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CAN CRYPTOCURRENCY MARKETS BE BEATEN? CALENDAR ANOMALIES ASPECT

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ABSTRACT

The cryptocurrency market is so new and emerging. As in any financial market, the participants of this market act to beat it by using historical price data. In literature, traditional financial markets, such as stock and exchange, are not effective due to calendar anomaly, by period. This study applied to a comprehensive empirical research including 5 calendar effect anomaly on top 9 cryptocurrencies. Thanks to GARCH model, not only returns but also variances were examined. In general, cryptocurrencies have weak form and non-efficient market. In detail, each cryptocurrency has at least one calendar anomaly.

Keywords: *GARCH Models, Cryptocurrencies, Calendar Anomalies.*

JEL Codes: *C32, C58, C87.*

1. INTRODUCTION

Cryptocurrencies emerged as a replacement for traditional money, claiming to be a medium of trade as well as a tool for speculation, portfolio diversification, and passive investment. The recent growth of the cryptocurrency market has been spectacular, attracting intense interest from investors and speculators. While there were only 50 cryptocurrencies on the market in August 2013, there were 500 in October 2014, 1500 in February 2018, and 2670 in June 2020 (Ballis and Drakos, 2021). By October 2021, the cryptocurrency market will have more than 13,000 cryptocurrencies traded on 424 exchanges, worth more than $2.5 trillion (CoinMarketCap.com). Actually, they are risky investment tools in the digital currency market (Mariana, Ekaputra and Husodo, 2021), (Conlon and McGee, 2020), since their price fluctuations are very high. However, they are the focus of investors' attention because of the large profits they serve in short periods of time. Investors make heroic efforts to beat the cryptocurrency market such dangerous ground.

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Fama (1970) claimed the non-efficient weak form market behavior as prices can be predicted by historical data. Thus, existence of calendar anomalies for a market can be defined the non-efficient weak form. Several conventional financial markets (stock market and foreign exchange market) have weak form, that is, non-efficient due to calendar effect (Kumar, 2016; Popovic and Đurovic, 2014; Rodriguez, 2012; Kurihara, 2011; Yamori and Kurihara, 2004; Thatcher and Blenman 2001; Brooks and Persand, 2001; Aggarwal and Rivoli, 1989; McFarland, Pettit and Sung 1982). Cryptocurrencies are a younger, shallower market than traditional markets. We expect that there are calendar anomalies similar to traditional markets in crypto markets. Although there are literatures that reveal the calendar effect of cryptocurrencies, they are limited (Evci, 2020; Robiyanto, Susanto and Ernayani ,2019; Ma and Tanizaki, 2019; Eyüboğlu, 2018; Kurihara and Fukushima, 2017). We comprehensively investigated 5 different calendar effects of the market: days of the week, months of the year, New Year (Christmas), year-end, and turn of the month effects, for the top 9 cryptocurrencies (Bitcoin_Cash, Binance Coin, Bitcoin, Cardano, Ethereum, ChainLink, Litecoin, Theta, XRP) and the cryptocurrency index (CCI30). To detect anomaly effects in crypto markets, we used dummy variables in GARCH models. Thus, our results tell us about returns in mean models and volatility effects in variance models. The empirical results show that most of the studied cryptocurrencies have calendar effects, especially the market-dominating bitcoin. In general, cryptocurrencies have a weak shape and a non-efficient market. In detail, each cryptocurrency has at least one calendar anomaly.

This study begins with literature review in part 2; the latter continues with methodology that implies the calendar effect anomalies in part 3. Then, the empirical results are presented in detail in part 4.

2. LITERATURE REVIEW

There are many studies on calendar anomalies in the reviewed literature: the stock market (Rodriguez, 2012; Brooks and Persand, 2001; Aggarwal and Rivoli, 1989) and the foreign exchange market (Kumar, 2016; Popovic and Đurovic, 2014; Kurihara, 2011; Yamori and Kurihara, 2004; Thatcher and Blenman ,2001; McFarland et al.,1982). In recent years, calendar effects have been one of the most curious topics in the cryptocurrency market, especially in bitcoin. Although the most extensively researched calendar effect in the literature is the day of the week anomaly, there are also studies that analyze time-specific anomalies in stock markets, such as the Monday effect, the January effect, and the Halloween effect. However, these studies examining the impact of calendar anomalies on the cryptocurrency market are limited. Therefore, we also included the stock market and foreign exchange market literature to understand the mechanisms of calendar effect anomalies in more detail. First part of the review is that to understand the calendar effect anomaly on conventional markets, second part refers to limited cryptocurrency market literatures and compare with conventional ones.

2.1 Conventional Markets

There are several empirical researches whether the conventional financial markets such as stock and exchange markets, efficient or not in aspect of weak form of the market. To start with foreign exchange markets, McFarland et al. (1982) study was among the first studies that investigated the existence of calendar anomalies in foreign exchange markets. He investigated the existence of the day of the week anomaly for the period 1975-1979 by using the values of 7 currencies (pound, mark, yen, franc, Australian dollar, peso, krona) against the dollar. As a result, price changes in dollars are high on Mondays and Wednesdays and low on Tuesdays and Fridays for all currencies. The Wednesday-Tuesday result is consistent with the settlement procedures used in dollar-denominated foreign exchange transactions. The Friday-Monday result is consistent with the increase in dollar demand before the weekend. Yamori and Kurihara (2004) tried to find out the existence of calendar effects by examining the daily returns of 29 exchange rates in the New York market. They found that the day-of-week effect existed for some, but not all, currencies in the 1980s. The fact that the day-of-week effect was only present for some currencies suggests that the U.S. trading mechanism alone cannot explain the anomaly. Moreover, the day-of-week effect disappeared for almost all currencies in the 1990s. Thatcher and Blenman (2001) showed that there are day-of-week anomalies in the dollar/sterling market. These models are related to the returns of artificial and real futures and the returns of spot transactions. As a result of the analysis, significant calendar effects were observed on Wednesdays. This can be attributed to significantly different risks on Wednesdays. The weekend anomalies observed in futures returns persist and amplify the returns at the beginning of the next trading week. Also, the general returns of futures speculation are inverted on Friday and Monday. Kurihara (2011) examined the efficiency of the Tokyo foreign exchange market whether the day of the week anomaly. They concluded that the market is not fully efficient. Popovic and Durovic (2014) investigated the existence of weekday and intraday anomalies in the spot foreign exchange (FOREX) market. Using hourly time series data of the euro-dollar (EUR/USD) exchange rate in the Swiss FOREX market from January 1, 2004 to January 11, 2014, they examined the interaction between weekday, intraday, and day/time trading anomalies over a 10-year period. They found that the interaction between intraday and day/time anomalies in EUR/USD trading in the spot FOREX market has existed for 10 years Kumar (2016) examined the effect of the day of the week, January and the end of the month in developed and emerging currencies from 1985 to 2014. Monday, Tuesday, and Wednesday returns were positive and significantly different from zero. Thursday and Friday returns were negative and significantly less than the first three days of the week. January returns were higher than returns for the rest of the year. Month-end returns were negative and significantly lower than non-month-end returns. It was found that calendar anomalies are stronger for emerging market currencies than for developed market currencies. Eyüboğlu and Eyüboğlu (2018) tested the existence of the day of the week and the January effect in the Turkish foreign exchange market for the period 2006-2016 using the daily returns of the dollar/TL, euro/TL, franc/TL, pound/TL, and yuan/TL exchange rates. The results show that only the USD/TL rate has an anomaly of the day of the week. In addition, the results of the study revealed that there wasn't any January anomaly for these 5 different exchange rates.

In the literature focusing on stock markets, calendar anomalies are also present. Aggarwal and Rivoli (1989) are at the forefront of studies investigating the existence of the calendar effect in stock markets. Aggarwal and Rivoli (1989) examine the seasonal and daily movements of stock returns in four emerging markets (Hong Kong, Singapore, Malaysia, and the Philippines). The analysis uses daily data for the 12 years from September 1, 1976 to June 30, 1988. The results support the existence of a seasonal pattern in these markets. Returns in January are higher than in other months for all markets except the Philippines. A strong day-of-week effect was also found. These markets exhibit their own weekend effect in the form of lower returns on Monday. Rodriguez (2012) examined the day of the week effect for the main Latin American stock markets in Argentina, Brazil, Chile, Colombia, Mexico, and Peru during the period 1993-2007. He conducted three different analyses, including GARCH models, for returns and volatility of daily returns by day of the week for the main stock market indices in the region. He found substantial evidence of a Monday Effect (lower than expected returns) or a Friday Effect (higher than expected returns) in many cases in the region. Brooks and Persand (2021) examine evidence of a day-of-week effect in five Southeast Asian stock markets (South Korea, Malaysia, the Philippines, Taiwan, and Thailand). They find significant evidence of seasonality in three of the five markets.

Both stock and currency markets have anomalies on the basis of time and assets. Cryptocurrency is a younger and shallower market than conventional markets. In our empirical result, we were not surprised to see anomaly effects in cryptocurrency markets.

2.2 Cryptocurrency Markets

The second part of the review relates to the limited anomaly effect of cryptocurrencies. Kurihara and Fukushima (2017) investigated the day of the week anomaly in the bitcoin market between 2010 and 2016. The empirical results show that the market was not efficient due to the presence of price anomaly on weekends. Baur, Cahill, Godfrey, and Liu (2019) investigated the effect of intraday hours, day of the week, and month of the year on bitcoin returns and trading volume. Using more than 15 million observations from the continuously trading Bitcoin exchange, they found anomalies in returns. Caporale and Plastun (2017) also studied the effect of the day of the week in the cryptocurrency market using statistical techniques such as mean analysis, student t-test, ANOVA, Kruskal-Wallis test, regression analysis with dummy variables, and simulation method. Their results show that the day of the week anomaly was not observed in most currencies other than Bitcoin (LiteCoin, Ripple, Dash). BitCoin, whose returns on Mondays are significantly higher than on other days of the week. Eyüboğlu (2018) examined the effects of the day of the week and the month of the year in the cryptocurrencies

Bitcoin and Litecoin. In the study, the dataset from May 1, 2013 to December 21, 2017 was used and the analysis was conducted using the GARCH (1,1) model. The results of the analysis show that there are day-of-week and month-of-year effects in Bitcoin and Litecoin returns. Bitcoin prices on Monday, Tuesday and Friday. On the other hand, Saturday has a positive and significant effect on Litecoin prices. In addition, while the effects of February, October and November were observed on Bitcoin prices, it was observed that August was effective on Litecoin prices. Evci (2020) examined the existence of a day-of-week effect on Bitcoin prices using daily prices between 2013 and 2019 with an asymmetric GARCH model. Monday, Thursday, and Sunday have negative effects on bitcoin returns and that Thursday leads to the largest losses. Thus, the market was not efficient by observing the effect of the day of the week in the bitcoin market in the relevant periods. Robinto et al. (2019) investigated the existence of the day of the week effect and the month of the year effect in the crypto money market, especially in Bitcoin and Litecoin, using the GARCH (1,1) model between 2014 and 2018. The day of the week and month of the year anomalies were observed in the crypto money market, so the market was not efficient. They suggest that investors should buy bitcoin at the end of January and sell it at the end of February. While day traders can trade bitcoin on Mondays, Wednesdays and Thursdays, these days bitcoin has the potential to generate daily profits.

Ma and Tanizaki (2019) investigate the effect of the day of the week on both the return and volatility of bitcoin (BTC) from January 2013 to December 2018, using daily data from the CoinDesk Bitcoin Price Index. The estimation results show that the effect of the day of the week in the return equation varies according to the sample periods, and that significantly higher volatility is observed on Mondays and Thursdays. Therefore, the significantly higher average return of bitcoin on Monday was found to cause higher volatility. Aharon and Qadan (2019) examined the effect of the day of the week on Bitcoin returns and volatility using the least squares method and GARCH models, using daily data from 2010-2017. The results of the study showed that the day-of-week anomaly was observed not only in bitcoin returns, but also in bitcoin volatility. Yaya and Ogbonna (2019), between 2015-2019, thirteen cryptocurrencies with high market capitalization (Bitcoin, Dash, Digibyte, Doge, Ethereum, Litecoin, Maidsafecoin, Monero, Nem, Ripple, Stellar, Verge, Vertcoin) prices and market They examined the existence of the day-of-week effect on the value of the dummy variables. They found that there's no day-of-week effect on both the returns and volatility of cryptocurrencies, except for the possible effects of Monday and Friday on bitcoin volatility.

In this study, unlike the literature, the calendar anomaly has been investigated in a wide range in the 9 largest coins in the market as of July 2021 and the CCI30 coin index created from them, day of the week, months of the year, turn of the month anomaly, new year and year end effects have been studied in detail for all cryptocurrencies discussed. In this respect, this study contributes to the understanding of the calendar anomaly effect on cryptocurrencies with comprehensive work, making important contributions to the literature.

3. DATA AND METHODOLOGY VERİ SETİ

In this section, we describe the data set we used and present the methodological framework of the empirical analysis.

3.1. Data Set

Our study asks whether the 9 most traded cryptocurrencies in the crypto money market (Bitcoin_Cash, Binance Coin, Bitcoin, Cardano, Ethereum, ChainLink, Litecoin, Theta, XRP) and the cryptocurrency index (CCI30) have an anomaly of days of the week, months of the year, Christmas, presence of year-end and turn of the month. For this purpose, analyses were performed using the Eviews 9 package program with 1257 daily observations between 01/01/2018 and 10/07/2021. This date range was included in the study to examine the periods when cryptocurrency prices were active. A dummy variable is defined to detect anomalies. In order not to fall into the dummy variable trap, the constant term was excluded from the model (Güriş and Çağlayan, 2010). The formula (Pt-Pt-1/Pt-1) is used to convert financial variables into return series.

3.2. Methodology

One of the important features of financial asset returns is the volatility cluster. According to Mandelbrot (1963), when large price changes occur in financial assets, large price changes, small price changes follow small price changes and form a cluster. This situation is referred to as "volatility clustering". The methods that best model the resulting volatility clusters are the ARCH, GARCH, ARCH-M, GARCH-M, EGARCH, and GRJGARCH(TGARCH) models, known as the ARCH family of models. The ARCH model and its extensions (GARCH, EGARCH, etc.) are among the most popular models for market returns, volatility and forecasting.

For volatility models, a mean model is needed first. The mean model was fitted with the 1-period lagged value of the dependent variable. The GARCH (1,1) model was used to detect anomalies. The reason for using the GARCH(1,1) model is the majority of studies that have successful results in the literature (Aharon and Qadan,2019; Robiyanto et al.,2019; Rodriguez,2012).

Bollerslev (1986) extended the linear ARCH model by including the current (present) conditional variance values in the past conditional variance equation and introduced the Generalized Autoregressive Conditional Variance (GARCH) model. This model predicts volatility better than the ARCH model. It also offers the advantage of incorporating the past values of an infinite number of error frames into the model. The GARCH model is computed as follows (Çil, 2018);

$$y_t = \phi y_{t-1} + \varepsilon_t$$
$$\varepsilon_t = \eta_t \sqrt{h_t}$$
$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$$

$$\omega > 0 \quad \alpha \geq 0 \quad \beta \geq 0 \quad \alpha + \beta < 1$$

In the GARCH model, there is a positivity condition for the parameters. In addition, the sum of the ARCH and GARCH parameters must be less than 1. The closer this sum is to 1, the greater the persistence of volatility.

3.3. Calendar Effects

3.3.1. Days of the Week Anomaly

The DOW (Date Of Week) dummy Dt,d, defined to detect the weekday anomaly, takes the value Dt,d every d days, otherwise zero. The DOW effect was included in the analysis for each day of the week, from d = 1 (Monday) to d = 7 (Sunday). The DOW effect assumes that certain DOWs can generate abnormal returns or risks.

The GARCH(1,1) dummy variable variance model is as follows;

$$h_t = \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + V_1 D_{t,1} + V_2 D_{t,2} + V_3 D_{t,3} + V_4 D_{t,4} + V_5 D_{t,5} + V_6 D_{t,6} + V_7 D_{t,7} \quad (1)$$

The GARCH(1,1) dummy variable mean model is as follows;

$$y_t = \emptyset y_{t-1} + V_1 D_{t,1} + V_2 D_{t,2} + V_3 D_{t,3} + V_4 D_{t,4} + V_5 D_{t,5} + V_6 D_{t,6} + V_7 D_{t,7} \quad (2)$$

3.3.2. Months of the Year Anomaly

The MOY (Month Of Year) dummy Mt,m, which is used to detect anomalies in the month of the year, takes the value Mt,m once in m, otherwise zero. All months between January (m = 1) and December (m = 12) are included in the analysis. The MOY effect assumes that investors can earn abnormal returns in a given month. It can also be used to identify different levels of volatility between months.

The variance equation of the dummy variable GARCH(1,1,) model, which is used to determine the month of the year anomaly, is as follows;

$$h_t = \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + V_1 M_{t,1} + V_2 M_{t,2} + V_3 M_{t,3} + V_4 M_{t,4} + V_5 M_{t,5} + V_6 M_{t,6} + V_7 M_{t,7} + V_8 M_{t,8} + V_9 M_{t,9} + V_{10} M_{t,10} + V_{11} M_{t,11} + V_{12} M_{t,12} \quad (3)$$

The mean equation of the dummy variable GARCH(1,1,) model is as follows;

$$y_t = \emptyset y_{t-1} + V_1 M_{t,1} + V_2 M_{t,2} + V_3 M_{t,3} + V_4 M_{t,4} + V_5 M_{t,5} + V_6 M_{t,6} + V_7 M_{t,7} + V_8 M_{t,8} + V_9 M_{t,9} + V_{10} M_{t,10} + V_{11} M_{t,11} + V_{12} M_{t,12} \quad (4)$$

3.3.3. End of December and Christmas Anomaly

To determine the year-end anomaly, the date of December 27-31 each year is assigned a value of 1 and the other days are assigned a value of 0. For the New Year's anomaly, the date from December 24 to January 3 is assigned a value of 1 and all other days are assigned a value of 0.

The purpose of these dummy variables is to determine whether investors can earn an abnormal return at the end of the year as well as at the beginning of the year, and to measure the difference in volatility levels. In this context, dummy variables are included in both the variance and mean equations of the GARCH(1,1) model.

The GARCH(1,1) dummy variable variance model is as follows;

$$h_t = \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + V_1 D_{t,d} + V_2 D_{t,c} \quad (5)$$

The GARCH(1,1) dummy variable mean model is as follows;

$$y_t = \emptyset y_{t-1} + V_1 D_{t,d} + V_2 D_{t,c} \quad (6)$$

The Dt,d dummy in these equations is used to determine the year-end, Dt,c New Year's anomaly.

3.3.4. Turn of The Month Anomaly

For the turn of the month anomaly, the 31st of each month and the first 3 days of the following month are assigned a value of 1 (for Dt,d, d = 31,1,2,3,1), the other days are assigned a value of 0 (Lakonishok and Smidt, 1988). Thus, we wanted to see if there was a difference in returns and volatility levels at the end of the month.

The dummy variable GARCH (1,1) variance model created for the month end anomaly is as follows;

$$h_t = \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + V_1 D_{t,m} \quad (7)$$

The model of the GARCH (1,1) mean with a dummy variable created for the turn of the month anomaly is as follows;

$$y_t = \emptyset y_{t-1} + V_1 D_{t,m} \quad (8)$$

Since this study aims to examine not only the calendar effects on returns, but also their effects on risk, the calendar effect dummy variables mentioned above are also included in the variance equation of the GARCH (1,1) model.

4. EMPIRICAL RESULTS

This section reports the results of the GARCH dummy model on five different calendar anomalies: days of the week, months of the year, New Year's (Christmas), year-end, and month-end effects, and examines the effects on the returns and volatility of cryptocurrencies.

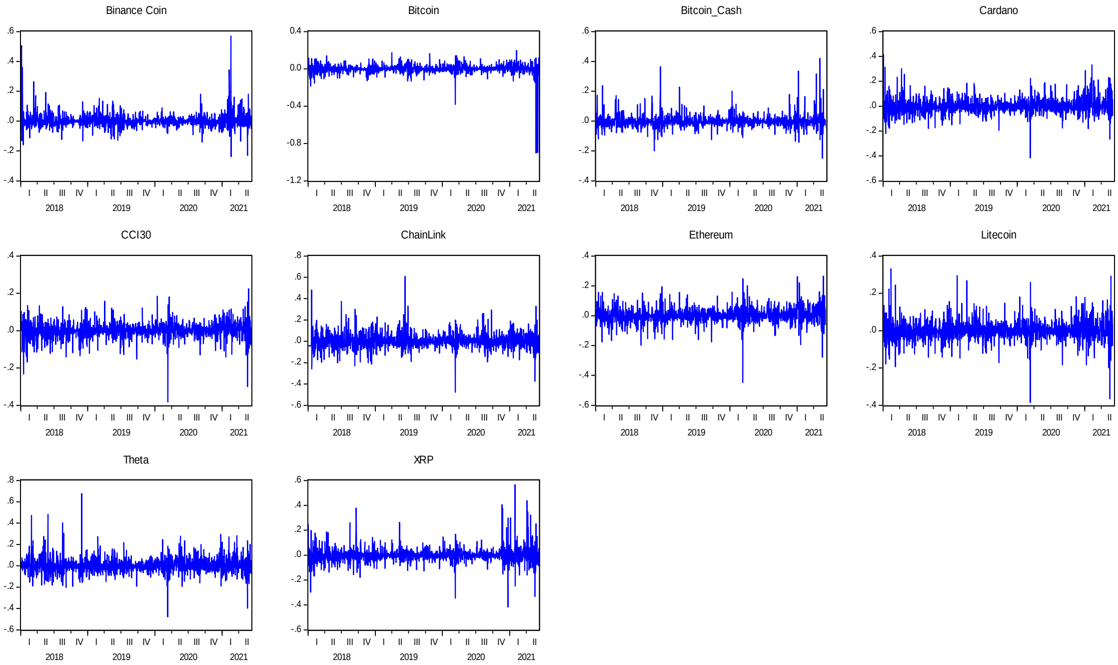
First, the descriptive statistics of the cryptocurrencies included in the analysis were examined and the results are presented in Table 1. The table shows the average, median, maximum, minimum and standard deviation of the cryptocurrencies.

Table 1. Descriptive Statistics of Cryptocurrencies

	BINANCE COIN	BITCOIN	BITCOIN CASH	CARDANO	CCI30	CHAINLINK	ETHEREUM	LITECOIN	THETA	XRP
Mean	0.003373	-0.000501	-0.0009	0.002699	0.001261	0.005154	0.002474	0.001413	0.006522	0.001401
Median	-0.00094	0.001320	-0.004658	0.007849	0.002621	0.008934	0.000926	-0.001154	0.002567	-0.000509
Maximum	0.570901	0.195644	0.419843	0.417323	0.223979	0.608696	0.264635	0.331613	0.677239	0.566730
Minimum	-0.238087	-0.38178	-0.249507	-0.414945	-0.383263	-0.477807	-0.447032	-0.385396	-0.477296	-0.417844
Std. Dev.	0.051183	0.060076	0.045426	0.064970	0.045909	0.077556	0.052967	0.056983	0.077864	0.065598
Skewness	3.228032	-8.108662	2.296111	0.545218	-0.784069	0.753580	-0.313349	0.145668	0.997923	1.327132
Kurtosis	31.74246	122.1981	20.03633	7.917790	10.13945	9.685568	9.865421	9.130268	11.97201	16.28902
Jarque-Bera	45451.55	757928.3	16305.65	1328.948	2798.439	2459.967	2489.214	1972.707	4424.655	9618.305
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1257	1257	1257	1257	1257	1257	1257	1257	1257	1257

It is observed that the mean values of cryptocurrency returns are smaller than the standard deviation values. The cryptocurrencies belonging to the financial time series group generally follow a random walk process. For a normal distribution, the skewness should be 0 and the kurtosis should be 3. Looking at the kurtosis values of the return series, they have a steeper distribution than the normal distribution. As known, in the Jarque-Bera test, the null hypothesis is tested for normal distribution, while the alternative hypothesis is not suitable for normal distribution. When examining the statistics of the Jarque-Bera test, it is understood that the distribution of the return series according to the probability value is not normal. Considering these characteristics of return series, cryptocurrencies have typical financial time series characteristics.

Graph 1. Time Path Graphs of Cryptocurrencies



When the graphs of the return series are examined, volatility clustering is noticeable. ARCH family models can be applied to return series where volatility clustering is detected. In addition, there was a sudden drop in all cryptocurrencies except Binance_Coin and Bitcoin_Cash towards the end of the first quarter of 2020. Considering that the first case was seen on March 11, 2020, the effect of Covid-19 is dominant in the cryptocurrency market.

In addition to descriptive statistics, the unit root and stationarity of cryptocurrencies should also be tested. The existence of unit root was tested using Augmented Dickey Fuller and Philips Perron unit root tests. The results of the tests are shown in Table 2.

Table 2. Results of Augmented Dickey Fuller and Phillips Perron Unit Root Tests

	ADF		**PP**	
	Intercept	**Intercept+Trend**	**Intercept**	**Intercept+Trend**
Binance_Coin	-33.77038 (0.0000)	-33.75766 (0.0000)	-34.65927 (0.0000)	-34.67024 (0.0000)
Bitcoin	-2.852280 (0.0174)	-3.493662 (0.0404)	-38.28120 (0.0000)	-38.47370 (0.0000)
Bitcoin_Cash	-33.76213 (0.0000)	-33.76768 (0.0000)	-33.79769 (0.0000)	-33.80171 (0.0000)
Cardano	-23.07059 (0.0000)	-23.37854 (0.0000)	-37.47523 (0.0000)	-37.74578 (0.0000)
Chainlink	-38.91761 (0.0000)	-38.90642 (0.0000)	-38.76650 (0.0000)	-38.75681 (0.0000)
Ethereum	-34.91449 (0.0000)	-34.91449 (0.0000)	-34.91449 (0.0000)	-34.97748 (0.0000)
Litecoin	-38.29662 (0.0000)	-38.35661 (0.0000)	-38.18958 (0.0000)	-38.26661 (0.0000)
Theta	-39.10226 (0.0000)	-39.22070 (0.0000)	-39.03668 (0.0000)	-39.22177 (0.0000)
XRP	-35.42850 (0.0000)	-35.50545 (0.0000)	-35.49119 (0.0000)	-35.54394 (0.0000)
CCI30	-23.58070 (0.0000)	-23.73908 (0.0000)	-39.34539 (0.0000)	-39.49211 (0.0000)

Notes: For the ADF test constant model, the critical values at 1%, 5% and 10% confidence levels are -3.435411, -2.863662, -2.567950, respectively. For the ADF test constant + trend model, the critical values at 1%, 5% and 10% confidence levels are -3.965369, -3.413393, -3.128732, respectively. For the PP test constant model, the critical values at 1%, 5% and 10% confidence levels are -3.435344, -2.863633, -2.567934, respectively. For the PP test constant trend model, the critical values at the 1%, 5%, and 10% confidence levels are -3.965369, -3.413393, and -3.128732, respectively.

The hypotheses used for the ADF and PP unit root tests are shown below;

H_0 : Series unit root

H_1 : Series stationary

According to the results of ADF and PP unit root tests, the probability value is less than 0.05 for all series. In other words, the critical values of the ADF and PP tests are greater than the calculated values. In this case, the null hypothesis of the unit root process can be rejected. In other words, all cryptocurrencies included in the analysis are stationary according to the ADF and PP tests.

In the later stages of the study, calendar effects are examined for the cryptocurrencies included in the analysis. To detect calendar effects, the dummy variables described above were added to both the mean and variance equations. If the dummies added to the mean and variance equation are found to be statistically insignificant, it means that investors do not earn abnormal returns and do not face abnormal risks. If the dummy values are negative and significant, it indicates that investors receive abnormally negative returns or significantly reduced volatility. If the dummies are statistically insignificant, no calendar effect can be detected.

Table 3. Days of the Week Anomaly

MEAN EQUATION										
	Binance Coin	**Bitcoin**	**Bitcoin Cash**	**Cardano**	**CCI30**	**Chainlink**	**Ethereum**	**Litecoin**	**Theta**	**XRP**
MONDAY	-0.000759	0.000453	-0.004198	8.19E-05	0.001508	0.006364	-0.00109	-0.001253	0.007385	-0.002441
	(-0.7399)	(-0.8093)	(-0.0478)	(-0.983)	(-0.6)	(-0.1697)	(-0.7185)	(-0.6924)	(-0.1324)	(-0.366)
TUESDAY	-0.003669	0.002408	-0.008163	-0.000632	0.001566	0.008268	0.000502	-0.002227	0.005175	-0.000751
	(-0.0575)	(-0.2142)	(0.0000)	(-0.8605)	(-0.5488)	(-0.0561)	(-0.8638)	(-0.4761)	(-0.244)	(-0.762)
WEDNESDAY	-0.003599	-0.002872	-0.007996	-0.009742	0.003009	-0.005159	-0.003843	-0.006397	-0.003592	-0.008244
	(-0.0242)	(-0.1091)	(0.0000)	(-0.0021)	(-0.2244)	(-0.1878)	(-0.1452)	(-0.0251)	(-0.355)	(-0.0011)
THURSDAY	0.002348	0.001555	-0.005162	0.001604	-0.000925	0.006788	0.001838	0.006008	0.00743	-0.000764
	(-0.0346)	(-0.3072)	(-0.0032)	(-0.5949)	(-0.669)	(-0.0767)	(-0.4535)	(-0.0322)	(-0.0273)	(-0.6794)
FRİDAY	0.000461	0.001007	0.000815	0.004891	0.004081	0.000981	0.004872	0.00685	0.003027	0.003652
	(-0.7414)	(-0.0188)	(-0.6404)	(-0.1124)	(-0.044)	(-0.7886)	(-0.0412)	(-0.0176)	(-0.386)	(-0.0502)
SATURDAY	-0.000939	0.00134	-0.000346	0.001298	0.006363	-0.001796	0.003597	-0.002514	-0.001278	-0.000546
	(-0.6157)	(-0.5813)	(-0.852)	(-0.7471)	(-0.0014)	(-0.69)	(-0.2638)	(-0.4429)	(-0.7302)	(-0.8399)
SUNDAY	0.000461	0.000966	-0.006783	9.40E-05	0.002813	0.00135	0.002549	-0.00584	0.00604	-0.001864
	(-0.7414)	(-0.6716)	(-0.0008)	(-0.9819)	(-0.3139)	(-0.7833)	(-0.4356)	(-0.0787)	(-0.2216)	(-0.5304)
VARIANCE EQUATION										
	Binance Coin	Bitcoin	Bitcoin Cash	Cardano	CCI30	Chainlink	Ethereum	Litecoin	Theta	XRP

α	0.190761 (0.0000)	0.044397 (-0.006)	0.291387 (-0.0016)	0.129008 (-0.0003)	0.083367 (-0.0001)	0.101776 (0.0000)	0.13326 (-0.0023)	0.093368 (-0.0008)	0.139848 (-0.0001)	0.16259 (-0.0075)
β	0.740588 (0.0000)	0.92488 (0.0000)	0.706608 (0.0000)	0.817504 (0.0000)	0.901449 (0.0000)	0.870568 (0.0000)	0.842316 (0.0000)	0.895734 (0.0000)	0.806645 (0.0000)	0.793387 (0.0000)
MONDAY	0.000526 (-0.0036)	0.002854 (0.0000)	0.000121 (-0.6684)	0.001172 (-0.0492)	0.001559 (0.0000)	0.001328 (-0.0712)	0.00026 (-0.5702)	0.000109 (-0.8212)	0.002473 (-0.0023)	0.000712 (-0.1747)
TUESDAY	5.95E-05 (-0.7004)	-2.23E-05 (-0.9169)	-3.45E-06 (-0.9906)	0.000324 (-0.5527)	0.00049 (-0.0784)	0.001036 (-0.1508)	0.000466 (-0.321)	0.000222 (-0.6401)	0.001882 (-0.0341)	0.00048 (-0.382)
WEDNESDAY	-0.000271 (-0.0476)	-0.002663 (-0.1979)	-0.000157 (-0.5586)	-0.00117 (-0.0376)	0.000157 (-0.5658)	-0.000635 (-0.3696)	-0.000628 (-0.1676)	-0.00066 (-0.1567)	0.00021 (-0.7914)	-0.000772 (-0.1279)
THURSDAY	-0.000766 (0.0000)	-0.000826 (-0.0008)	-0.000509 (-0.0792)	-0.001677 (-0.0017)	-0.000572 (-0.0373)	-0.001642 (-0.0117)	-0.001324 (-0.0033)	-0.000731 (-0.1313)	-0.00283 (0.0000)	-0.001593 (-0.0141)
FRIDAY	-0.000575 (0.0000)	-0.004247 (-0.0213)	-0.000479 (-0.074)	-0.002205 (0.0000)	-0.00085 (-0.002)	-0.002171 (-0.0015)	-0.001641 (-0.0009)	-0.000909 (-0.0546)	-0.002059 (-0.0082)	-0.002047 (-0.0087)
SATURDAY	-0.000162 (-0.3679)	0.00073 (-0.0058)	-0.000175 (-0.5429)	0.001245 (-0.0771)	-0.001189 (0.0000)	-0.000512 (-0.5002)	0.000835 (-0.1237)	0.00016 (-0.7585)	-0.001703 (-0.0411)	0.000445 (0.4304)
SUNDAY	-0.000575 (0.0000)	0.001217 (-0.0002)	0.000609 (-0.0936)	0.002226 (-0.0014)	0.000292 (-0.3661)	0.002426 (-0.0029)	0.001997 (-0.0007)	0.001489 (-0.0076)	0.002852 (-0.0019)	0.002634 (-0.0016)

The results of the weekday anomaly in the returns and volatility of the most traded variables in the cryptocurrency market are as follows;

It has been noticed that the returns on Binance_Coin decrease on Tuesday and Wednesday and increase on Thursday. There is higher volatility on Mondays, while volatility is significantly lower on Wednesdays, Thursdays, Fridays and Sundays. While Bitcoin returns increase on Fridays, its volatility increases on Mondays, Saturdays and Sundays, and decreases on Thursdays and Fridays. Bitcoin Cash returns decreased on Mondays, and its volatility increased on Thursday and Friday, and increased on Sunday. While a decrease in Cardano returns was observed on Wednesdays, its volatility was found to increase on Monday, Saturday and Sunday, and decrease on Wednesday, Thursday and Friday. Chainlink returns increased on Tuesday and Thursday, while its volatility increased on Sunday and Monday, and decreased on Thursday and Friday. The returns of the CCI30 index increased on Friday and Saturday, its volatility increased on Monday and Tuesday and decreased on Thursday, Friday and Saturday. An increase in Ethereum returns on Fridays, a decrease in its volatility on Thursday, Friday and an increase on Sunday were noted. It was observed that Litecoin returns decreased on Wednesday and Sunday, increased on Thursday and Friday, and its volatility increased on Friday and Sunday. Theta returns increased on Thursday, its volatility increased on Monday, Tuesday and Sunday, and decreased on Thursday, Friday and Saturday. XRP returns decreased on Wednesday, increased on Friday, decreased volatility on Thursday, Friday and increased volatility on Sunday.

As a result, day-of-week anomalies were found in the returns and volatility of cryptocurrencies. In contrast to returns, volatility shows a more pronounced day-of-week effect. There is a general decrease in returns on Wednesday and an increase in returns on Thursday and Friday. On the other hand, there is an increase in volatility on Sunday and Monday, and a decrease on Thursday and Friday. The 'Thursday Effect', 'Friday Effect' and 'Sunday Effect' have been identified in the volatility of the cryptocurrencies included in the analysis. The 'Friday Effect' was observed in the returns of leading coins such as the CCI30 Index, Bitcoin, Etherium, Litecoin and XRP. It was observed that the returns started to increase and the anomalies took a negative value.

Table 4. New Year's and Year-End Anomaly

MEAN EQUATION										
	Binance Coin	**Bitcoin**	**Bitcoin Cash**	**Cardano**	**CCI30**	**Chainlink**	**Ethereum**	**Litecoin**	**Theta**	**XRP**
Christmas	0.005420 (0.2144)	0.011827 (0.0350)	-0.00123 (0.9488)	0.020698 (0.0218)	0.009639 (0.1492)	0.003208 (0.7707)	0.016973 (0.0271)	0.017768 (0.0315)	0.007630 (0.2412)	0.004879 (0.4169)
Endyear	0.010400 (00753)	0.007809 (0.3836)	-0.00444 (0.4894)	0.006927 (0.5539)	0.002548 (0.8021)	-0.00174 (0.9192)	0.013436 (0.2579)	0.005444 (0.6960)	0.014056 (0.2460)	0.000448 (0.9161)
VARIANCE EQUATION										
	Binance Coin	**Bitcoin**	**Bitcoin Cash**	**Cardano**	**CCI30**	**Chainlink**	**Ethereum**	**Litecoin**	**Theta**	**XRP**
α	0.197134 (0.0000)	0.114566 (0.0014)	0.150000 (0.0245)	0.129287 (0.0002)	0.083779 (0.0003)	0.094969 (0.0000)	0.132533 (0.0026)	0.091981 (0.0007)	0.140563 (0.0003)	0.174134 (0.0088)
β	0.767127 (0.0000)	0.831932 (0.0000)	0.600000 (0.0000)	0.820707 (0.0000)	0.908435 (0.0000)	0.883253 (0.0000)	0.842562 (0.0000)	0.894974 (0.0000)	0.803420 (0.0000)	0.789298 (0.0000)
Christmas	2.80E-05 (0.7647)	0.000216 (0.2305)	0.000710 (0.5270)	6.75E-05 (0.8284)	7.17E-05 (0.5069)	0.000507 (0.2486)	0.000283 (0.4251)	0.000288 (0.3076)	-0.00038 (0.1256)	-5.66E-05 (0.6843)
Endyear	7.82E-05 (0.7568)	0.000242 (0.3500)	-0.00051 (0.0006)	-0.00021 (0.6617)	5.01E-05 (0.7922)	0.000464 (0.5084)	0.000351 (0.5617)	0.000339 (0.5196)	-0.00043 (0.6473)	-0.00299 (0.3555)

According to Table 4, which was created to examine the Christmas and year-end effects in the crypto money market, there is a positive increase in the year-end returns of Binance_coin, and an increase in the returns of Bitcoin, Cardano, Ethereum, and Litecoin at the beginning of the year. Bitcoin_cash volatility only shows a year-end decrease.

Table 5. Turn of The Month Anomaly

MEAN EQUATION										
	Binance Coin	Bitcoin	Bitcoin Cash	Cardano	CCI30	Chainlink	Ethereum	Litecoin	Theta	XRP
Turn Of The Month	0.000551 (-0.7709)	0.003947 (-0.0687)	-0.003131 (-0.1286)	2.71E-05 (-0.9937)	0.005679 (-0.0222)	0.006412 (-0.1666)	0.002389 (-0.4072)	0.005583 (-0.0825)	0.009807 (-0.0234)	0.000647 (-0.7902)
VARIANCE EQUATION										
α	0.204789 (0.0000)	-0.105632 (0.0000)	0.299398 (-0.0013)	0.124298 (-0.0002)	0.080919 (-0.0004)	0.101173 (0.0000)	0.132463 (-0.0025)	0.093879 (-0.0009)	0.14385 (-0.0003)	0.074152 (-0.0088)
β	0.757588 (0.0000)	0.510145 (-0.0118)	0.701143 (0.0000)	0.823945 (0.0000)	0.909684 (0.0000)	0.875031 (0.0000)	0.838854 (0.0000)	0.89483 (0.0000)	0.805548 (0.0000)	0.888907 (0.0000)
Turn of The Month	-4.72E-05 (-0.4454)	-0.000614 (-0.3781)	7.76E-05 (-0.571)	-0.000387 (-0.0277)	-9.18E-05 (-0.2854)	-8.35E-05 (-0.7138)	-0.000173 (-0.2676)	-2.84E-05 (-0.853)	-0.00023 (-0.432)	1.13E-05 (-0.9452)

The turn of the month effect, on the other hand, is more pronounced in returns than in volatility. The turn of the month anomaly was observed in Bitcoin, CCI30, Litecoin and Theta returns, and the returns followed a positive trend. The turn of the month anomaly in volatility was only significantly lower for Cardano.

Table 6. Months of the Year Effect Anomaly

MEAN EQUATION										
	Binance Coin	**Bitcoin**	**Bitcoin Cash**	**Cardano**	**CCI30**	**Chainlink**	**Ethereum**	**Litecoin**	**Theta**	**XRP**
JANUARY	0.001551	-0.000545	-0.005894	0.006519	0.006154	-0.001318	0.005447	0.003964	0.004472	-0.003382
	(-0.5734)	(-0.8441)	(-0.0494)	(-0.2085)	(-0.0757)	(-0.812)	(-0.1625)	(-0.3969)	(-0.2741)	(-0.3566)
FEBRUARY	0.004184	0.002774	-0.005343	0.004044	0.006823	0.007186	0.006289	0.005917	0.02215	0.001431
	(-0.294)	(-0.4418)	(-0.0819)	(-0.4271)	(-0.0602)	(-0.246)	(-0.1477)	(-0.2518)	(-0.0023)	(-0.7015)
MARCH	0.001076	0.001422	-0.003865	-0.000992	0.002966	-0.000187	-0.002672	0.000418	-0.003251	-0.000984
	(-0.7518)	(-0.5356)	(-0.0921)	(-0.8552)	(-0.3465)	(-0.9734)	(-0.4676)	(-0.9219)	(-0.6035)	(-0.6884)
APRIL	0.00101	0.003662	-0.000473	0.006616	0.011078	0.007842	0.011265	0.00567	0.0103	0.001149
	(-0.7563)	(-0.2223)	(-0.87)	(-0.8515)	(-0.0012)	(-0.1168)	(-0.0042)	(-0.1923)	(-0.0491)	(-0.7372)
MAY	-0.00116	-0.005965	-0.005695	0.001919	0.003304	0.006317	0.004894	0.00059	0.013264	-2.09E-05
	(-0.6906)	(-0.0036)	(-0.0387)	(-0.7329)	(-0.3378)	(-0.2324)	(-0.2393)	(-0.8764)	(-0.0961)	(-0.9948)
JUNE	-0.001214	0.003575	-0.004884	-0.002928	0.001582	0.001133	0.00021	-0.003005	-0.006496	-0.002285
	(-0.482)	(-0.1963)	(-0.0067)	(-0.539)	(-0.5865)	(-0.8486)	(-0.9493)	(-0.3496)	(-0.2326)	(-0.3727)
JULY	-0.002321	0.003842	-0.002717	-0.001166	0.00472	0.001976	0.001677	-0.001053	-0.000539	0.001828
	(-0.4499)	(-0.1595)	(-0.239)	(-0.8244)	(-0.1373)	(-0.8099)	(-0.6425)	(-0.8002)	(-0.927)	(-0.5665)
AUGUST	-0.002241	0.002445	-0.007223	-0.006076	-0.000174	-0.000105	-0.003769	-0.006116	-0.002737	-0.003065
	(-0.4304)	(-0.3061)	(-0.0013)	(-0.1705)	(-0.9565)	(-0.9861)	(-0.3517)	(-0.1336)	(-0.6709)	(-0.3209)
SEPTEMBER	-0.001338	-0.000628	-0.00302	-0.001575	0.00121	-0.005398	0.001048	-0.001048	-0.002173	-0.001618
	(-0.4046)	(-0.7593)	(-0.2315)	(-0.7394)	(-0.6738)	(-0.3902)	(-0.7972)	(-0.7575)	(-0.5747)	(-0.5958)
OCTOBER	-0.000715	0.00148	-0.001213	-0.000582	-0.000282	0.009805	-0.000768	-0.000841	0.003597	-0.0008
	(-0.9775)	(-0.3758)	(-0.5649)	(-0.8559)	(-0.9059)	(-0.0412)	(-0.7807)	(-0.7759)	(-0.3391)	(-0.7575)
NOVEMBER	-0.003582	-0.001032	-0.007789	-0.000587	0.000777	-0.002074	-0.001165	-0.002543	-0.004956	-0.000898
	(-0.0476)	(-0.738)	(-0.006)	(-0.9032)	(-0.8315)	(-0.7003)	(-0.7639)	(-0.5884)	(-0.3049)	(-0.8016)
DECEMBER	-0.00176	0.001083	-0.003494	-0.002405	-6.59E-05	-0.003482	-0.000843	-0.003226	0.011559	-0.005649
	(-0.401)	(-0.7229)	(-0.1787)	(-0.6148)	(-0.9856)	(-0.5483)	(-0.8438)	(-0.5377)	(-0.0664)	(-0.1051)
VARIANCE EQUATION										
	Binance Coin	Bitcoin	Bitcoin Cash	Cardano	CCI30	Chainlink	Ethereum	Litecoin	Theta	XRP

α	0.185731	0.114439	0.209763	0.13077	0.070289	0.099257	0.130856	0.088913	0.116546	0.071275
	(0.0000)	(-0.0011)	(-0.0016)	(-0.0002)	(-0.0003)	(0.0000)	(-0.0025)	(-0.001)	(-0.0003)	(-0.0093)
β	0.761146	0.833516	0.692026	0.817502	0.91177	0.876692	0.84189	0.895346	0.829038	0.891217
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
JANUARY	5.93E-05	-5.86E-06	0.000104	7.69E-05	7.35E-06	0.000126	5.88E-05	0.000157	-0.000129	2.20E-05
	(-0.3341)	(-0.8558)	(-0.4842)	(-0.6379)	(-0.8678)	(-0.3949)	(-0.6155)	(-0.1751)	(-0.4141)	(-0.8177)
FEBRUARY	0.000256	0.00657	0.00014	5.11E-05	5.01E-05	6.89E-05	0.000186	0.000229	0.000972	9.94E-05
	(-0.1271)	(-0.3987)	(-0.3117)	(-0.7168)	(-0.3463)	(-0.5786)	(-0.2242)	(-0.1805)	(-0.0232)	(-0.4527)
MARCH	0.000123	-1.13E-05	5.47E-05	0.000206	-1.32E-05	-1.01E-05	-1.56E-05	-3.46E-05	2.96E-05	-6.65E-05
	(-0.1896)	(-0.4551)	(.-0.6025)	(-0.2536)	(-0.6564)	(-0.9284)	(-0.8496)	(-0.5829)	(-0.9142)	(-0.1855)
APRIL	9.95E-05	0.002524	0.000164	0.00015	6.07E-05	2.79E-05	0.000115	0.00012	0.000259	6.32E-06
	(-0.2759)	(-0.1744)	(-0.2861)	(-0.3829)	(-0.2768)	(-0.815)	(-0.3939)	(-0.342)	(-0.285)	(-0.9438)
MAY	6.33E-05	-0.000932	0.000121	0.000342	5.13E-05	8.21E-05	0.000178	3.59E-05	0.001417	4.06E-05
	(-0.3677)	(-0.2757)	(-0.4272)	(-0.1112)	(-0.3414)	(-0.547)	(-0.2377)	(-0.6663)	(-0.0197)	(-0.6778)
JUNE	-7.28E-05	-0.00059	-0.000191	-2.31E-05	-3.75E-05	-0.000107	-9.74E-05	-0.000101	-0.000179	-8.83E-05
	(-0.0051)	(-0.1985)	(-0.0163)	(-0.8405)	(-0.1558)	(-0.2428)	(-0.193)	(-0.0566)	(-0.353)	(-0.0937)
JULY	0.000109	-0.002374	-7.75E-05	2.40E-05	1.13E-06	7.90E-05	-5.03E-05	-8.57E-06	0.000116	8.65E-05
	(-0.235)	(-0.56)	(-0.3649)	(-0.866)	(-0.9717)	(-0.6519)	(-0.5495)	(-0.8901)	(-0.5905)	(-0.3465)
AUGUST	5.94E-05	-9.63E-06	-9.68E-05	-4.66E-05	2.97E-05	-6.60E-05	6.45E-05	5.24E-05	9.93E-05	1.83E-05
	(-0.3747)	(-0.6891)	(-0.2455)	(-0.6765)	(-0.5152)	(-0.5603)	(-0.5446)	(-0.5288)	(-0.7135)	(-0.8184)
SEPTEMBER	-0.000194	-4.09E-05	-2.35E-05	-0.000107	-4.55E-05	-1.05E-05	-4.18E-05	-0.000113	-0.000499	-5.39E-05
	(-0.0004)	(-0.0171)	(-0.8223)	(-0.3057)	(-0.0508)	(-0.9279)	(-0.6709)	(-0.0088)	(-0.0012)	(-0.3757)
OCTOBER	0.005661	-0.0055	-9.42E-05	-0.000276	-7.04E-05	-0.000157	-0.000211	-0.000213	-0.000341	-6.32E-05
	(-0.3091)	(-0.3078)	(-0.2483)	(-0.0044)	(-0.0111)	(-0.0551)	(-0.0111)	(-0.0002)	(-0.0188)	(-0.29)
NOVEMBER	-4.78E-05	-0.002053	-1.29E-06	4.56E-05	7.49E-05	1.58E-05	2.44E-05	0.000149	-0.00011	0.000205
	(-0.1579)	(-0.7559)	(-0.9923)	(-0.7311)	(-0.0851)	(-0.8902)	(-0.8)	(-0.0945)	(-0.5491)	(-0.133)
DECEMBER	-2.57E-05	0.001521	-0.000101	-2.17E-05	7.80E-06	1.73E-05	6.60E-05	0.000111	0.000207	1.58E-05
	(-0.4512)	(-0.7145)	(-0.2449)	(-0.8659)	(-0.8403)	(-0.8863)	(-0.559)	(-0.2791)	(-0.4954)	(-0.8601)

A decrease in Binance _ Coin returns was observed in November and a decrease in its volatility in September. A decrease in Bitcoin returns was observed in May and a decrease in its volatility in September. Bitcoin cash returns were observed to decrease in January, February, March, May, June, August, and November, while its volatility decreased in June. No anomaly was detected in the return of Cardano, but a decrease in its volatility was detected in October. While a positive increase in the returns of the CCI30 index was detected in January, February and April, a decrease in its volatility was detected in September and October and an increase in November. Chainlink returns increased in October and its volatility decreased in November. Ethereum returns increased in April and its volatility decreased in October. No anomaly was detected in Litecoin returns, but a decrease in its volatility was detected in June, September, October and an increase in November. While theta returns increased in February, April, May and December, it was noted that volatility increased in February and May and decreased in September and October. No anomalies were detected in XRP returns. However, a negative decrease in its volatility was observed in June.

As a result, Cardano, Litecoin, and XRP returns didn't detect a month-of-year anomaly. For Bitcoin_cash, anomalies in the months of the year were found in returns rather than in volatility. As one of the leading coins, Bitcoin returns of the month anomalies were observed in May and Etherium in April. While an anomaly was detected in the returns of cryptocurrencies in general in February, April and May, anomaly was detected in their volatility in September, October and November.

There are a limited number of studies in the literature that identify anomalies in the cryptocurrency market. Ma and Tanizaki (2019) and Caporale and Plastun (2017), among the studies that deal with day of the week anomaly, found that bitcoin returns are higher on Mondays. In addition, Eyüboğlu (2018) found anomalies in bitcoin prices on Monday, Tuesday, and Friday; litecoin prices, on the other hand, found anomalies on Saturdays. Yaya and Ogbonna (2019), among thirteen high cap cryptocurrencies (Bitcoin, Dash, Digibyte, Doge, Ethereum, Litecoin, Maidsafecoin, Monero, Nem, Ripple, Stellar, Verge, Vertcoin) on Monday and Friday, found anomaly only in Bitcoin volatility. They found that there are possible effects of their days. Eyüboğlu (2018), one of the studies investigating the anomaly of the months of the year, found the effect of February, October, and November on Bitcoin prices, while the effect of August was found on Litecoin prices. Robinto et al. (2019) also determined the effect of months of the year for bitcoin and litecoin.

Table 7. Summary Table for Calendar Effect Anomaly on Cryptocurrencies

	BINANCE_COIN	BITCOIN	BITCOIN_CASH	CARDANO	CCI30	CHAINLINK	ETHEREUM	LITECOIN	THETA	XRP
Mean Equation										
Days of the week	Tuesday Wednesday Thursday	Friday	Monday Tuesday Wednesday Thursday Sunday	Wednesday	Friday Saturday	Tuesday	Friday	Wednesday Thursday Friday Sunday	Thursday	Wednesday Friday
Months of the year	November	May	January February March May June August November	(-)	January February April	October	April	(-)	February April May December	(-)
Christmas (new year)	(-)	(+)	(-)	(+)	(-)	(-)	(+)	(+)	(-)	(-)
Year-end	(+)	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
Turn of the month effects	(-)	(+)	(-)	(-)	(+)	(-)	(-)	(+)	(+)	(-)

Variance Equation										
Days of the week	Mondays Wednesday Thursday Friday Sunday	Monday Thursday Friday Saturday Sunday	Thursday Friday Sunday	Monday Wednesday Thursday Friday Saturday Sunday	Monday Tuesday Thursday Friday Saturday	Monday Tuesday Friday Sunday	Thursday Friday Sunday	Friday Sunday	Monday Tuesday Thursday Friday Saturday Sunday	Thursday Friday Sunday
Months of the year	June September	September	June	October	September October November	October	October	June September October November	February May September October	June
Christmas (new year)	(-)	(-)	(-)	(-)	(-)	(-)	(+)	(-)	(-)	(-)
Year-end	(-)	(-)	(+)	(-)	(-)	(-)	(+)	(-)	(-)	(-)
Turn of the month effects	(-)	(-)	(-)	(+)	(-)	(-)	(-)	(-)	(-)	(-)

The findings from the analysis follow a parallel course with the literature. Table 7 summarizes all the calendar anomaly findings from this research. The 'Thursday Effect', 'Friday Effect' and 'Sunday Effect' have been identified in the volatility of cryptocurrencies. The 'Friday Effect' has been observed in the returns of leading coins such as the CCI30 Index, Bitcoin, Etherium, Litecoin and XRP. Similarly, when examining the effect of the months of the year, an anomaly in the returns of cryptocurrencies has been detected in February, April and May, and an anomaly in their volatility in September, October and November. In addition, a positive spike in the year-end returns of Binance_coin and an increase in the returns of Bitcoin, Cardano, Ethereum and Litecoin are observed. When examining the effect of the months of the year, the turn of the month anomaly was detected in the Bitcoin, CCI30, Litecoin and Theta returns, and the returns followed a positive trajectory. The effect of days of the week and months of the year, as well as the effect of the turn of the month and the end of the year were identified in the leading Bitcoin. The CCI30 index reflects the top 30 cryptocurrency prices, and it also has the effect of calendar anomalies.

5. CONCLUSION

The cryptocurrency market is so new and emerging. It attracts the interest of many investors. They are in this market because of the portfolio diversification and aimed to get profit by speculating or scalping. A weak form of non-efficient market could provide the mentioned expectations to these investors. In the literature, many conventional financial markets, e.g. stock and stock exchange, have been revealed as non-efficient due to calendar anomalies by period. We analyzed the cryptocurrency markets to determine whether they consist of calendar anomaly or not. We examined 5 calendar anomalies: days of the week, months of the year, New Year (Christmas), year-end and turn of the month effects, for the top 9 cryptocurrencies (Bitcoin_Cash, Binance Coin, Bitcoin, Cardano, Ethereum, ChainLink, Litecoin, Theta, XRP) and the cryptocurrency index (CCI30). To detect anomaly effects in crypto markets, we used dummy variables in GARCH models. The data interval starts from 01/01/2018 to 10/07/2021 with 1257 daily observations. At least one calendar anomaly was observed for each cryptocurrency. Except for Ripple (XRP), every cryptocurrency has at least two different calendar anomalies. In return equations, the leader Bitcoin and the secondary Etherium have days of the week, months of the year, Christmas (New Year) anomaly. In addition, Bitcoin has a turn of the month anomaly. Other altcoins generally have day and month anomaly effect. In addition, in variance equation each market has days of the week, months of the year anomaly. CCI30 represents leading 30 cryptocurrency index, calendar anomalies were also revealed by findings for CCI30. Therefore, in the researched data interval, cryptocurrencies can be defined as non-efficient.

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