granger cause ETH** | **3.608532** | **0.0575*** | **Reject** |
| **BNB does not Granger cause DOT** | **5.270109** | **0.0217**** | **Reject** |
| BNB does not Granger cause XRP | 2.017812 | 0.1555 | Do not reject |
| **ADA does not Granger cause BTC** | **3.061182** | **0.0802*** | **Reject** |
| ADA does not Granger cause BNB | 0.046554 | 0.8292 | Do not reject |
| ADA does not Granger cause ETH | 0.002716 | 0.9584 | Do not reject |
| ADA does not Granger cause DOT | 0.113653 | 0.7360 | Do not reject |
| ADA does not Granger cause XRP | 0.043156 | 0.8354 | Do not reject |
| ADA does not Granger cause DOGE | 0.006978 | 0.9334 | Do not reject |
| DOGE does not Granger cause BNB | 0.205474 | 0.6503 | Do not reject |
| DOGE does not Granger cause BTC | 0.186461 | 0.6659 | Do not reject |
| DOGE does not Granger cause ADA | 0.011146 | 0.9159 | Do not reject |
| DOGE does not Granger cause ETH | 1.559593 | 0.2117 | Do not reject |
| **DOGE does not Granger cause DOT** | **2.895445** | **0.0888*** | **Reject** |
| DOGE does not Granger cause XRP | 0.264797 | 0.6068 | Do not reject |
| **ETH does not Granger cause BNB** | **2.841414** | **0.0919*** | **Reject** |
| ETH does not Granger cause BTC | 0.989086 | 0.3200 | Do not reject |
| ETH does not Granger cause ADA | 0.659726 | 0.4167 | Do not reject |
| **ETH does not Granger cause DOGE** | **5.010224** | **0.0252**** | **Reject** |
| ETH does not Granger cause DOT | 0.061246 | 0.8045 | Do not reject |
| ETH does not Granger cause XRP | 0.835911 | 0.3606 | Do not reject |
| DOT does not Granger cause BNB | 0.006661 | 0.9350 | Do not reject |
| DOT does not Granger cause BTC | 0.748734 | 0.3869 | Do not reject |
| DOT does not Granger cause ADA | 0.638255 | 0.4243 | Do not reject |
| DOT does not Granger cause DOGE | 0.013390 | 0.9079 | Do not reject |
| DOT does not Granger cause ETH | 0.238030 | 0.6256 | Do not reject |
| DOT does not Granger cause XRP | 0.326703 | 0.5676 | Do not reject |
| XRP does not Granger cause BNB | 0.118805 | 0.7303 | Do not reject |
| XRP does not Granger cause BTC | 0.314416 | 0.5750 | Do not reject |
| XRP does not Granger cause ADA | 1.645020 | 0.1996 | Do not reject |

Table 7 (Continued): **VEC Granger Causality Test Results**

| Null Hypothesis | Chi- sq (χ2) | p- values | Decision |
|---|---|---|---|
| **XRP does not Granger cause DOGE** | **8.371548** | **0.0038*** ** | **Reject** |
| XRP does not Granger cause ETH | 0.113463 | 0.7362 | Do not reject |
| **XRP does not Granger cause DOT** | **3.110376** | **0.0778*** | **Reject** |

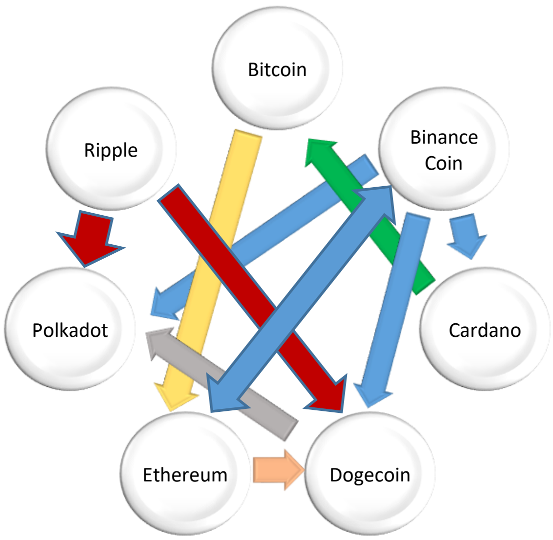
**Note:** *** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level. BNB stands for Binance Coin, BTC stands for Bitcoin, ADA stands for Cardano, DOGE stands for Dogecoin, DOT stands for Polkadot, ETH stands for Ethereum and XRP stands for Ripple

As shown in table 7, Binance Coin is the Granger cause of Cardano and Dogecoin at the 1% significance level, Polkadot at the 5% significance level and Ethereum at the 10% significance level. In addition, Ethereum is the Granger cause of Binance Coin at 10% level of significance. This shows that there is a unidirectional causality running from Binance Coin to Cardano, Dogecoin and Polkadot. Also there exists a significant bidirectional causality between Binance Coin and Ethereum. On the other hand, while there is a one-way causality from Bitcoin to Ethereum at the 10% significance level, there is also a one-way causality from Cardano to Bitcoin. Taken together, these results indicate that Bitcoin affects the price movements of Ethereum in the short-run but Ethereum does not have any statistically significant effect on the price of Bitcoin. Similarly, Cardano Granger causes Bitcoin. However, there is no causality running from Bitcoin to Cardano.

Test results report that there is a one-way causal relationship from Ethereum to Dogecoin at the 5% significance level but Dogecoin does not Granger cause Ethereum. Besides there is a unidirectional causality from Dogecoin to Polkadot. This relationship is statistically significant (p <0.10).

When Table 7 is examined with special attention to Ripple, it is seen that there are unidirectional causality relationships from Ripple to both Polkadot and Dogecoin. Ripple has a strong significant effect on Dogecoin's short-run price movements at 1% level of significance, while it has an effect at the 10% significance level on Polkadot. However, none of the cryptocurrencies in the study Granger cause Ripple. In other words, cryptocurrencies do not have a significant effect on Ripple in the short-run.

Figure 1: **Demonstration of Causality Relationships Among Cryptocurrencies**




Taken all together, it is noteworthy that Binance Coin is dominant among cryptocurrencies. It is the Granger cause of the four cryptocurrencies, namely Cardano, Ethereum, Polkadot and Dogecoin. While Ripple has an effect on the short-run price movements of two cryptocurrencies

(Polkadot and Dogecoin), Bitcoin, the most well-known and the biggest of the cryptocurrencies, has only an effect on Ethereum. In addition to these findings, while there is no causality running from Polkadot to any other cryptocurrencies, Polkadot is affected by three cryptocurrencies (Binance Coin, Dogecoin and Ripple). These causal relationships between cryptocurrencies are presented in a visual format on Figure 1.

## 6. Concluding Remarks

Cryptocurrencies attracts more and more attention every day. Many people from almost all segments of society, regardless of whether they have knowledge of financial markets and instruments or not, are trying to understand these new technologies. People's desire to take advantage of speculative price movements and to gain high returns in a short period of time plays an important role in the popularity of cryptocurrencies. In addition, these assets also attract the attention of investors, academia and even governments. Investors consider including cryptocurrencies in their portfolios as a diversification tool. On the other hand, the number of academic researches on cryptocurrencies is gradually increasing and governments consider to regulate both the cryptocurrencies and the markets where these cryptos are traded.

Uncovering the relationships of cryptocurrencies with each other (or with the other financial instruments such as stocks) would be beneficial in terms portfolio management. Therefore, it is of great importance to detect long and short run interactions between cryptocurrencies. In this sense, the purpose of the study is to explore the cointegration and causality relationships of cryptocurrencies. Seven cryptocurrencies with a market cap above $ 20 billion were included in the study. These are Binance Coin (BNB), Bitcoin (BTC), Cardano (ADA), Dogecoin (DOGE), Ethereum (ETH), Polkadot (DOT) and Ripple (XRP). Tether (USDT) was not analyzed since it is ʹʹstablecoinʹʹ and has different characteristics. The study period spans from August 21, 2020 to April 19, 2021 and covers 242 observations on a daily basis.

The result of the analyses reveal that there are strong significant correlations between cryptocurrencies. Ripple alone has relatively low correlations with other cryptocurrencies. The stationarities of the time series of cryptocurrencies were tested using the Augmented Dickey-Fuller (ADF) test and it was found that the series are not stationary in their levels. Thereupon tests were conducted with the first differences of the series and it was determined that they are integrated of order one, that is $I(1)$.

Johansen Cointegration test results prove the presence of cointegration relationship among cryptocurrencies. In other words, cryptocurrencies affect each other and move together in the long-run. However, these findings do not provide evidence for short-run interactions. For this reason, causality analyses need to be employed. VEC Granger Causality test was performed by including the error correction term (ECT) in the model, instead of traditional Granger Causality test. Results show that there is a one-way causality from Binance Coin to Cardano. While Binance Coin also Granger causes both Dogecoin and Polkadot, a unidirectional causality exists between Binance Coin and Ethereum. That is to say Binance Coin affects the price movements of Cardano, Dogecoin and Polkadot. Besides Binance Coin and Ethereum affect each other in the short-run. On the other hand, a one-way causality is observed from Ripple to Dogecoin. Moreover, Ripple has an affect on Polkadot. Causality analyses indicate the existence of undirectional causal relationships from Cardano to Bitcoin, from Bitcoin to Ethereum, from Ethereum to Dogecoin and from Dogecoin to Polkadot. All in all, it is seen that cryptocurrencies interact intensely with each other in both the short and long run.

Today, in parallel with the increasing popularity of cryptocurrencies, many new cryptocurrencies are launched and cryptocurrency exchanges are founded. Even futures contracts can be traded in the crypto derivatives markets nowadays. However, very limited number of studies have examined the relationship between these contracts and spot prices of cryptocurrencies. Sebastião and Godinho (2020) argue that Bitcoin futures contracts are an effective tool for hedging Bitcoin (and even other cryptocurrencies) and can significantly alleviate losses in the spot market. Akyıldırım et al. (2020) conclude that Bitcoin futures play a decisive role and lead price changes in the spot prices of Bitcoin. While the decentralized and unregulated nature of cryptocurrencies attracts people's attention, it also brings some problems. Due to the highly speculative, volatile and hence risky characteristic of cryptocurrencies, trading in these markets must be taken with great caution. So much so that a simple post on Twitter or a news spread on social media can lead sharp price movements in cryptocurrency markets. Besides, cryptocurrency markets are not subject to any regulatory scrutiny whatsoever. Thence there may be a risk of these markets suddenly collapse. As a matter of fact, Turkey has experienced the shock of the cryptocurrency markets that shut down one after another in April 2021. Since the monies transferred to these markets are not under the guarantee of any public authority, investors have suffered greatly. In this case, it would not be wrong to say that seeking compensation is like playing a losing game, at least for the moment.

Further studies may wish to use different cryptocurrencies, sample periods and methodologies to enhance the findings of this study. Thus, the dynamics between cryptocurrencies may be understood in more detail and investment decisions can be more accurately made. Investigating the relationships of cryptocurrencies with stocks, mutual funds, exchange rates and commodities could be useful to create better investment strategies.

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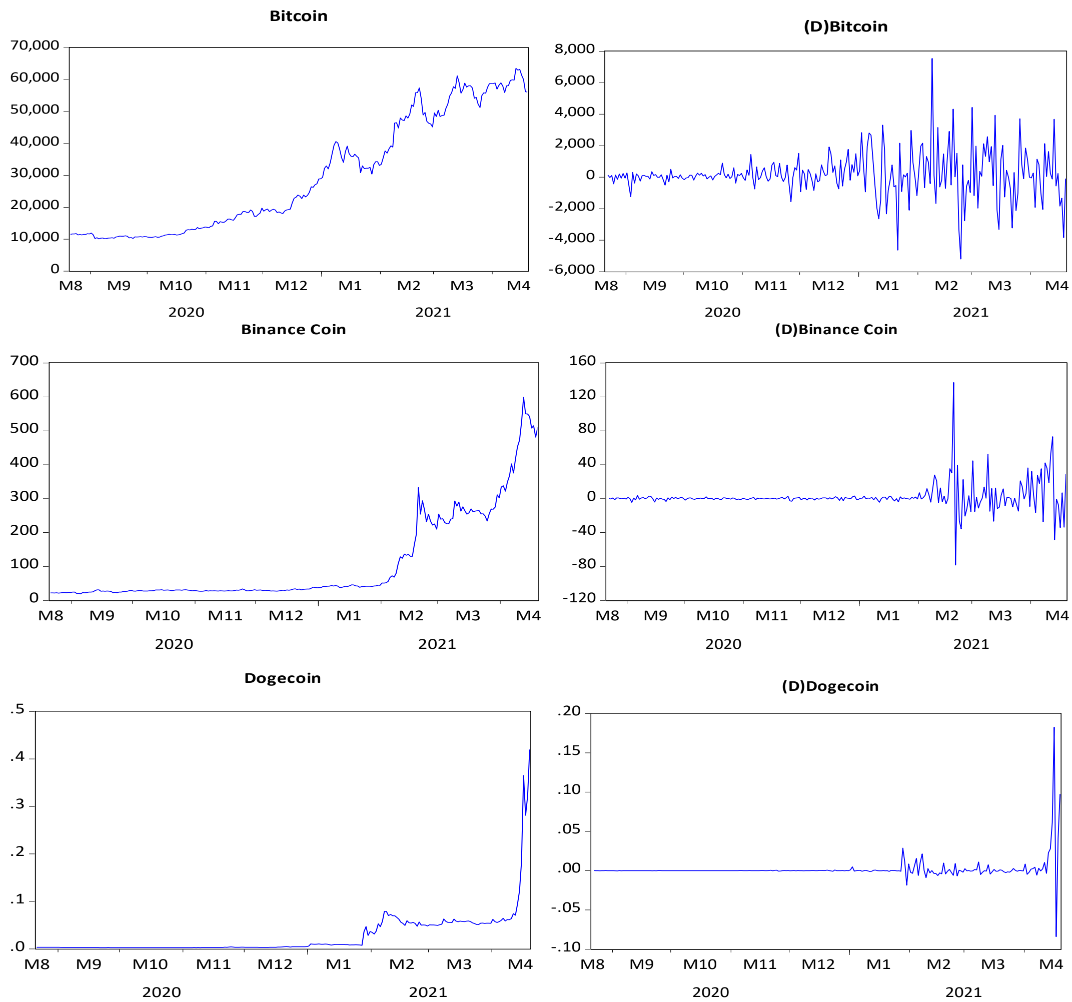
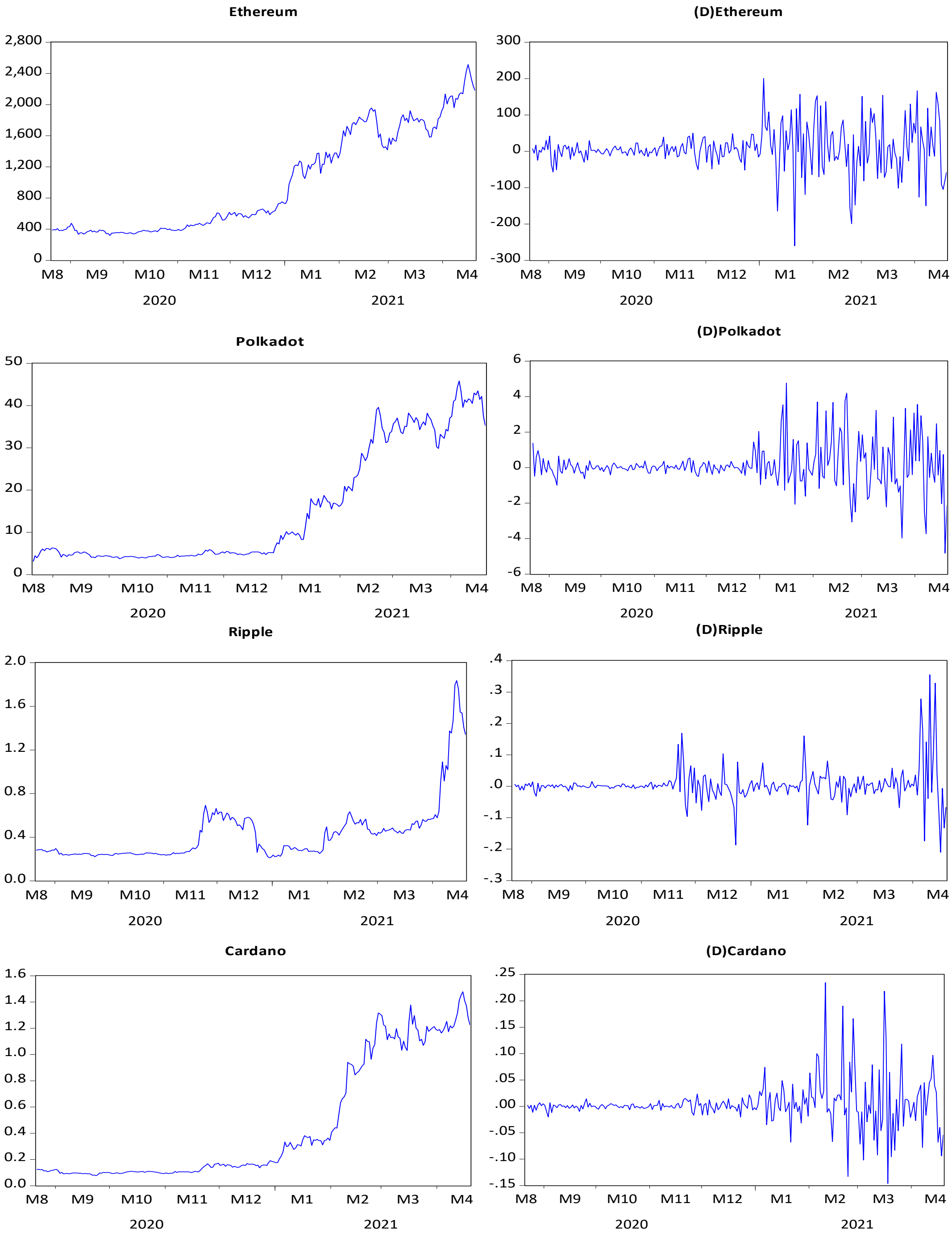
## Appendix

## Graphics of the Cryptocurrencies




Ethereum
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2,400
2,000
1,600
1,200
800
400
0
M8 M9 M10 M11 M12 M1 M2 M3 M4
2020 2021
(D)Ethereum
300
200
100
0
-100
-200
-300
M8 M9 M10 M11 M12 M1 M2 M3 M4
2020 2021
Polkadot
50
40
30
20
10
0
M8 M9 M10 M11 M12 M1 M2 M3 M4
2020 2021
(D)Polkadot
6
4
2
0
-2
-4
-6
M8 M9 M10 M11 M12 M1 M2 M3 M4
2020 2021
Ripple
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1.2
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0.0
M8 M9 M10 M11 M12 M1 M2 M3 M4
2020 2021
(D)Ripple
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.3
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-.3
M8 M9 M10 M11 M12 M1 M2 M3 M4
2020 2021
Cardano
1.6
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2020 2021
(D)Cardano
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M8 M9 M10 M11 M12 M1 M2 M3 M4
2020 2021