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Seasonal Anomalies in the Cryptocurrency Market

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The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

Preface and Acknowledgements

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In the process of writing my Bachelor's Thesis, I have learned to collect the data yourself, make a proper schedule for each task, investigate the correct way to test the anomalies, and fully write an academic paper.

Abstract

This paper examines the efficiency of the cryptocurrency market through testing for the existence of calendar anomalies, using the returns of seven cryptocurrencies and 5 years of data. The data is subsampled between two periods: July 2016 to May 2020 and May 2020 to August 2021. There were no significant results for the Day of the Week effect found across the coins (Bitcoin, Ethereum, Xrp, Litecoin, Stellar, Monero, and Dash). The Twist on the Monday effect is significantly present in the cryptocurrency market. Across all cryptocurrencies, Monday's return after a negative week is significantly less than a Monday's return after a positive week. The Second Quarter effect is also visible, where the second quarter for each coin significantly outperforms the other quarters. Empirical results show the inefficiency of the cryptocurrency market by the existence of multiple anomalies.

Keywords: Cryptocurrency, Calendar Anomalies, Day of the Week effect, Twist on the Monday effect, Second Quarter effect.

JEL Classification: G12, G14.

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1. Introduction

When people are investing in the markets, they tend to look for certain patterns to predict where the market is heading. Therefore, the stock market has been a well-researched sector with various models trying to predict stock returns, testing the efficiency of the market, and analyzing people their behavior. A well-known theory is the Efficient Market Hypothesis, which describes how publicly available information is processed into asset prices (Fama, 1970). However, people do not consistently make rational decisions based on the information and the hypothesis does not always hold. There are different examples found rejecting the theory of the efficiency of the market, like calendar anomalies which are time-related contradictions. For example, the existence of lower returns on Stocks in the S&P500 on Monday compared to other weekdays confirmed by French (1980). Keim & Stambaugh (1984) found the co-called Weekend Effect, an effect where the Monday shows significantly different results compared to the rest of the week. The Twist on the Monday effect was discovered by Jaffe, Westerfield, and Ma (1989), who concluded that the returns on a Monday after a negative week were significantly lower than the returns on Monday after a positive week.

The cryptocurrency market, on the other hand, is a quite new topic for mass investors in the financial world. In comparison with the stock market is it also a relatively new space looking at the existing research and written literature. The cryptocurrency market is younger and way more volatile than the stock market, which could lead to more inefficiency and more opportunities for abnormal returns using trading strategies (Dwyer, 2015). Finding certain patterns in this market can be of great relevance and because the research done on calendar anomalies in the cryptocurrency market is limited, this study will contribute significantly to this quickly changing environment. The research question which will be studied in this paper will therefore be:

Is the Cryptocurrency Market efficient in its behavior?

In this study, there will be specifically tested whether calendar anomalies found in the stock market tend to exist in the cryptocurrency market. The research question will be answered through testing for the existence of the Day of the Week Effect, Twist on the Monday Effect, and tested for a new unidentified effect as further explained as the Second Quarter Effect.

After the introduction, the relevant literature to this paper will be discussed. Thereafter, the data and the research methodology are explained. Finally, the empirical results of this paper are presented and the concerning remarks of the research paper are discussed.

2. Relevant Literature

At first, the relevant literature on cryptocurrencies is discussed to give a further understanding of cryptocurrencies and certain terms which are used in the paper. Afterward, existing literature on the topic of calendar anomalies and different patterns which are found in a variety of financial markets are discussed. To finish this section, the second quarter effect will be explained which has not been documented in research papers yet.

2.1. Cryptocurrency Market

Financial intermediaries help in economic transactions, in finding an opposite party, connections, and retain the trust in contracts and agreements. The intermediaries are, therefore, having tremendous power which they use to interact with the financial system according to their policy (Chen & Bellavitis, 2020). This raises the concern over the power of financial institutions, wherein the current digitalization of financial technology comes into play. Financial technology is not centralized by a bank, government, or other financial intermediary but an online peer-to-peer system allowing digital payment to be sent directly to the other party (Nakamoto, 2008). The advantages of decentralized finance are transparency, transaction costs reduction, and not having to rely on a third party.

Blockchain-based decentralized finance is a step further, controlling an online currency within its system. Bitcoin is the first blockchain-based currency created, which has its running system on the blockchain. The blockchain system is designed to validate transactions to prevent money laundering. In the system, multiple transactions are captured and validated in a block, where each transaction creates an original code based on a string of codes from previous transactions (Nofer et al., 2017). The chain of data blocks is validated by the network and given a personal timestamp, hash value of the previous block, and an own value-number. Each block is checked for inaccuracies before being added to the chain and has to be accepted by the whole network. This way, the blockchain creates a closed digital system where the creation of money by an individual or an institution is rejected and overruled.

The process of securing and verifying Bitcoin transactions is called mining, which a party is rewarded for. The reward for mining Bitcoin is cut in half every 210,000 blocks, roughly every four years. The reward cut is more referred to as the halving of Bitcoin. The price index with the representative halving dates is shown in Figure 1 (*Bitcoin Price Index 7/19/10–4/29/21. Indexed to 1 on 7/19/10 with Halving Dates Shown. Logarithmic Scale.*, 2021). The reward for one block was in the last halving cut to the current rate of 6.25 BTC per block (containing 1 megabyte worth of transactions). The decreasing

supply causes Bitcoin to be scarce and having a limited amount, it will only ever have an outstanding supply of 21 million Bitcoin.

Figure 1: Bitcoin price index with the corresponding halving dates



In the past halving cycles, an interesting pattern is found which has been repetitive over the years as shown in Figure 2 (*Bitcoin Halving Cycles – BTC Price Index, Indexed to 1 on Halving Dates. Logarithmic Scale.*, 2021). Following the halving days, Bitcoin has experienced a significant positive run the first two years. The repeating pattern shows a crash after these runs and ending the cycle in a slow positive movement. Here the interest and market hype has bottomed out to the end of the cycle, perhaps gaining strength for the new cycle to begin.

Figure 2: Halving cycles of Bitcoin, starting on halving dates. Logarithmic scale.



At the moment, we have experienced another run-up after the halving in May 2020 and even a fierce correction of 54% from the top. Previous chart patterns lead many discussions whether this phase represents the same price action as the year 2017. Not only Bitcoin experienced a tremendous drop in price other cryptocurrencies did as well, where most of them dropped significantly more in percentage terms. This is in line with the conclusions of Yi et al. (2018), who showed that cryptocurrencies with a small market capitalization tend to be more volatile than high market cap cryptocurrencies.

The cryptocurrency market is relatively new in comparison with different asset markets like the stock- or bond market, which results in the entire market is more volatile (Conrad et al., 2018). Assets markets are markets in which people buy and sell financial assets, not only for monetary means from a business point of view, also individuals and institutions investing and trading in the space to expand their financial wealth. Market volatility, in asset markets, can be used for creating trading strategies and investment opportunities and can be of significant value. Finding certain patterns or anomalies in the markets can make investors and traders examine a favorable strategy for creating monetary profits.

2.2. Calendar Anomalies

Kurihara and Fukushima (2017) had the first study examining anomalies in cryptocurrencies, empirically testing the market efficiency of the space. Focussing exclusively on Bitcoin, the paper found evidence showing significant inefficiency in Bitcoin, where on the weekend anomalies of the prices tend to exist. The complete period from 7/17/2010 to 12/29/2016 is split in half to look for certain changes in the results over time. An interesting result came to light that the anomalies seem to disappear in the second sample period, indicating that the market shows the possibility to become more efficient over time.

Caporale & Plastun (2019) tested the existence of the day of the week effect in the cryptocurrency market in the period 2013 till 2017. In their paper, four cryptocurrencies were used to determine the daily differences in return namely Bitcoin, Litecoin, Xrp, and Dash. A variety of statistical methods, Student's *t*-test, ANOVA, Dummy Regressions, Kruskal-Wallis, and Mann-Whitney tests were applied to examine whether the anomaly creates exploitable profit opportunities. Empirical findings resulted in clear evidence in favor of the existence of an anomaly in the case of Bitcoin, the presence of a significant positive effect in the Monday returns (Caporale & Plastun, 2019).

Based on the existing research about the day of the week effect the following hypothesis and specific sub hypothesis will be tested for in this paper:

H1: There is evidence indicating the existence of the Day of the Week effect in Cryptocurrencies.

Only Bitcoin shows a significant effect in its returns on Monday compared with the returns of the other days of the week.

Secondly, the Twist on the Monday effect is a well-known anomaly largely researched in multiple asset markets. Jaffe et al. (1989) found the effect in the stock market, stating that the return on Monday tends to follow the prior week's behavior. Six different datasets from the stock markets of the United States (two subsamples), Canada, Australia, England, and Japan are used in the study, and a significant positive correlation between the Monday's- and previous week's return was found for each market.

The Twist on the Monday Effect has not been documented on the cryptocurrency market yet. Therefore, this paper is of significant relevance. The cryptocurrency market is a relatively new space, because of this the statement can be withdrawn that the overreaction on a Monday after a negative week does exist, following up to the second hypothesis:

H2: The return on a Monday after a negative week is significantly less than Monday's return after a positive week.

This effect can be found over the entire cryptocurrency space, therefore the effect can be found across all the currencies covered.

The Monday effect or Weekend effect is a seasonal pattern found in the stock markets referring to negative or lower returns on Monday compared to the rest of the week (Fench, 1980). A possible explanation for this effect is the information and behavior saved on the weekend which expresses itself on Monday (Abraham & Ikenberry, 1994). In this paper is the Monday effect, often used interchangeably with the Weekend effect, not taken into consideration because the relevant difference between the stock- and cryptocurrency market is the fact that the cryptocurrency market is, as opposed to the stock market, open during the weekends.

2.3. Second Quarter Effect

The month of the year effect is a seasonality that has been examined in very different markets. In his paper, Choudhry (2001) investigate seasonal anomalies in the mean stock returns of Germany, the United Kingdom, and the United States pre-World War I. The results provided clear evidence for the January effect and introduced findings on a month of the year effect in the UK and the US. In the

conclusion, Choudry indicates the need for more research on the field of calendar anomalies in the stock markets, for different countries, and different periods.

Later, the month of the year effect was proved in the Australian stock market with significantly higher returns in April, July, and December (Marrett & Worthington, 2011). Onyuma (2009) concluded that the January effect was significantly present in the Keynesian stock market. From 1980, a significant positive January effect was proved throughout the whole period to 2006. Multiple papers indicate the importance of the month of the year effect as a seasonal anomaly, therefore interesting to analyze in the cryptocurrency market.

Robiyanto et al. (2019) analyzed the month of the year effect in the cryptocurrency market by regression analyses with dummy variables. In the paper, only Bitcoin and Litecoin were implemented and described. The highest average return of Bitcoin was found in May (0.21561) and the lowest in March (0.14642). The same is found in the risk which comes with the volatility of the returns, the month of May shows the highest standard deviation and March the lowest. Meanwhile, the highest monthly return of Litecoin is found in June (0.02433) and the lowest in January (- 0.01430). The highest and lowest Litecoin risk level were found in, respectively, December and July. The monthly return of Bitcoin and Litecoin can be seen in Table 9 in the Appendix .

From Table 9 (Robiyanto et al., 2019) can be drawn that for Bitcoin and Litecoin, the months in the second quarter tend to perform better than other months. In the Appendix, Table 10 with Bitcoins monthly returns is showed where the same idea is visible over this paper's period (2016-2020). Following the table, a figure with Bitcoins price movement is added with the quarters indicated (Figure 3). In the figure, the second quarter also seems to outperform the different quarters. Therefore the question arises whether the existence of a quarterly pattern is more prominent than a monthly pattern. In this paper, the existence of the Second Quarter effect will be tested for giving the following third hypothesis:

H3: The Second Quarter performs significantly better in comparison with the other quarters.

In the next section, the examined data, period, and cryptocurrencies will be discussed. Section 4 describes how the different hypotheses regarding the Day of the Week effect, the Twist on the Monday effect, and the Second Quarter effect are analyzed.

3. Data

In this section, the data is explained as well as the source of the information. The qualification for the choice of cryptocurrencies is discussed and the reason why certain coins are excluded from the research. Further details of the covered cryptocurrencies are shown in a descriptive statistics table and their associated returns.

3.1. CoinMarketCap

In this research, daily price data of seven cryptocurrencies are obtained from the site *CoinMarketCap*. *CoinMarketCap* is the most used site based on cryptocurrency information. The site calculates the weighted average of the cryptocurrency prices among different platforms according to trading volume. The Snapshot page will be used for retrieving historical data concerning the historical market capitalizations. The seven currencies used for testing the existence of the anomalies are Bitcoin (BTC), Ethereum (ETH), Xrp (XRP), Litecoin (LTC), Stellar (XLM), Monero (XMR), and Dash (DASH).

3.2. Data Selection

The data consists of two samples of daily price data: The first sample from the 9th of July 2016 till the 11th of May 2020. This period represents the second cycle between the halving of the reward for mining Bitcoin. The second sample is the third halving period, which runs from the 12th of May 2020 and will probably end approximately the summer of 2024. Lately, trading and investing in cryptocurrencies has come to the great attention of retail- and institutional investors, so the most recent data is used in the research. Therefore, this paper is of significant relevance indicating the existence of certain patterns in this upcoming asset market which can potentially be used for profitable trading strategies.

In this study, research is done on the existence of calendar anomalies in seven cryptocurrencies. These seven coins are selected based on approximately four years of data, coins that were among the top coins by market capitalization these years and which were relevant in this period. For example, the coin Dogecoin was not taken into consideration for this study. Even though the coin has a market capitalization of 44 billion US dollars as of March 2021, the coin has not been relevant in the cryptocurrency market up until the year 2021. Cryptocurrencies that are linked to other currencies, assets, or exchanges are excluded from the sample as well. Examples of these cryptocurrencies are Binance Coin, Tether, USD Coin, and FTX Token.

Table 1: Overview of the market capitalisation of the cryptocurrencies (01-08-2021)

Name	Ticker	Price	Circulating Supply	Market Cap
Bitcoin	BTC	\$39,974.90	18,773,956 BTC	\$750,472,428,208
Ethereum	ETH	\$2,561.85	116,939,454 ETH	\$299,564,961,374
Xrp	XRP	\$0.7259	46,312,443,360 XRP	\$33,619,230,717
Litecoin	LTC	\$140.74	66,752,415 LTC	\$9,394,436,650
Stellar	XLM	\$0.2762	23,393,654,109 XLM	\$6,460,780,553
Monero	XMR	\$236.23	17,965,023 XMR	\$4,243,833,052
Dash	DASH	\$160.56	10,262,334 DASH	\$1,647,593,117

This study will research calendar anomalies on a weekly and daily basis, four years of data will give reasonably enough data points for the results to be valid. Coins with a low market capitalization, are not used in this study due to the little effect on the cryptocurrency market as a whole and these coins are highly volatile creating outliers in the data resulting in invalid conclusions. In Table 2 and 3, the mean returns of the coins are summarized for both samples.

Table 2: Descriptive Statistics of the Daily Returns over the Second Halving Period

Return	Bitcoin	Ethereum	Xrp	Litecoin	Stellar	Monero	Dash
Mean	0.00182	0.00199	0.00240	0.00163	0.00250	0.00243	0.00160
Maximum	0.22512	0.29012	1.02746	0.51035	0.72315	0.58464	0.43775
Minimum	-0.46473	-0.55071	-0.61638	-0.44901	-0.41004	-0.49421	-0.45927
Std. Dev.	0.04218	0.05753	0.07305	0.05973	0.07986	0.06619	0.06122
Observations	1,403	1,403	1,403	1,403	1,403	1,403	1,403

Table 3: Descriptive Statistics of the Daily Returns over the Third Halving Period

Return	Bitcoin	Ethereum	Xrp	Litecoin	Stellar	Monero	Dash
Mean	0.00354	0.00586	0.00302	0.00279	0.00340	0.00313	0.00191
Maximum	0.17182	0.23070	0.44461	0.24841	0.55932	0.34493	0.45126
Minimum	-0.14811	-0.31746	-0.55040	-0.44119	-0.36236	-0.53418	-0.46546
Std. Dev.	0.03795	0.05250	0.07866	0.05815	0.07044	0.05774	0.06698
Observations	446	446	446	446	446	446	446

The descriptive statistics show that the conclusion of Yi et al. (2018) on the volatility of the different market-cap cryptocurrencies is respected. Bitcoin has the highest market capitalization among the currencies and is, in line with the literature, the least volatile.

4. Methodology

In this section, the methods of research will be examined and precisely explained how the effects are tested for. In this paper, a significance level of 5% is used for determining conclusions. After the anomaly explanations, the multi-way fixed effect model is discussed in detail which is used for controlling the sentiment of the market.

4.1. Cryptocurrency Returns

The returns between each day are first calculated of each currency so that the data can be used in the analysis. The paper uses logarithmic returns to test for the existence of the seasonalities. The advantage of logarithmic returns is that logarithmic returns are time-additive, therefore more valid for generating returns on different time scales like weekly, monthly, or quarterly returns. The returns are computed as follows:

$$R_i = \log (Close_i/Close_{i-1})$$

where R_i – returns on the i th day in %;

$Close_i$ – close price on the i th day;

$Close_{i-1}$ – close price on the $(i-1)$ th day.

4.2. Day of the Week effect

The Day of the Week effect is analyzed by regression analysis with dummy variables for each day. A dummy variable, dummy Saturday for example, will have the value 1 when the trading day is a Saturday otherwise it will be given the value 0. This occurs on all other weekdays where the market is open for trading, which is every day in the cryptocurrency market. In the regression analysis, there will be tested whether a specific day has significantly different returns compared to the rest of the week. An F-test can test whether the returns are significantly different for some days. In the F-test, the null hypothesis states that all the examined variables are equal and the alternative hypothesis is that a dummy variable tends to differ. The regressions to identify the day of the week effect will be constructed as follows:

$$R_i = A_0 + A_1D_{Mon} + A_2D_{Tue} + \dots + A_6D_{Sat} + e_i$$

where R_i – returns on the i th day

A_n – mean return on the n day of the week

D_{Mon} – a dummy variable for each day of the week, the value of 1 for observations corresponding to that day and the value of 0 otherwise

e_i – error term for period i

4.3. Twist on the Monday Effect

For the test of the Twist on the Monday effect, a dummy variable is created to indicate whether the previous week was positive or negative. Even though the weekends are still trading days in the stock market, the Twist on the Monday test can still be interesting. The return of the week before Monday is calculated from the difference between Sunday's closing prices.

To make sure the results we obtain are statistically different, the paper carries out F-tests for equality of the means. In the F-test, the null hypothesis states that a negative week does not significantly affect the returns on Monday. In the alternative hypothesis, the negative week does significantly affect the return on Monday where the results will show the sign and strength of the effect. The following regression model is used to test the Twist on the Monday effect:

$$R_i = A_0 + A_1 D_{NegWeek} + e_i$$

where R_i – return on the i th day

A_0 – mean return of the Monday after positive week sentiment

A_1 – mean return of the effect of a negative week prior to the Monday

$D_{NegWeek}$ – dummy variable for a negative week, given the value of 1 for observations that have a negative return over the week and the value of 0 otherwise

e_i – error term for period i

4.4. Second Quarter Effect

The last discussed calendar anomaly testing the efficiency of the cryptocurrency market is the second quarter effect mentioned earlier. Due to an inadequate amount of data points in the second subsample, only the returns of the first subsample (second halving period) are used to test the effect. After the regression, we test whether the second quarter significantly affects the cryptocurrency's return compared to the other quarters. The regression model estimating the effect includes:

$$R_i = A_0 + A_1 D_{SecondQuarter} + e_i$$

where R_i – return on the i th day

A_0 – mean return of the rest of the year

A_1 – mean return of the effect of the second quarter on the return

$D_{SecondQuarter}$ – dummy variable for the second quarter, given the value of 1 for observations in the second quarter of a year and the value of 0 otherwise

e_i – error term for period i

4.5. Multi-Way Fixed Effect Model

In this paper, multiple effects are tested for in a very volatile and strong behaving market. The trend of the market must be filtered out to determine the precise effect of an anomaly. An extensive regression technique called the Multi-Way Fixed Effect model provides the method intended. The model is an efficient estimator of linear models with multiple levels of fixed effects (Correia, 2016). The estimator performs particularly well with the large cryptocurrency dataset which contains high-dimensional data and 1,403 data points per cryptocurrency (subsample 1). The Two-Way Fixed Effect model is implemented in the paper absorbing the yearly fixed effects (yearly sentiment), estimating the actual effect of the anomaly.

The fixed effects method is not documented in the existing research on the cryptocurrency market. The relatively young market had many significant swings over the years, creating new all-time highs and devastating market bottoms. There is a reason to believe that the sentiment of the market can influence the effect an anomaly potentially has. Therefore, the fixed effects model is implemented in each regression generating more valid regression results.

5. Empirical Findings

5.1. Day of the Week Effect

Firstly, the Day of the Week effect is studied. Table 4 shows the results of the regression analysis with dummy variables for each weekday. The means of the daily returns are presented for the seven cryptocurrencies. Only one significant effect is found, where Litecoin shows a significant effect in the first subsample. In this period (Second Halving Period), Litecoin showed a significant positive effect (0.0096) on Saturday. However, the F-test testing for the equality of the means can not be rejected (f-value of 1.87) so we accept the null hypothesis stating that the means of the returns do not significantly differentiate.

Table 4: Regression results for the Day of the Week effect for cryptocurrencies over the Second Halving Period

Day	Bitcoin	Ethereum	Xrp	Litecoin	Stellar	Monero	Dash
Monday	0.0048* (0.0029)	0.0015 (0.0039)	- 0.0023 (0.0052)	- 0.0024 (0.0039)	0.0048 (0.0058)	0.0058 (0.0051)	- 0.0029 (0.0042)
Tuesday	0.0026 (0.0029)	0.0044 (0.0043)	0.0023 (0.0049)	0.0046 (0.0043)	0.0018 (0.0059)	0.0030 (0.0050)	- 0.0009 (0.0040)
Wednesday	0.0018 (0.0029)	0.0007 (0.0039)	0.0009 (0.0041)	- 0.0005 (0.0044)	0.0025 (0.0055)	0.0021 (0.0045)	0.0069 (0.0049)
Thursday	- 0.0012 (0.0042)	- 0.0026 (0.0051)	0.0062 (0.0068)	- 0.0057 (0.0054)	- 0.0056 (0.0059)	- 0.0091* (0.0052)	- 0.0034 (0.0049)
Friday	0.0028 (0.0028)	0.0074* (0.0039)	0.0084* (0.0049)	0.0072 (0.0044)	0.0045 (0.0053)	0.0061 (0.0041)	0.0040 (0.0036)
Saturday	0.0031 (0.0024)	0.0027 (0.0033)	- 0.0022 (0.0030)	0.0096*** (0.0035)	0.0064 (0.0052)	0.0041 (0.0038)	0.0068* (0.0041)
Sunday	- 0.0012 (0.0023)	- 0.0003 (0.0037)	0.0036 (0.0061)	- 0.0015 (0.0031)	0.0030 (0.0058)	0.0049 (0.0047)	0.0007 (0.0043)
F-test	0.72 (0.62)	0.73 (0.60)	0.58 (0.79)	0.08 (1.87)	0.84 (0.45)	0.35 (1.11)	0.45 (0.96)
R-Squared	0.0113	0.0160	0.0156	0.0177	0.0095	0.0142	0.0186
Anomaly	Not confirmed	Not confirmed	Not confirmed	Not confirmed	Not Confirmed	Not Confirmed	Not Confirmed

* p-value < 0.1, ** p-value < 0.05, ***p-value < 0.01

In the second subsample, the current Third Halving Period, there was no indication of a significant daily effect. In Table 5, the means of the daily returns are presented, including the corresponding F-test results. Across the seven cryptocurrencies, none of the null hypotheses (mentioning the means of the returns to be equal) could be rejected. The means of the returns are less significantly different compared to the first subsample, so the possibility exists that the cryptocurrency market is becoming more efficient over time.

Table 5: Regression results for the Day of the Week effect for cryptocurrencies over the Third Halving Period

Day	Bitcoin	Ethereum	Xrp	Litecoin	Stellar	Monero	Dash
Monday	0.0076 (0.0060)	0.0107 (0.0081)	0.0140 (0.0128)	0.0051 (0.0091)	0.0047 (0.0094)	- 0.0012 (0.0078)	0.0072 (0.0094)
Tuesday	0.0020 (0.0041)	0.0035 (0.0052)	- 0.0034 (0.0078)	0.0029 (0.0054)	0.0092 (0.0090)	0.0045 (0.0045)	0.0033 (0.0067)
Wednesday	0.0075 (0.0059)	0.0066 (0.0079)	- 0.0086 (0.0133)	0.0016 (0.0104)	0.0017 (0.0136)	- 0.0029 (0.0108)	- 0.0050 (0.0101)
Thursday	0.0016 (0.0054)	0.0005 (0.0068)	0.0088 (0.0089)	- 0.0017 (0.0066)	0.0011 (0.0087)	0.0031 (0.0085)	0.0029 (0.0082)
Friday	0.0008 (0.0043)	- 0.0001 (0.0059)	- 0.0019 (0.0069)	0.0024 (0.0064)	- 0.0020 (0.0073)	- 0.0002 (0.0058)	- 0.0071 (0.0071)
Saturday	0.0041 (0.0033)	0.0094 (0.0058)	0.0138 (0.0112)	0.0100* (0.0057)	0.0108* (0.0064)	0.0106* (0.0056)	0.0140 (0.0092)
Sunday	0.0010 (0.0037)	0.0104* (0.0059)	- 0.0013 (0.0051)	- 0.0007 (0.0062)	0 0.0018 (0.0049)	0.0079 (0.0060)	- 0.0019 (0.0077)
F-test	0.92 (0.33)	0.79 (0.53)	0.63 (0.72)	0.88 (0.40)	0.75 (0.58)	0.78 (0.53)	0.63 (0.73)
R-Squared	0.0073	0.0066	0.0124	0.0050	0.0045	0.0066	0.0102
Anomaly	Not Confirmed	Not Confirmed	Not Confirmed	Not Confirmed	Not Confirmed	Not Confirmed	Not Confirmed

* p-value < 0.1, ** p-value < 0.05, ***p-value < 0.01

This paper's findings are not in line with the existing literature written by Caporale & Plastun (2017), stating that Bitcoin has a significant positive effect on Monday. The results do not show a significant effect in favor of any outperforming day among the cryptocurrencies covered. Therefore, the hypothesis stating the existence of the day of the week effect can not be accepted due to the lack of evidence.

5.2. Twist on the Monday Effect

Secondly, the Twist on the Monday effect is examined in the paper. Descriptive statistics of the Monday mean returns are described in Table 6 where the data is split in Mondays after a positive week and Mondays after a negative week. In the first period, Bitcoin saw the most positive weeks and Stellar the least, 120 and 93 respectively. From the results two conclusions can be drawn, one concerning the effect of the negative week on the Monday and one concerning the volatility after a negative week.

Table 6: Average Monday Return and related statistics for subsamples based on Returns over the previous week (Second Halving Period).

	Bitcoin	Ethereum	Xrp	Litecoin	Stellar	Monero	Dash
<i>Subsample where previous week's return is positive</i>							
Average Monday's return	0.0162 (0.0038)	0.0197 (0.0054)	0.0126 (0.0087)	0.0128 (0.0058)	0.0342 (0.0088)	0.0245 (0.0081)	0.0128 (0.0068)
t-value	4.25	3.62	1.44	2.23	3.88	3.04	1.87
Number of observations	120	105	106	107	93	102	100
<i>Subsample where previous week's return is negative</i>							
Average Monday's return	- 0.0109 (0.0056)	- 0.0175 (0.0077)	- 0.0185 (0.0099)	- 0.0190 (0.0078)	- 0.0220 (0.0110)	- 0.0138 (0.0100)	- 0.0182 (0.0090)
t-value	- 4.84	- 4.81	- 3.14	- 4.07	- 5.11	- 3.81	- 3.42
Number of observations	81	96	95	94	108	99	101
Difference in means t-value	24.96	21.59	5.93	12.30	23.11	13.34	8.40

The Twist on the Monday effect is visible in the Second Halving Period. The mean return on a Monday after a negative week is significantly lower among all cryptocurrencies studied in the paper. Stellar has the biggest difference in return (0.0562), even as the most volatility on Monday. The negative effect of a negative week is the smallest for Bitcoin (0.0271), which is also the least volatile.

Another noticeable finding is the increasing volatility on the Monday after a negative week. A possible explanation for the increased volatility can be the creation of anxiety and fear by negative returns. People tend to react heavier to negative returns than positive returns with equal percentages (Tversky & Kahneman, 1991).

In Table 7, the results of the Twist on the Monday effect for the second subsample are presented. Dash has the biggest difference in return (0.0781) and the difference is the lowest for Bitcoin (0.0466). Xrp has experienced the most volatility, where the explanation can probably be based on the ongoing lawsuit from the Security and Exchange Commission against Xrp its parent company named Ripple. In the past year (2020-2021), multiple cases have been won by different parties leading to corresponding moves in favor or against Xrp.

Table 7: Average Monday Return and related statistics for subsamples based on Returns over the previous week (Third Halving Period).

	Bitcoin	Ethereum	Xrp	Litecoin	Stellar	Monero	Dash
<i>Subsample where previous week's return is positive</i>							
Average Monday's return	0.0277 (0.0081)	0.0375 (0.0091)	0.0504 (0.0213)	0.0377 (0.0116)	0.0333 (0.0135)	0.0202 (0.0073)	0.0514 (0.0126)
t-value	3.42	4.13	2.36	3.26	2.47	2.76	4.07
Number of observations	37	40	33	34	32	39	28
<i>Subsample where previous week's return is negative</i>							
Average Monday's return	- 0.0189 (0.0109)	- 0.0370 (0.0145)	- 0.0259 (0.0246)	- 0.0307 (0.0164)	- 0.0298 (0.0165)	- 0.0338 (0.0158)	- 0.0267 (0.0176)
t-value	- 4.28	- 5.13	- 3.10	- 4.16	- 3.82	- 3.42	- 4.43
Number of observations	26	23	30	29	31	24	35
Difference in means t-value	17.21	27.07	8.09	16.76	11.33	13.40	20.83

The equality of the means has been tested for, where the null hypotheses of equality is rejected for all seven cryptocurrencies in both samples. To summarize, the Twist on the Monday effect is significantly present in the cyptocurrency market for the Second Halving Period and the current Third Halving Period.

5.3. The Second Quarter Effect

The third calendar anomaly researched in this paper to test the efficiency of the cryptocurrency market is the Second Quarter Effect. The historical price action of cryptocurrencies and results of other papers inspired to test for a second-quarter effect. Literature showed that the months in this quarter were the best performing months of the year (Robiyanto et al., 2019). Therefore, the question arose for the existence of a quarter effect as a whole.

In Tabel 8, the results are presented for the first subsample of the paper. The second subsample has not been considered due to the lack of sufficient datapoints. The seven cryptocurrencies all showed a significant postive effect of the Second Quarter on the return. According to the F-test results, it can be concluded that the returns of the cryptocurrencies in the Second Quarter significantly differ from the other quarters. Xrp saw the biggest effect of the anomaly (0.8184) and Dash the lowest (0.2179).

Table 8: Regression results of the Second Quarter Effect (Second Halving Period)

Regression	Bitcoin	Ethereum	Xrp	Litecoin	Stellar	Monero	Dash
Second Quarter	0.5312*** (0.0185)	0.8184*** (0.0150)	0.7289*** (0.0307)	0.6287*** (0.0223)	0.7004*** (0.0407)	0.2593*** (0.0152)	0.2179*** (0.0253)
Rest of the Year	0.0395*** (0.0097)	- 0.0162 (0.0126)	0.0485** (0.0215)	0.0060 (0.0133)	0.0487* (0.0289)	0.1626*** (0.0106)	0.0921*** (0.0138)
F-test	0.00 (382.88)	0.00 (965.79)	0.00 (190.45)	0.00 (363.86)	0.00 (97.57)	0.00 (17.71)	0.00 (12.73)
R-Squared	0.6583	0.7847	0.6289	0.7017	0.4091	0.7466	0.7122
Anomaly	Confirmed	Confirmed	Confirmed	Confirmed	Confirmed	Confirmed	Confirmed

* p-value < 0.1, ** p-value < 0.05, ***p-value < 0.01

According to the results, the existence of the Second Quarter effect can be confirmed. The second quarter performs significantly better than other quarters for all the covered cryptocurrencies. At this point, a viable explanation for this effect is yet unknown.

6. Conclusion

This study contributes to the discussion on the market efficiency of the cryptocurrency market by analyzing certain seasonal patterns, previously documented for other financial markets. To test the efficiency of the market, the existence of three seasonalities is examined. The Day of the Week effect is not significantly present in the cryptocurrency market. This conclusion is in contrast to other papers investigating the effect in this space. All cryptocurrencies (Bitcoin, Ethereum, Xrp, Litecoin, Stellar, Monero, and Dash) showed the existence of the Twist on the Monday effect, where the returns on Monday are lower after a negative week than after a positive week. This conclusion is new to the literature concerning the cryptocurrency market since the Twist on the Monday effect has not been documented in the cryptocurrency space. Lastly, a unique effect is found which in this paper is described as the Second Quarter effect. From the regression results, it can be concluded that the second quarter significantly other quarters outperformed. Two of the three calendar anomalies examined in this paper are significantly found in the cryptocurrency market. Therefore, this paper concludes that the cryptocurrency market is in its entirety not efficient.

7. Discussion

This paper only tests for the Day of the Week effect, the Twist on the Monday effect, and the Second Quarter effect, in future research more seasonal anomalies found in the asset markets can be investigated, like the weekend effect or other behavioral contraries. Furthermore, this paper uses seven cryptocurrencies to test the existence of certain effects, perhaps the list of cryptocurrencies can be expanded. Additionally, anomalies in volume and volatility can be searched for where certain periods or events can have a significant influence.

Further in time, this paper its results can be matured and the market can become more efficient. Therefore, it is relevant to keep on researching the calendar anomalies whose significant existence can change over time.

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Appendix

Table 9: Descriptive Statistics of Bitcoin and Litecoin monthly return (2014-2018) (Robiyanto et al., 2019)

Bitcoin	January	February	March	April	May	June
Mean	-0.10954	0.03915	-0.14642	0.12633	0.21561	0.07111
Maximum	0.16491	0.23178	-0.03901	0.33191	0.70377	0.26677
Minimum	-0.31338	-0.38868	-0.32809	-0.03432	-0.18882	-0.14886
Std. Dev.	0.19583	0.25294	0.12601	0.15897	0.35505	0.15520
	July	August	September	October	November	December
Mean	0.06086	0.01991	-0.04858	0.15510	0.11216	0.12217
Maximum	0.21141	0.64227	0.05970	0.47943	0.54184	0.39245
Minimum	-0.07186	-0.19124	-0.19430	-0.12958	-0.36782	-0.15120
Std. Dev.	0.13073	0.35173	0.35173	0.25111	0.32707	0.23127
Litecoin	January	February	March	April	May	June
Mean	-0.01430	-0.00058	0.00253	0.02241	0.01404	0.02433
Maximum	0.00000	0.24066	0.88329	1.20141	0.65771	1.51534
Minimum	-0.30627	-0.30292	-0.42456	-0.13333	-0.20159	-0.31475
Std. Dev.	0.05616	0.05309	0.12998	0.16155	0.09594	0.21285
	July	August	September	October	November	December
Mean	-0.00102	-0.00436	-0.00467	-0.00201	0.00217	0.02368
Maximum	0.11220	0.72322	0.05674	0.19128	0.54847	1.63579
Minimum	-0.16557	-0.38158	-0.24127	-0.18691	-0.35890	-0.24090
Std. Dev.	0.02880	0.11924	0.03408	0.04081	0.08563	0.21463

Table 10: Descriptive statistics of Bitcoins monthly returns (Second Halving Period)

	January	February	March	April	May	June
Mean	-0.0010949	0.0021031	-0.0058229	0.0089321	0.0075380	0.0017417
Maximum	0.1109445	0.1087092	0.1671036	0.1600432	0.1217555	0.1039096
Minimum	-0.1845817	-0.1739821	-0.4647298	-0.0919321	-0.0913392	-0.1518193
Std. Dev.	0.0459681	0.0411263	0.0603693	0.0338513	0.0401303	0.0443201
	July	August	September	October	November	December
Mean	0.0017880	0.0021254	-0.0019387	0.0047972	-0.0010597	0.0037037
Maximum	0.2145957	0.1162575	0.1423295	0.1447609	0.1082245	0.2251190
Minimum	-0.1393769	-0.1020178	-0.2075298	-0.0723120	-0.1435615	-0.1332232
Std. Dev.	0.0450887	0.0313458	0.0381208	0.0272378	0.0382129	0.0497951

Figure 3: Bitcoin price chart, data split into calendar quarters. Measured in US Dollar (Second Halving Period)

