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Calendar anomalies in the cryptocurrency markets

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1 Introduction:

The calendar anomalies continue their legacy as one of the most exciting subjects in the financial economics debate. These anomalies are defined by unusual patterns of abnormal stock returns that are time-related. Rozeff and Kinney (1976) first documented that returns of small-capitalization stocks were highly concentrated in January. Keim and Stambaugh (1984) found the "weekend effect", where Monday's findings considerably differ from those of the rest of the week. Bouman and Jacobsen (2002) introduced the sell-in-May anomaly, which is later referred to as the "Halloween effect". The idea is to sell stocks in May and then buy them back in the winter because stocks have diminished value in the summer compared to the value in the winter. Calendar anomalies are inconsistent with Fama's (1970) well-known Efficient Market Hypothesis. This suggested that historical returns and other public information, including calendar days, should not be able to predict future stock values. Calendar anomalies show that there is a possibility. Thus, prices in the financial markets could be predictable.

Several theories have evolved to explain anomalies in crypto markets Baur et al (2019) analyzed seven international exchanges and were among the first to notice seasonality in Bitcoin pricing and trading volume and found a significant Weekend effect in terms of trade volume. Caporale, Plastun, and Oliinyk (2019) tested daily Bitcoins returns from 2013 to 2018, and found no evidence for seasonal patterns. Kinateder and Papavassiliou (2021). examined the calendar effects on daily returns of Bitcoin for the period 2013-2019. They tested day of the week (DOW), Halloween, and month of the year (MOY) effects. Their results find neither evidence for Halloween calendar anomaly nor the day of the week effect. Ma and Tanizaki (2019) investigated the day-of-the-week effect on both volatility and returns of the Bitcoin by using daily data obtained from the Bitcoin price index from January 2013 to December 2018. The main finding was that the significantly high mean return of Bitcoin on Monday was related to higher volatility. Grobys and Sapkota (2019) By retrieving a collection of 143 samples of different cryptocurrencies from 2014 to 2018, the investigation was for a common momentum strategy applied in the cryptocurrency market. In contrast to previous studies, the findings do not indicate any evidence of significant momentum gains, supporting the view that the cryptocurrency market is much more efficient than suggested in previous studies. Shen, Urquhart, and Wang (2020). Examine a three factors model containing the size, value, and momentum. They conclude that the model significantly improved when compared to Capital Asset Pricing Model and small cryptocurrencies tend to obtain higher returns than large coins.

However, The applications for the stock markets are rich in indices, while a few addressed the presence of market anomalies such as seasonality in cryptocurrency markets. Moreover, these studies showed conflict in their conclusions. Therefore, it will be interesting to evaluate these anomalies by applying

advanced time frames and currencies with combining methods. Nevertheless, there is a difficulty examine calendar effects because it is more joint test of asset pricing models and market efficiency.

This paper mainly focuses on evaluating whether calendar anomalies that are common in the stock market are also present in the market for cryptocurrencies. The January Effect, Halloween, Second Quarter Effect, and Monday Effect will all be evaluated to provide an answer to the study issue.

Therefore, the research question of this thesis is: *"To what extent do calendar anomalies exist in the cryptocurrency market?"*

This research question is examined for a sample of five main cryptocurrencies in the crypto market over the period between January 2015 to April 2020. The analysis extends from previous analyses and considers three regressions that are the Capital Asset Pricing Model (CAPM), Fama-French's three factors, and Carhart's four factors by applying a dummy variable that represents the anomaly under the test. That will present the Monday effect, January, Second Quarter, and Halloween effects, thus when the dummy significant indicate to existing of the effect. The main finding of the analysis is that there is no Monday effect in the coins of the study while there is a January effect for Ethereum. The Bitcoin shows evidence of a reverse Halloween effect and there was no evidence for observing the second quarter effect.

This finding has the potential to have a substantial impact on investors' decision-making since it might suggest that the investors as individuals normally who do their analysis and any firms or managers who may be interested to invest in crypto should disregard the anomalies patterns when their analysis has done. This thesis also suggests that additional research is still needed on this subject. Moreover, this study is unique in examining the other factors and effects as the value, size, and momentum on the excess returns of the coins. In addition to all of the previous results, it has found strong evidence between risk factors and excess return.

This thesis presents the theoretical framework in the second chapter. Then in the third chapter, the data and the research methods will be discussed. The fourth chapter is for results, and finally, the conclusion and limitations are presented in the fifth chapter.

2. Theoretical framework:

2.1. Efficient Market Hypothesis :

Fama (1965) defines the concept of the efficient market Hypothesis (EMH) for the first time. According to the EMH, a market is "efficient" when the prices in the market reflect all available information in it and there is no way to achieve abnormal returns depending on the information which is more related to the concept of Random walk thus the prices are changing independently. Fama (1965) in his article described the theory of random walk, which considers that future evaluation of prices cannot be predicted depending on past prices because the prices of stocks follow the random walk, and if the markets are efficient, the prices reflect all the information. Therefore, using additional analysis is pointless until new information arrived. Lo and MacKinlay (2011) tested the random walk in weak form, they found that markets are not completely random and that predictable components do exist in recent stock and bond returns. Fama (1970) makes a few changes and looked at the predictability of returns over more extended periods. Moreover, this paper reviews the empirical and theoretical distinctions between the three forms of efficiency, which are weak, semi-strong, and strong. First weak form in which that the current prices reflect historical information. Then the Semi-Strong form in which the prices are efficient by adjusting all available information. Finally, strong form concerned that the prices of stocks recognized all information as historical, public, and even private. During the following years and up to the present, there are various opinions about the efficiency of capital markets. There are many different points of view and it is worth reviewing them and seeing if there is a predominant one that can prevail over the others

Economists and analysts continue to debate the cryptocurrency market's efficiency. On the one hand, proponents of market efficiency argue that the vast amount of information available to market participants, combined with the speed and ease of use of modern trading technologies, ensures that prices reflect all available information about a specific cryptocurrency. Thus, when the market is efficient and acts rational that will be challenging to find patterns to pet the market. While in the other hand, Market efficiency critics emphasize that the cryptocurrency market is highly speculative and prone to bubbles and crashes, implying that prices may not always reflect the fundamental value and has some noise. It should be noted that the cryptocurrency market is still in its early stages and does not yet have the same level of regulation and oversight as traditional financial markets. Furthermore, this market is exceptionally volatile, with prices changing rapidly in response to the news which makes this market hazardous.

Many studies have examined the efficiency of crypto markets with inconsistency in their founding. Nadarajah and Chu(2017) used eight different tests on the Bitcoin returns, to sum up, that a simple power of transformation does satisfy the efficiency of the market hypothesis while Urquhart (2016) found that the

return of Bitcoin does satisfy the efficiency. Moreover, Baur et al (2019) found that the Mondays returns appear to be above-average returns to conclude that Bitcoin has a Day of the Weekend effect.
The conflict in the previous studies of the efficiency of the crypto market shows there is a need to re-investigate with more depth in theory by using different methods and coins

2.2. Cryptocurrency markets:

The market of cryptocurrencies is still blooming and growing with time by applying innovation in finance. The technology implemented in this market is based on decentralized finance (Defi). This concept means an economic system that allows the processing of financial operations without the need for additional intermediaries or even third parties. The new era started by Bitcoin Nakamoto (2008) introduced the first version of software and database for Bitcoin. This operating system was the earlier blockchain-based currency created and the cornerstone for the start of a major financial system revolution. Because the cryptocurrency market is relatively new in comparison to other asset markets such as the stock or bond markets, the overall market is more volatile (Conrad et al., 2018). Asset markets are markets in which people can speculate on financial assets for monetary purposes, but also for individuals and institutions investing and trading in the space to increase their financial wealth. Market volatility in asset markets can be valuable for developing trading strategies and investment opportunities. Finding certain patterns or anomalies in the markets can cause investors and traders to reconsider a profitable strategy for making money and this is the heart of this paper examining to find patterns that may help to understand the crypto markets.

Bitcoin has the highest market capitalization and it is the oldest coin in the crypto coins. This coin has a value of more than 424 billion dollars according to the coin market cap website on March 2023. However, over the years, many alternative cryptocurrencies evolved, some of them disappearing and others still existing and making a name for themselves. In the following, the five cryptocurrencies are used in this paper.

- Bitcoin:

Bitcoin is the first crypto coin based on decentralized digital currency that allows for secure peer-to-peer transactions without any need for a central authority, such as a government or central bank. All these processes happen directly online between equal independent peers. However, Bitcoin has a digital value determined by the supply and demand dynamics. Their primary use resembles that of traditional currencies such as the transfer and storing of value, and unit of account. The first known Bitcoin commercial transaction occurred in 2010 with a value of 0.08 dollars to be more than 27000 dollars per Bitcoin nowadays.

- Ethereum

Ethereum is a decentralized blockchain platform that allows developers and users to build and develop decentralized applications and smart contracts. The first time Ethereum launched was in 2015, with Ether being its natural currency like Bitcoin features. Therefore, Ethereum has its cryptocurrency called (ETH) which is used to pay for transactions and computational services on the Ethereum network. The uniqueness of Ether is the programmable blockchain and its usability of applications called decentralized applications.

- XRP-USD

In 2012 Ripple Labs Inc created its crypto coin. Which is designed to facilitate fast and efficient cross–border payments thus it needs just five seconds to process the transactions. It's special by not being based on blockchain, but it rather uses a different kind of ledger technology called XRP ledger. XRP traded on various cryptocurrencies including the US dollar(XRP-USD).

- Litecoin

Litecoin is a digital math-based currency established in 2011, which is cost-free transactions between users around the world. Like other cryptocurrencies, the open-source LTC network is decentralized, and the Blockchain can handle higher transaction volumes than the popular Bitcoin. The network is protected by math, and it shows much faster transaction approval and upgraded storage efficiency.

- Stellar USD

Stellar is a peer-to-peer decentralized network created by Stellar Development Foundation in 2014. XLM acts as an intermediate currency for operations to pay transaction fees and helps with cross-border transactions, overcoming the problems of high costs and slow procedures.

Table 1 of an overview of the market capitalization of cryptocurrencies (08-03-2023)

Number	*Name*	*Ticker*	*Market cap*	*Data start date*
1	Bitcoin	BTC	424.121 B	01/01/2015
2	Ethereum	ETH	189.474 B	07/08/2015
3	Ripple USD	XRP	20.048 B	01/01/2015
4	Litecoin	LTC	6.073 B	01/01/2015
5	Stellar USD	XLM	2.194 B	01/01/2015

2.3. January effect

The January effect or "Turn of the year effect" is one of the most famous anomalies, that admits a remarkable return in January to outperform the returns to the other months in the year. Wachtel (1942) studied the United States stock market and was the first who observe the abnormal return in January to be significant. Rozeff and Kinney (1976) studied the Stock Exchange the New York Stock for the period 1904 to 1974. Their results found an anomaly in the monthly return to be the first paper to record official empirical evidence for this phenomenon. While Kaiser (2019) concluded his study on cryptocurrencies by presenting a negative return in January as a "reverse to January effect" especially for Bitcoin and Bitcoin cash.
The reasons behind this effect have been widely examined in the literature on the stock markets. Reinganum (1983) found that small firms have significant returns in January compared to large firms, however, this higher return is consistent with tax-loss selling. This concept means the investors may sell loss stocks at the end of the financial year to offset gains and reduce tax liability. This selling pressure can lead to lower prices in December, followed by rebound returns in January when the investors buy back these positions. Therefore, tax-loss selling led to unusual returns in January. Other papers argue that the January effect is driven by the Windows-dressing hypothesis. This hypothesis means the financial managers of the largest portfolios, tend to sell smaller stocks at the end of the year to clean their portfolios and to show the best financial performance in line with the riskiness of their holding. While, higher demand for buying them again in January (Lakonishok et al,1991). Thus, at the beginning of the following calendar year (January), the portfolio managers will reverse the process by selling large winners' stocks and buying small stocks with more risky stocks.

When it comes to cryptocurrencies, there are several reasons for observing this effect. For instance, the end-year bonuses because many investors and traders receive end-year bounce and they may use these bounces to invest in crypto in January. The sentiment in the market at the begging of the year is often seen as a new start with renewed positive sentiment. This can translate to increase buying in the first month of the year and makes the prices to be higher than other months during the same fiscal year. The seasonal factors play a role to influence the price of the crypto markets, The Chinese new year for instance, has an effect "reverse January" when the majority of Chinese investors sold their position in the crypto to enjoy the holidays or set new goals for the next year, however, the Chinese investors widely affect the crypto markets (Mei Hui, 2019). Despite this, a few little studies have analyzed such issues in the crypto market, thus there is a need to test this phenomenon with different cryptocurrencies and new periods, therefore, the main hypothesis for this effect is:

H: There is a January effect on the cryptocurrency market.

2.4. Halloween effect

The Halloween effect known also as the winter effect "sell in May and go away" means the tendency of stocks to perform better between November and April compared to the other months of the year. This was introduced by Bouman and Jacobsen (2002) who found this effect to be significant in 36 out of 37 countries for the period between 1970 and 1998. Moreover, they showed that the length of summer vacations is crucial to appear this effect. They argued that countries with strong traditions of summer vacations will influence the liquidity because the investors may spend more money during summer vacations thus they liquid their position at the end of April. Therefore, the returns from November to April will be significantly higher from May to September. After this study many papers have tested this effect, to understand in depth this phenomenon. There has been a conflict by examine this effect depending on the sample chosen for the study (Witte,2010). These results were confirmed by Andrade et al. (2013) after applying the same sample countries of (Bouman & Jacobsen, 2002). They found after deeper analysis of the individual stocks level that Dow Jones observes the Halloween effect. They sum up to the whole index is driven by a handful of stocks that strongly consist of the Halloween effect. Lloyd et al. (2017) tested the influence of the financial crisis in 2008 on the Halloween effect, it could be this effect did not survive after such time. The authors found that the effect still appears in 34 of 35 investigated countries.

These indicators have been re-examined by Lucey and Zhao (2008) and they found weak to no strong evidence for this effect in the US market for the period 1926 to 2002. Moreover, they found the evidence of this effect in the long term may be a reflection of the January effect. Kaustia and Rantapuska (2016) investigated summer vacation holidays in Finland and found that the trading patterns of the investors are in line with the vacation hypothesis and other factors such are mood and weather are individually significant. While Dichtl and Drobetz (2015) argued that the Halloween effect weaken and disappeared in recent years. This study tested different markets by applying various parameters thus there is no additional abnormal return or "free lunch" by adapting the Halloween strategy. Plastun, Drofa, and Klyushnik (2019) have shown that July and August's returns are much lower than the returns of other months for Bitcoin. However, a few papers as well on this subject are on crypto coins and there is no deep analysis for that. Bouman and Jacobsen (2002) discovered that the effect is strongly related to the length and timing of summer vacations, as well as the impact of summer vacations on trading activity in various countries. That could be the reason to observe this effect in crypto markets, thus the hypothesis for the effect is:

H: *There is a Halloween effect on the cryptocurrency market.*

2.5. The Second Quarter effect

The second quarter effect is a seasonal pattern that accrues when the second quarter return outperforms other quarters. Penman (1987) was first introduced, the study was on aggregating the past 55 years' returns on average of stock market indexes. The founding was that the second quarter generate higher returns than the others. Moreover, this effect appears in the line of the earning announcement, the companies tend to report positive news in the second quarter while the inconvenience news is more in the other quarters. While there is a development in the literature on the seasonality of cryptocurrency, there is still a limitation to focusing on the quarterly effect. Qadan et al. (2022) have tested this effect on eight different crypto coins and they failed to find clear evidence of the quarter effect. Robiyanto et al., (2019) analyzed monthly returns in the cryptocurrency market by regression analysis with dummy variables. They found that both Bitcoin and Litecoin have the month-of-the-year effect and the second quarter seems to outperform the other quarters. This paper concluded that the cryptocurrency market is not efficient.

It can be seen The lack of adequate research into this effect calls for further investigation, thus the main hypothesis for this effect is:

H: *There is a second-quarter effect on the cryptocurrency market.*

2.6. Monday effect:

This effect describes that the returns on Monday tend to be significantly lower than the other returns days during the week. Osborne (1962) was the first who introduced this effect in the US stock markets and after that much literature followed over the years. According to Lakonishok and Maberly (1990), investors trade more on Mondays reacting to the news and events that occurred over the weekend. Thus the trading habits of discerning investors can be a determining factor for the appearance of the Monday effect. Many studies tried to explain this phenomenon, Bildik (2004) found there is a relation between Monday's return and return on Friday in the prior week because investors underreacted to the new information from last week and need more time to realize. Foster and Viswanathan. (1990) report significantly higher trading costs and lower trading volume on Mondays. Abu Bakar, Siganos, and Vagenas (2014) tried to find a relationship between the mood of the investors and the Monday effect. That is because a greater proportion of the investors are more pessimistic in the early days of the week. However, this paper used novel daily mood data from Facebook across twenty international markets to explore the impact of mood on the Monday effect. The analysis showed that mood drives the Monday effect. Rogalski (1984) confirmed that negative returns from Friday close to Monday close occurs in the stock market indexes and showed that the difference is indeed caused by the weekend when there is no trading. French (1980) provided further evidence on the S&P index

from 1953 to 1977. The result showed that Monday's returns were not only lower but significantly negative returns compared to other weekdays and higher for Fridays.

More recently, Bishal et al.(2019) tested the individual investors to what extent influence the Monday effect in the US market. They used secondary data from NYSE-listed firms between 2004 and 2013. The main founding was that Monday stock returns were negative on average and lower than other weekdays and that was consistent with the Monday effect.

However, Baur et al (2019) studied the trading volume of Bitcoin according to the time of the day and day of the week effects and their founding proves that the effect of Monday presents higher than the average returns for the period between 2013 and 2017. Since the investors may trade every day and the bitcoin market is not dominated by individual investors, the results show that Bitcoin may characterize By institutional investors. Therefore, this thesis will test this effect but for more than Bitcoin and examine how would be significant, thus the hypothesis for this effect is:

H: *There is a Mondy effect on the cryptocurrency market.*

2.7. Aim of thesis and research problem:

The cryptocurrency market is an interesting special case because it is relatively new, unexplored, and extremely vulnerable to anomalies due to its high volatility relative to other financial markets. Due to being a newly introduced financial instrument in the financial markets, studies related to cryptocurrencies are limited. Bitcoin is the first cryptocurrency introduced in the financial system. For this reason, the first studies about cryptocurrencies are about Bitcoin, and after that many studies have been done in crypto but there is still a limitation in literature and studies for crypto coins. Moreover, this market is rich with currencies that appear and still blooming intensively. According to the website of the coin market cap, the value of existing cryptocurrency is around 1.3 trillion dollars at the end of January 2023. Therefore, this market will still be attractive to doing more research and studies especially, for calendar anomalies same as the assets market which showed changes in these patterns. Plastun et al (2020) concluded their research that seasonal anomalies were common during the last century, but have disappeared in recent years from major financial markets. Robins and Smith (2016) reported in their study that the weekend effect disappeared after 1975 and argued that the Weekend effect is no more anomaly in the US stock market. Marquering et al (2006) showed evidence that most of the calendar anomalies were arbitraged after they were observed. Strong evidence was found for the weekend effect, the holiday effect, and the time of the month effect, however, the timing of disappearing anomalies was more related to the time of academic publications.

In the case of the cryptocurrency market, only a few market anomalies have already been discussed. Caporale and Plastun (2019), for example, investigate overreactions in the cryptocurrency market and discover evidence of price patterns following overreactions. Chevapatrakul and Mascia (2019) use the quantile autoregressive model to show that as Bitcoin prices rise, days with extremely negative returns are likely to be followed by periods with negative returns and weekly positive returns. However, several studies have been interested in daily returns in crypto while rarely found in monthly returns and there was inconsistency in the results they obtained. Therefore, this paper will deep analysis both daily and monthly returns in cryptocurrency to examine the calendar anomalies by consideration of additional seasonality patterns. These patterns will be January, Halloween, Second-quarter, and Monday effects. The test implements main three different models, which are CAPM, Fama-French's three factors, and Carhart's Four factors with different crypto coins.

2.8. Other seasonal effects:

In addition to the previous calendar anomalies, literature also observed other seasonal effects such as the Day of the Week Effect, Turn of the Month effect, and Holiday effect.

The day-of-the-week effect describes the combination of the Monday effect and the weekend effect. Thus when the Monday effect indicates that returns tend to be significantly negative or below the average returns of the other days of the week. The day of the week effect emphasis on the returns on Friday higher compared to the rest of the week. It suggested that Friday returns are higher than Monday returns (Cross, 1973). Gayaker, Yalcin, and Berument (2020) Provided empirical evidence of the relation between the day-of-the-week effect and overnight interest rates, due to the date of the trade-in equity markets is not the same as the date of payment being made and that may explain these differences in returns. Kiymaz and Berument (2003) researched this effect by investigating major indexes in Canada, Japan, the US, the UK, and Germany from 1988 to 2002. They found both volatility and returns affect the day-of-the-week phenomena. They argued that high volatility would occur with low trading value because when the prices are more volatile, liquidity traders are resistant to trade in this period.

While for the turn of the month effect (TOM), indicate to the returns in the stock markets tend to be maximal at the end of the month and the beginning of the following month (Ariel,1987). Hensel and Ziemba (1996) tested the TOM effect for the period between 1928 and 1993. The main founding was that the US market showed higher returns on the last day of the month same as the second and third trading days of the next month.

The Holiday effect indicates that the returns will be more violated because of the public holiday and will be higher before the vacation compared to after it. Reverse to the other effects such as Mondy and January effects. Therefore, the Holiday effect may differ within the various markets in terms of duration and timing of consideration. McGuinness and Harris (2011) examined the Chinese Lunar New Year (CLNY) of the mainland Chinese (Shanghai and Shenzhen) and Hong Kong over the 1995 to 2010 time frame. The analysis was for three days before the CLNY holiday and one day after, they concluded that the Hong Kong market showed higher returns on all these days compared to other trading days.

All of the previous literature shows that there is intensive research and papers regarding calendar anomalies in the stock market and only a few scholars tested seasonal patterns in the cryptocurrency market.

3. Data and methods of the research.

This chapter will be for the empirical methods that will be used in the thesis, and an explanation of all data, tests, and variables. That will be based on the existing studies of calendar anomalies in the cryptocurrency market of the preceding chapter. Therefore, this section describes the data and methodology that was used to further analyze calendar anomalies and where that data was collected.

3.1. Data

The CCI30 index tracks the prices of the coins with historical data, which contains the opening and closing prices, the market capitalization, and the volume, thus the CCI30 index will be used as a benchmark

The initial sample consists of the five largest cryptocurrencies(Bitcoin, Ethereum, XRP, Litecoin, and Stellar) over the period 2015 until 2020. These currencies have the highest capital in crypto markets which is the main reason for choosing these currencies as a sample for this study and they are the most dominant in the crypto market, this is in line with previous research and provides a solid basis for comparison (Philip et al, 2018). Moreover, many other currencies were excluded from the study, because, of a lack of data recorded or even higher volatility which will affect the conclusion at the end. The other coins were excluded due to trade it very little.

When adapting research, there are mainly two different categories to collect the data, quantitive and qualitative. On the one hand, qualitative data are collected through observations, interviews, etc. Quantitive data, on the other hand, is based on numerical variables that will be analyzed through statistical models and diagrams. For this study, the source of data will be historical cryptocurrency prices, which implies the use of quantitative data. All the tests have been done by using statistical measures hence, a quantitive approach is suitable (Saunders, Lewis & Thornhill, 2007). One of the main features of the quantitative method is that

it takes less time to collect data. On the contrary, very large data can be collected in a short time. In addition, this method differs from the qualitative method by the possibility to generalize the results of large groups(Rahman, 2020)

This study adopted quantitative research to examine the effect of market anomalies existing on the expected return across the CCI30 index. This methodology will be carried out instantly by using panel data analysis to determine these anomalies in the market of crypto. The dependent variable used in this study is the excess return of the coin and the independent variables are market risk premium and calendar anomalies for January, Halloween, Monday, and the second quarter. These variables will be controlled by size, momentum, and value variables. Table 1 provides an overview of the start date and the coins that were implemented in the study.

All data was gathered from the Coin market cap.com, For a risk-free rate, the US Treasury bill for six months was used and obtained from Yahoo finance.com. Moreover, the data was collected in US dollars as known in the crypto market. The data is chosen according to their capitalization in the market (the coins have more than one billion) and the availability of the data. It is important to note that in the subsequent analysis of calendar anomalies, it will not be possible to obtain an accurate comparison of all cryptocurrencies due to the inconsistent periods of recording data, thus this study has chosen these currencies with different starting dates.

3.2. Variables

This chapter will show and discuss the variables used in this thesis, and the elaboration concern their relevance to the research question. These variables were in three main categories: dependent, independent, and control variables.

Dependent variables:

The dependent variables are the return of cryptocurrency. These returns are calculated by the logarithm of dividing the new price by the old price. It indicates the total return level obtained, and it is calculated by using the following formula for daily and monthly returns:

Equation (1): calculation of returns,

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

For this thesis using natural logarithm is more crucial to achieve normal distribution (Strong, 1992). $R_{i,t}$ is the return of the coin under the study, while P_t is the closing price of the coin at time t and P_{t-1} is the closing price of the previous period. This formula is commonly used in the literature for instance(Kaiser 2019).

Independent variables:

January Effect:

To test if January significantly higher return than other trading months, the dummy variable will represent this anomaly. This dummy is $D_{January}$ equal to one if the month is January, while for all other months, this dummy will equal zero.

Halloween effect:

To test if the return in the winter is higher than the return in the summer period, the dummy variable for this (D_H) will have a value of one if this anomaly is present in the period from November to April, while this dummy is equal to zero otherwise.

The second quarter effect:

To test the return by the end of the second quarter to show if there is an anomaly according to it, the dummy variable (D_Q) has a value of one for the second quarter to represent the effect while it has zero otherwise.

Monday effect:

This independent variable to test if there is a Monday effect, thus the dummy variable(D_{Mon}) will be has a value of one on Mondays and zero otherwise.

Control variables:

Several control variables are included in the regression of Fama-French's three factors and Carhart's four factors. These variables are to a large extent determinants of calendar anomalies, and they are frequently used in the literature. The incorporated control variables are size, value, and momentum. All these variables are calculated manually based on coin returns on a separate Excel sheet

Value effect (HML): This control independent variable of value effect shows the different returns between small and large coins in the crypto market according to their values. The HML in the stock market demonstrates the different returns between firms or stocks with high book-to-market value ratios with other stocks or firms that have lower ratios. Therefore, there is a need to test this factor in the crypto market. However, the cryptocurrency market does not have a day off thus trading on this market works for the whole financial year. It is impossible to calculate the price-to-earnings ratio, which is used in stock markets to specify the highest and lowest book-to-market value ratio. Therefore, this paper used the Network Velocity Metrics (NVT) ratio as an alternative method to calculate the control variables for the cryptocurrency class of asset (Stoffels, 2017). The NVT ratio describes the relationship between the transfer volume and market cap of the coin and is calculated as follows

$$\textit{NVT Ratio} = \frac{Market\ cap}{Ttansaction\ volume}$$

The average return per day of the currencies with the most significant ratio was subtracted from the one with the lowest percentage and the same was for the monthly data (Pontoh & Rizkianto, 2020).

Size effect (SMB): This is another control-independent variable of size effect. The main meaning is to distinguish between value and growth stock. However, applying this variable to the regression of crypto coins to see if the size is powerful and tends to have a higher return than growth coins. Moreover, the growth coins may they are undervalued by the market and have a higher potential for future growth. To calculate this risk factor of small minus big for the t period is constructed by ranking the market capitalization in t-1 in descending order and sorting all the coins according to their rank. The average daily return of the largest coins is then subtracted from the average daily return of the smallest coins.

Momentum: This concept was introduced by Jegadeesh and Titman (1993) for the stock market's abnormal return, which means the evaluation for past winners and loser stocks stays the same for the short term from the next 6 to 12 months. This phenomenon will apply in the regression in the crypto coins to investigate if this pattern exists. Stoffels (2017) has tested the momentum factors in different strategies in the crypto market. The main finding was the shorter evaluation for this strategy appeared to work better than the longer one, However, his paper suggested to be this period from three to four weeks therefore, this thesis has used four weeks to evaluate the momentum strategy for cryptocurrencies. At the beginning of each month, coins were ranked in ascending order based on their returns over the past month. Based on this ranking, the coins are divided into two groups, winner and loser. The coins with the highest past returns were called the winner while the one containing the coins with the lowest returns was called the loser. At the end of the sampling period, the momentum was calculated by the average returns of the winning coins minus the average returns of the loser. Table 2 provides a summary of all previous variables:

Table 2: variables definition

Variable	Variable description
Dependent variable	
Rit-rf	The return of the cryptocurrency minus the risk-free rate
Independent variable	
E(RM) – rf	Expected market return minus the risk-free rate
Control variables	
HML	A value premium: the average return of high based on (NVT) for coins minus the low ones.
SMB	Size, The average returns of the small coins minus the average of the big
Mom	Momentum, The average return of the past winner minus the average of the past loser

Testing of statistical significance:

Calculations of daily and monthly returns have been tested on the bases of the hypothesis. Thereby, the definition of the null hypothesis is that average returns for specific days or months are equal to the overall average. A rejection of the null hypothesis would imply an anomaly in the behavior of returns on specific days or months within a year depending on the analyzed calendar used. However, the significant level in this paper was 5 %. Therefore the hypothesis will be as follow:

H_1: There is a January effect on the cryptocurrency

H_2: There is a Monday effect on the cryptocurrency

H_3: There is Second quarter effect on the cryptocurrency

H_4: There is a Halloween effect on the cryptocurrency

3.3. Methodology and Hypothesis

The methodology for this thesis is based on three regression CAPM, Fama-French, and Carhart models. The OLS regression will be considered for a significant coefficient different from zero at level 5%

- **The first regression: CAPM model**

The first method is the Capital assets pricing model CAPM will be used, this model is a commonly used method in finance (Sharpe, 1964). The CAPM is used to determine the relationship return of individual coins and risk. This model uses a single risk factor known as market beta. However, the applicability of this regression has been investigated over decades as a sole risk factor model (Reilly& Brown, 2011). The model

included a dummy variable for calendar anomaly testing. Thus, when the coefficient significance of this dummy means there is an effect as well. The CAPM is described below in the equation (1):

$$R_{it} - r_{ft} = \beta_J [E(R_m) - r_{ft}] + D_{nt} + \varepsilon_{ji} \quad (1)$$

Where: R_{it} is the excess return for cryptocurrency i in the period of t; r_{ft} is the risk-free rate; β_{Ji} is the beta coefficient in time i; $R_m - r_{ft}$ which is the excess return or risk premium in time t; e_{it} is the error term of the regression for coin i in time t; and D_{nt} is the dummy variable. This dummy variable varies according to the calendar effect being tested and they take the value as follows:

Halloween dummy = Dummy variable D_h Halloween effect takes the value of 1 for the period November to April and 0 otherwise

Monday dummy= Dummy variable of Monday anomaly, the D_m takes the value of 1 on Mondays and 0 otherwise.

Second quarter dummy= Dummy variable of second quarter effect, the D_q takes the value of 1 if it refers to the second quarter and 0 if it does not.

January dummy = Dummy variable of January anomaly the D_J takes the value 1 in January and 0 otherwise.

- **The second regression: Fama and French three factors model (FF3-factor model)**

The FF3 factor model by Fama and French (1992) was developed as an alternative to the capital asset pricing model. The only adjustments to the model include the use of three factors, known as size, a book-to-market ratio or value, and market beta. However, the model will include a dummy variable to test the anomalies as well. The model FF3-factors model is presented as follows in equation (2):

$$Rit - rf = \beta 1(Rm - Rf) + \beta si\ SMBt + \beta ni\ HMLt + Dnt + \varepsilon_{it} \quad (2)$$

Where SMB_t is size and HML_t value; SMB represents the difference between the return of small and large cryptocurrencies while HML represents the difference between high and low coins. Thus the regression coefficients *βni* and *βsi* represent exposures to size and value risk in much the same way that *β1* measures the exposures to market risk. Other variables in equation two are the same as defined in equation one.

- **The third regression: Carthart's four -factors model (C4F)**

The Carthart four factors model is an extension model for Fama French's three factors (FF3). Introduced Carthart (1997) by applying a new factor of momentum anomaly. However, the model will include a dummy variable to test January, Halloween, the Turn of the month, and end of the quarter effects to investigate the significance of these anomalies, thus, the model is represented by equation (3) as follows:

$$Rit - rF = \alpha + \beta 1\ Dnt + \beta 2Momt + \beta 3SMBt + \beta 4\ HMLt + \beta 5\ (Rm - rf) + \varepsilon_{it} \quad (3)$$

Where MOM_t is the momentum factor, measured by 6 and 12 months; and β2Momt is the sensitive coin i return to the movement in the momentum risk premium.

These dummy regressions are conducted on each fundamental anomaly. From each of these regressions, the (p-value) values are obtained to test risk level which indicates randomness in the results. However, this level will be 5% and 1% used in this thesis. Furthermore, to avoid the so-called dummies trap, which occurs when all the dummies are included in our regression resulting in perfect Multicollinearity, constant terms drop out of these regressions (Selvarani & Jenefa, 2009).

4 Results and Main Analysis:

4.1 Descriptive statistics

The following tables report the statistical analysis of the sample under study, which provides us with a general idea of the variables that were used, along with the maximum, minimum values, mean, and standard deviation.

Table 3: Descriptive statistics on research daily data.

Variable	Observation	Mean	SD	Min	Max
Bitcoin	1946	-1.024196246	0.83849975	-2.53827882	0.3393683
Ethereum	1727	0.002508590	0.06867336	-0.75510629	0.4397748
Litecoin	1946	-1.024196246	0.83849975	-2.53827882	0.3393683
Xlm	1941	-1.026765555	0.84181327	-2.50867474	1.6078196
Xrb	1946	-1.024566082	0.83838157	-2.49169173	0.1468995
SMB	1946	0.004987031	0.14630848	-1.14855510	1.7536061
HML	1946	-0.007369767	0.11080347	-0.92602294	1.0130298
Mom	1946	0.010108573	0.04132917	-0.05425403	0.1606361
Cex	1946	-1.023863373	0.83819107	-2.49141581	0.1505429

Note: The coins in this table (Bitcoin, Ethereum, Litecoin, Xlm, and Xrb) represent the return of the coin minus the risk-free factor. While Cex represents market return minus risk-free factor. The other variables SMB, Mom, and HML are controls for analysis, however, all these variables are expressed in numbers.

Table 4: Descriptive statistics on research monthly data.

Variable	Observation	Mean	SD	Min	Max
Bitcoin	64	0.010220958	0.91394911	-3.00867229	3.3303579
Ethereum	57	0.083543860	0.42219921	-0.78000000	1.1574000
Litecoin	64	0.005984729	0.94044186	-3.24117606	3.2787953
Xlm	64	-0.036961146	0.97326788	-3.42294715	3.1412817
Xrb	64	-0.006745521	0.98376750	-3.29184715	2.8845224
SMB	64	0.089827061	0.89195908	-1.72089692	3.3175728
HML	64	-0.094661385	0.56376956	-1.04811821	1.3671603
Mom	63	0.010283891	0.04187761	-0.05425403	0.1606361
Cex	64	0.010317859	0.93243811	-3.14584715	3.2078224

Note: The coins in this table (Bitcoin, Ethereum, Litecoin, Xlm, and Xrb) represent the return of the coin minus the risk-free factor. While Cex represents market return minus risk-free factor. The other variables SMB, Mom, and HML are controls for analysis, however, all these variables are expressed in numbers.

Tables 3 and 4 indicate that the Bitcoin means are -1.02 and 0.01, However, this coin is highly volatile and used for speculative purposes. The expected returns from investing in Bitcoin should be higher than the returns from risk-free investments. The negative excess return could be that Investors may be willing to take more risks associated with Bitcoin for greater returns, even if it means accepting a negative risk-free rate which affects the mean of excess return negatively. Based on these tables the data does not contain outliers that could influence our Ordinary least-squared regressions because the OLS regressions in this paper did not use a portfolio but rather an independent analysis for each one.

Table 5: Correlation Matrix of Daily variables

Variables	Bitcoin	Ethereum	Litecoin	Xlm	Xrb	SMB	HML	Mom	Cex
Bitcoin	1								
Ethereum	0.031	1							
Litecoin	1.000	0.031	1						
Xlm	0.991	0.034	0.991	1					
Xrb	0.995	0.033	0.995	0.991	1				
SMB	0.043	0.042	0.043	0.103	0.061	1			
HML	0.000	-0.047	0.000	-0.020	-0.008	-0.018	1		
Mom	0.107	0.048	0.107	0.113	0.112	0.153	-0.104	1	
Cex	0.998	0.030	0.998	0.992	0.997	0.033	0.001	0.106	1

Table 6: correlation matrix of Monthly data:

Variables	Bitcoin	Ethereum	Litecoin	Xlm	Xrb	SMB	HML	Mom	Cex
Bitcoin	1								
Ethereum	0.031	1							
Litecoin	1	0.031	1						
Xlm	0.991	0.034	0.991	1					
Xrb	0.995	0.033	0.995	0.991	1				
SMB	0.043	0.042	0.043	0.103	0.061	1			
HML	0.000	-0.047	0.000	-0.020	-0.008	-0.018	1		
Mom	0.107	0.048	0.107	0.113	0.112	0.153	-0.104	1	
Cex	0.998	0.030	0.998	0.992	0.997	0.033	0.001	0.106	1

Tables 5 and 6, display the matrix correlation between the variables under the study for both daily and monthly data. From Table 6 The coefficient for XRB and Bitcoin is 0.995, XLM and Bitcoin 0.991. Both coefficients indicate a strong correlation between returns of the XLM and XRB with Bitcoin. Litecoin is highly correlated with XLM for a coefficient of 0.991 and XRB of 0.995 while XLM and XRB have a coefficient of 0.991 and approximately the same results in Table 6. These tables provide clear evidence that the cryptocurrencies correlated with each other but in our study, this would be not an issue because the paper test the anomalies based on cryptocurrency separately. The main interest of the paper analysis of the relationship between control variables which are SMB, MOM, and HML, and independent variables of

return coins. These tables show there is no correlation between variables related to our analysis, therefore, the multicollinearity test was not applied. Further, the crypto market in 2017 raised to be at the top by the end of December then after that had an enormous crash at the beginning of 2018. This market seems highly correlated and guided by the main currency which is Bitcoin. Illustrations concerning the evolvement of the returns and closing prices of all coins can be found in the Appendix (from Appendix 1-10).

4.2 Testing the hypothesis:

The results of the statistical analysis will be reported in this section and the main interpretations were based on the coefficient's sign and significance. The analysis in this paper depends on three regressions that are Capital Assets Pricing Model, Fama-French three factors, and Carhart four factors model. However, this analysis was conducted for testing the main four anomalies in the cryptocurrency market.

For the Monday effect table 7, shows the CAPM of the five crypto coins seems that the values for this variable (D) are all close to zero, indicating a weak or insignificant relationship with the cryptocurrency returns. Table 8 of Fama-French and 9 of Carhart have the same results Therefore, the conclusion for the Monday effect variable (D) there is no significant relationship between the occurrence of the Monday Effect and cryptocurrency returns. The findings suggest that the day of the week, specifically Monday, does not have a substantial impact on the returns of the analyzed cryptocurrencies. However, tables 7, 8, and 9 appeared that the regression models have high R-squared values, indicating a strong relationship between the risk factor and cryptocurrency returns. The size factor (SMB) was positively significant for all coins in Tables 8 and 9 indicating a positive relationship between size and excess returns except Bitcoin was negative. The value factor (HML) was generally small, and the XRB coefficient was statistically significant. The negative coefficient for others suggests that cryptocurrencies with higher value characteristics tend to have lower excess returns. The momentum factor (Mom) seems to have a significant negative relationship with excess returns for Ethereum, suggesting that cryptocurrencies with higher momentum tend to have lower returns. However, for the other cryptocurrencies, momentum does not appear to have a significant impact on their excess returns. Therefore the outcome is, the study failed to reject the null hypothesis and there is no evidence for the Monday effect.

Results testing of the Monday effect

Table 7: CAPM test for Monday Effect

	Rit-rf				
Variables	(Bitcoin)	(Ethereum)	(Litecoin)	(XLM)	(XRB)
Rm-rf	0.998***	0.999***	0.998***	1.000***	0.997***
	(0.001)	(0.002)	(0.001)	(0.000)	(0.002)
D	0.003	-0.008	0.002	0.000	-0.007
	(0.003)	(0.005)	(0.004)	(0.000)	(0.004)
Constant	-0.003*	0.001	-0.002	-0.000***	-0.003
	(0.002)	(0.003)	(0.002)	(0.000)	(0.003)
Observations	1,946	1,728	1,946	1,941	1,947
R2	0.997	0.992	0.996	1.000	0.993
Adjusted R2	0.997	0.992	0.996	1.000	0.993

Note: This Table reports CAPM results For the Monday effect. The dependent variable represents the excess return of coin I, the independent variables are the execs market return, and the Dummy variable of Monday effect is D. *** Significant level 1%. ** Significant level 5%. *Significant at 10% level.

Table 8 Fama-French test for Monday Effect

Variables			Rit-rf		
	(Bitcoin)	(Ethereum)	(Litecoin)	(XLM)	(XRB)
Rm-rf	0.998***	0.998***	0.998***	1.000***	0.996***
	(0.001)	(0.002)	(0.001)	(0.000)	(0.002)
SMB	-0.052***	0.154***	0.054***	0.000***	0.159***
	(0.006)	(0.012)	(0.009)	(0.000)	(0.010)
HML	-0.012	-0.015	-0.008	0.000***	-0.065***
	(0.009)	(0.016)	(0.011)	(0.000)	(0.013)
D	0.004	-0.005	0.001	0.000	-0.006
	(0.003)	(0.005)	(0.004)	(0.000)	(0.004)
Constant	-0.003	-0.001	-0.003	-0.000***	-0.005**
	(0.002)	(0.003)	(0.002)	(0.000)	(0.002)
Observations	1,946	1,728	1,946	1,941	1,946
R2	0.998	0.992	0.996	1.000	0.994
Adjusted R2	0.998	0.992	0.996	1.000	0.994

Note: this table represents the result of the Fama-French Model for the Monday effect. The dependent variable represents the excess return of coin I, the independent variables are the execs market return, and the Dummy variable of the Monday effect is D. The HML is for the value and SML is for the Size effects as controls variables. *** Significant level 1%. ** Significant level 5%. *Significant at 10% level.

Table 9: Carhart Four Factors model test for Monday Effect

	Rit-rf				
	(Bitcoin)	(Ethereum)	(Litecoin)	(XLM)	(XRB)
Rm-rf	0.998***	0.999***	0.998***	1.000***	0.996***
	(0.001)	(0.002)	(0.001)	(0.000)	(0.002)
SMB	-0.052***	0.161***	0.054***	0.000***	0.158***
	(0.007)	(0.012)	(0.009)	(0.000)	(0.010)
HML	-0.012	-0.022	-0.008	0.000***	-0.064***
	(0.009)	(0.016)	(0.011)	(0.000)	(0.013)
Mom	-0.014	-0.171***	0.002	0.000	0.023
	(0.023)	(0.045)	(0.031)	(0.000)	(0.035)
D	0.004	-0.005	0.001	0.000	-0.006
	(0.003)	(0.005)	(0.004)	(0.000)	(0.004)
Constant	-0.002	0.002	-0.003	-0.000***	-0.006**
	(0.002)	(0.003)	(0.002)	(0.000)	(0.002)
Observations	1,946	1,728	1,946	1,941	1,946
R2	0.998	0.992	0.996	1.000	0.994
Adjusted R2	0.998	0.992	0.996	1.000	0.994

Note: This table represents the result of Carhart Four Factors model testing for the Monday Effect. The dependent variable represents the excess return of coin I, the independent variables are the execs market return, and the Dummy variable of the Monday effect is D. The HML is for the value, SML is for the Size and Mom is for Momentum effects as controls variables. *** Significant level 1%. ** Significant level 5%. *Significant at 10% level.

Results testing of January effect

Based on Tables 10 11 and 12 The January effect seems to not exist for all coins except Ethereum was significantly positive, however, the coefficient for Bitcoin negative may reflect the reverse of the January effect but was still insignificant. The size factor has a significant negative impact on Bitcoin's excess returns and a positive for other coins without Litecoin. Both Bitcoin and Litecoin have a significant negative value factor. While Ethereum has a significant negative coefficient for the momentum factor and XRB positive. Thus the paper found 1 of 5 coins was significant and that not enough evidence to reject the null hypothesis.

Table 10: CAPM test for January Effect

	Rit-rf				
	(Bitcoin)	(Ethereum)	(Litecoin)	(XLM)	(XRB)
Rm-rf	0.959***	1.033***	0.990***	1.005***	1.005***
	(0.023)	(0.033)	(0.025)	(0.037)	(0.039)
Dj	-0.112	0.308***	0.027	0.058	-0.152
	(0.074)	(0.105)	(0.080)	(0.118)	(0.123)
Constant	0.011	-0.009	-0.007	-0.053	-0.003
	(0.023)	(0.032)	(0.025)	(0.036)	(0.037)
Observations	64	64	64	64	64
R2	0.966	0.941	0.962	0.923	0.919
Adjusted R2	0.965	0.939	0.961	0.921	0.916

Note: This Table reports CAPM results For the January effect. The dependent variable represents the excess return of coin I, the independent variables are the execs market return, and the Dummy variable of January effect is D. *** Significant level 1%. ** Significant level 5%. *Significant at 10% level.

Table 11: Fama-French test for January Effect

	Rit-rf				
	(Bitcoin)	(Ethereum)	(Litecoin)	(XLM)	(XRB)
Rm-rf	1.004***	0.999***	0.979***	0.978***	0.950***
	(0.015)	(0.034)	(0.027)	(0.039)	(0.033)
SMB	-0.143***	0.091**	0.022	0.084**	0.177***
	(0.016)	(0.036)	(0.028)	(0.041)	(0.035)
HML	-0.083***	-0.070	-0.092**	0.058	0.123**
	(0.024)	(0.053)	(0.041)	(0.060)	(0.052)
Dj	-0.060	0.275***	0.019	0.028	-0.216**

	(0.046)	(0.102)	(0.079)	(0.116)	(0.099)
Constant	0.010	-0.021	-0.017	-0.052	-0.0004
	(0.014)	(0.031)	(0.024)	(0.036)	(0.030)
Observations	64	64	64	64	64
R2	0.988	0.948	0.965	0.930	0.950
Adjusted R2	0.987	0.944	0.963	0.925	0.946

Note: This table represents the result of the Fama-French Model for the January Effect. The dependent variable represents the excess return of coin I, the independent variables are the execs market return, and the Dummy variable of the January effect is D. The HML is for the value and SML is for the Size effects as controls variables. *** Significant level 1%. ** Significant level 5%. *Significant at 10% level.

Table 12: Caehart test for January Effect

	Rit-rf				
	(Bitcoin)	(Ethereum)	(Litecoin)	(XLM)	(XRB)
Rm-rf	1.007***	1.006***	0.995***	0.982***	0.949***
	(0.016)	(0.034)	(0.027)	(0.040)	(0.033)
SMB	-0.135***	0.130***	0.003	0.112**	0.136***
	(0.018)	(0.038)	(0.030)	(0.045)	(0.037)
HML	-0.082***	-0.063	-0.089**	0.063	0.118**
	(0.024)	(0.051)	(0.040)	(0.060)	(0.050)
Mom	-0.418	-1.972**	0.807	-1.420	1.992**
	(0.365)	(0.775)	(0.606)	(0.915)	(0.757)
Dj	-0.082	0.182*	-0.019	-0.033	-0.151
	(0.051)	(0.108)	(0.085)	(0.128)	(0.106)
Constant	0.015	0.002	-0.026	-0.036	-0.023

	(0.015)	(0.031)	(0.024)	(0.037)	(0.031)
Observations	63	63	63	63	63
R2	0.987	0.950	0.967	0.928	0.951
Adjusted R2	0.986	0.946	0.964	0.921	0.946

Note: This table represents the result of Carhart Four Factors model testing for the January Effect. The dependent variable represents the excess return of coin I, the independent variables are the execs market return, and the Dummy variable of the January effect is D. The HML is for the value, SML is for the Size and Mom is for Momentum effects as controls variables. *** Significant level 1%. ** Significant level 5%. *Significant at 10% level.

Results testing of the Halloween effect

Tables 13,14 and 15 show that the dummy variable that represents the Halloween effect was significant negatively for Bitcoin and positive for Ethereum according to CAPM analysis in Table 13 and not for the other analysis in Tables 14 and 15 thus the evidence of existing the Halloween effect is weak. The size effect was negatively significant for Bitcoin, and positive for Ethereum, Xlm, and Xrb at a level of 1%. However, the value show effect for Bitcoin, Litecoin, and Xrb while momentum was negative for Ethereum and positive for Xrb at level 1%. The study failed to reject the null hypothesis and there is no Halloween effect in the crypto market.

Table 13: CAPM test for Halloween Effect

	Rit-rf				
	(Bitcoin)	(Ethereum)	(Litecoin)	(XLM)	(XRB)
Rm-rf	0.959***	1.027***	0.989***	1.007***	1.011***
	(0.023)	(0.034)	(0.025)	(0.037)	(0.039)
Dh	-0.090**	0.127**	-0.001	0.088	0.017
	(0.042)	(0.063)	(0.047)	(0.068)	(0.072)
Constant	0.048	-0.048	-0.004	-0.094*	-0.026
	(0.031)	(0.046)	(0.034)	(0.050)	(0.053)
Observations	64	64	64	64	64
R2	0.967	0.937	0.962	0.925	0.917
Adjusted R2	0.966	0.935	0.961	0.922	0.914

Note: This Table reports CAPM results For the Halloween effect. The dependent variable represents the excess return of coin I, the independent variables are the execs market return, and the Dummy variable of the Halloween effect is D. *** Significant level 1%. ** Significant level 5%. *Significant at 10% level.

Table 14: Fama-French model test for Halloween Effect

	Rit-rf				
	(Bitcoin)	(Ethereum)	(Litecoin)	(XLM)	(XRB)
Rm-rf	1.004***	0.993***	0.976***	0.983***	0.956***
	(0.015)	(0.036)	(0.027)	(0.039)	(0.035)
SMB	-0.140***	0.090**	0.026	0.075*	0.174***
	(0.017)	(0.039)	(0.029)	(0.042)	(0.037)
HML	-0.087***	-0.064	-0.094**	0.064	0.121**
	(0.024)	(0.056)	(0.041)	(0.060)	(0.054)
Dh	-0.037	0.083	-0.020	0.062	-0.047
	(0.028)	(0.064)	(0.048)	(0.069)	(0.062)
Constant	0.024	-0.038	-0.005	-0.081	0.004
	(0.019)	(0.045)	(0.034)	(0.049)	(0.044)
Observations	64	64	64	64	64
R2	0.988	0.943	0.965	0.931	0.946
Adjusted R2	0.987	0.939	0.963	0.926	0.942

Note: This table represents the result of the Fama-French Model for the Halloween Effect. The dependent variable represents the excess return of coin I, the independent variables are the execs market return, and the Dummy variable of the Halloween effect is D. The HML is for the value and SML is for the Size effects as controls variables. *** Significant level 1%. ** Significant level 5%. *Significant at 10% level.

Table 15 Carhart Four Factors Model test for Halloween Effect

	Rit-rf (Bitcoin)	(Ethereum)	(Litecoin)	(XLM)	(XRB)
Rm-rf	1.004***	1.010***	0.993***	0.987***	0.948***
	(0.016)	(0.035)	(0.027)	(0.041)	(0.034)
SMB	-0.134***	0.131***	0.005	0.100**	0.131***
	(0.018)	(0.039)	(0.030)	(0.046)	(0.038)
HML	-0.086***	-0.056	-0.091**	0.068	0.114**
	(0.024)	(0.052)	(0.040)	(0.060)	(0.051)
Mom	-0.322	-2.217***	0.815	-1.301	2.224***
	(0.357)	(0.767)	(0.589)	(0.888)	(0.749)
Dh	-0.040	0.060	-0.021	0.051	-0.027
	(0.028)	(0.060)	(0.046)	(0.070)	(0.059)
Constant	0.028	-0.013	-0.016	-0.065	-0.023
	(0.020)	(0.043)	(0.033)	(0.050)	(0.042)
Observations	63	63	63	63	63
R2	0.987	0.949	0.967	0.928	0.949
Adjusted R2	0.985	0.944	0.964	0.922	0.945

Note: This table represents the result of Carhart Four Factors model testing for the Halloween Effect. The dependent variable represents the excess return of coin I, the independent variables are the execs market return, and the Dummy variable of the Halloween effect is D. The HML is for the value, SML is for the Size and Mom is for Momentum effects as controls variables. *** Significant level 1%. ** Significant level 5%. *Significant at 10% level.

The result of the Second quarter analysis:

Based on Tables 16-17 and 18 the dummy variable Dq which represents the Second quarter effect was not significant in the three models thus the conclusion for this effect does not exist in the crypto market.

The size factor was negatively significant for Bitcoin and positive for other coins expected the Litecoin at a level 1%. The value factor show that both Bitcoin and Litecoin have negative significant coefficients while

positive for Xrb at level 1% Finally the momentum factor was negative for Ethereum and positive for Xrb at level 1% and not significant for other coins. Therefore, the paper failed to reject the null hypothesis and there is no evidence for the Second quarter effect.

Table 16: CAPM model test for Second Quarter Effect

	Rit-rf				
	(Bitcoin)	(Ethereum)	(Litecoin)	(XLM)	(XRB)
Rm-rf	0.965***	1.025***	0.986***	1.010***	1.009***
	(0.024)	(0.036)	(0.026)	(0.038)	(0.040)
Dq	-0.021	-0.031	0.035	-0.081	0.018
	(0.052)	(0.077)	(0.055)	(0.080)	(0.085)
Constant	0.005	0.027	-0.013	-0.027	-0.022
	(0.025)	(0.038)	(0.027)	(0.040)	(0.042)
Observations	64	64	64	64	64
R2	0.965	0.933	0.962	0.924	0.917
Adjusted R2	0.963	0.931	0.961	0.922	0.914

Note: This Table reports CAPM results For the Second Quarter effect. The dependent variable represents the excess return of coin I, the independent variables are the execs market return, and the Dummy variable of the Second Quarter effect is D. *** Significant level 1%. ** Significant level 5%. *Significant at 10% level.

Table 17: Fama-French model test For Second Quarter Effect

	Rit-rf				
	(Bitcoin)	(Ethereum)	(Litecoin)	(XLM)	(XRB)

Rm-rf	1.004***	0.989***	0.974***	0.986***	0.965***
	(0.015)	(0.036)	(0.027)	(0.038)	(0.035)
SMB	-0.149***	0.107***	0.020	0.093**	0.170***
	(0.016)	(0.038)	(0.028)	(0.040)	(0.036)
HML	-0.086***	-0.069	-0.096**	0.068	0.131**
	(0.024)	(0.056)	(0.041)	(0.060)	(0.054)
Dq	0.038	-0.049	0.047	-0.121	-0.055
	(0.032)	(0.074)	(0.054)	(0.078)	(0.071)
Constant	-0.005	0.016	-0.027	-0.019	-0.006
	(0.016)	(0.037)	(0.027)	(0.039)	(0.035)
Observations	64	64	64	64	64
R2	0.988	0.941	0.965	0.933	0.946
Adjusted R2	0.987	0.937	0.963	0.928	0.943

Note: This table represents the result of the Fama-French Model for the Second Quarter Effect. The dependent variable represents the excess return of coin I, the independent variables are the execs market return, and the Dummy variable of the Second Quarter effect is D. The HML is for the value and SML is for the Size effects as controls variables. *** Significant level 1%. ** Significant level 5%. *Significant at 10% level.

Table 18: Carhart Four Factors test For Second Quarter Effect

	Rit-rf				
	(Bitcoin)	(Ethereum)	(Litecoin)	(XLM)	(XRB)
Rm-rf	1.004***	1.008***	0.991***	0.992***	0.955***
	(0.016)	(0.035)	(0.027)	(0.040)	(0.034)
SMB	-0.143***	0.145***	-0.002	0.117***	0.130***
	(0.018)	(0.038)	(0.029)	(0.043)	(0.037)
HML	-0.086***	-0.058	-0.093**	0.073	0.122**
	(0.024)	(0.052)	(0.040)	(0.059)	(0.051)
Mom	-0.277	-2.286***	0.837	-1.353	2.262***
	(0.357)	(0.767)	(0.584)	(0.870)	(0.742)
Dq	0.039	-0.045	0.048	-0.119	-0.058
	(0.032)	(0.069)	(0.052)	(0.078)	(0.067)

Constant	-0.002	0.030	-0.040	-0.009	-0.023
	(0.016)	(0.035)	(0.027)	(0.040)	(0.034)
Observations	63	63	63	63	63
R2	0.986	0.948	0.967	0.930	0.950
Adjusted R2	0.985	0.944	0.964	0.924	0.945

Note: This table represents the result of Carhart Four Factors model testing for the Second Quarter Effect. The dependent variable represents the excess return of coin I, the independent variables are the execs market return, and the Dummy variable of the Second Quarter effect is D. The HML is for the value, SML is for the Size and Mom is for Momentum effects as controls variables. *** Significant level 1%. ** Significant level 5%. *Significant at 10% lev

5 Conclusion and discussion:

This study investigated the calendar anomalies of Monday, January, Halloween, and the second quarter's effects on the excess return of the crypto market. The test of this market was indeed based on a sample of five crypto coins (Bitcoin, Ethereum, Litecoin, Xlm, and XRB). This study aims to answer the following research question:

"To what extent do calendar anomalies exist in the cryptocurrency market?"

Using data from five crypto coins, retrieved from the coin market cap website to generate the main prices for this research, the CCI30 index was used as an indicator to market return and was obtained from CCI30.com. Moreover, this paper has used the three months United States treasury Bonds as a risk-free rate collected from Yahoo finance.com.

Over the last decades, research is still going on to determine the compass about the relationship between market return and seasonal effects. According to the literature discussed in this thesis, it is argued that the market is efficient (Efficient market theory) which means the market is efficient when the prices in the market reflect all information on it thus there is no free lunch for investors to obtain an abnormal return or any way to bit the market. Many studies have examined the efficiency of crypto markets with inconsistency in their founding. Nadarajah and Chu(2017) sum up, that a simple power of transformation does satisfy the efficiency of the market hypothesis while Baur et al (2019) found that the Mondays returns appear to be above-average returns to conclude that Bitcoin has a Day of the Weekend Effect that contradicts the efficiency of market theory. Eugene Fama (1970) described the theory of random walk, which considers that future evaluation of prices cannot be predicted depending on past prices because the prices of stocks follow the random walk and if the markets are efficient, the prices reflect all the information, therefore, using additional analysis is pointless until new information arrived. Lo and MacKinlay (2011) tested the random walk in weak form, they found that markets are not completely random and that predictable components do exist in recent stock and bond returns. While the efficiency of crypto markets with inconsistency in their founding. Nadarajah and Chu(2017) sum up, that a simple power of transformation does satisfy the efficiency of the market hypothesis. Moreover, Urquhart (2016) found that the return of Bitcoin does satisfy the efficiency. Moreover, Baur et al (2019) found that the Mondays returns appear to be above-average returns to conclude that Bitcoin has a Day of the Weekend Effect. Therefore, this thesis hypothesized that seasonal patterns influence the excess return of cryptocurrency.

The hypothesis has been tested through three models. The first model was the Capital Asset Pricing Model (CAPM) to test the relation between the risk factor and coin return and applied a dummy variable to present an anomaly under the test. The second model is the Fama-French model, this model indeed was an improvement to the CAPM model by adding control variables that were size, value, and dummy variables.

The third and last model was the Carhart four factors, this model indeed just has one more control variable that represents the momentum effect. The results did not support the hypothesis that there is a Monday effect in the crypto market. The main finding for the January effect was that Ethereum observed the January effect in the three models while for the other coins no evidence. Moreover, the results showed there was no second-quarter effect and the Halloween effect was significant in the CAPM model for Ethereum and Bitcoin But for other models was not. The relation between the excess return of crypto coin and the risk factor was positively significant in all regressions. Finally, for control variables, the results find evidence for the size effect on all coins except the Litcoin and the Bitcoin negatively significant and the momentum has been observed only in Ethereum.

The interpretation of such a result might be that such seasonal patterns appear more in the stock markets, However, after long observation and analysis of this phenomenon by investors may impact the existence of it because it was well known to everyone in the markets. The new coins in the crypto market have more clear calendar effects that would disappear after such a period, nevertheless, future studies can test and compare these patterns between new and old coins.

This study has several shortcomings and limitations, the data is still the highest challenging to investigate for patterns in cryptocurrencies. While Bitcoin may have long historical data, the other crypto coins did not which lead to insufficient finality. Furthermore, due to limited research exploring the market of cryptocurrency, it would be expected that there will be more studies in the future. May these studies will apply the same anomalies with huge datasets or may not retest the classical anomalies but could follow the trend and technology as a Google trend or could be sentiments of the investor's behavior. However, this paper applied three models in their analysis and tried to cover deep the crypto market as much as possible but that was based on just five dominant currencies. Therefore future studies may use different coins or apply more than what this paper has done. While for methods of testing the theory, the autoregressive conditional heteroscedasticity (GARCH) regression with a dummy variable is capable of capturing volatility clustering and non-normality in the prices of cryptocurrencies therefore, it would be recommended for future research in this field.

6 References:

Abu Bakar, A., Siganos, A., & Vagenas-Nanos, E. (2014). Does mood explain the Monday effect? *Journal of Forecasting*, *33*(6), 409-418.

Arendas, P., Malacka, V., & Schwarzova, M. (2018). A closer look at the Halloween effect: The case of the Dow Jones Industrial Average. International Journal of Financial Studies, 6(2), 42.

Ariel, R. A. (1987). A monthly effect in stock returns. *Journal of financial economics*, *18*(1), 161-174.

Baur, D. G., Cahill, D., Godfrey, K., & Liu, Z. F. (2019). Bitcoin time-of-day, day-of-week, and month-of-year effects on returns and trading volume. Finance Research Letters, 31, 78-92.

BC, B., Wang, W., Gurun, A., & Cready, W. (2019). Individual investors and the Monday effect. *Managerial Finance*, *45*(9), 1239-1252.

Bildik, R. (2004). Are calendar anomalies still alive?: Evidence from Istanbul Stock Exchange. Evidence from Istanbul Stock Exchange (May 27, 2004).

Bouman, S., & Jacobsen, B. (2002). The Halloween indicator, "sell in May and go away": Another puzzle. American Economic Review, 92(5), 1618-1635.

Caporale, G. M., & Plastun, A. (2019). Price overreactions in the cryptocurrency market. Journal of Economic Studies, 46(5), 1137-1155.

Caporale, G. M., Plastun, A., & Oliinyk, V. (2019). Bitcoin fluctuations and the frequency of price overreactions. *Financial Markets and Portfolio Management*, *33*, 109-131.

Carhart, M. M. (1997). On persistence in mutual fund performance. The Journal of finance, 52(1), 57-82.

Chevapatrakul, T., & Mascia, D. V. (2019). Detecting overreaction in the Bitcoin market: A quantile autoregression approach. Finance Research Letters, 30, 371-377.

Conrad, C., Custovic, A., & Ghysels, E. (2018). Long-and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis. Journal of Risk and Financial Management, 11(2), 23.

Cross, F. (1973). The behavior of stock prices on Fridays and Mondays. *Financial analysts journal*, *29*(6), 67-69.

Dichtl, H., & Drobetz, W. (2015). Sell in May and go away: still good advice for investors?. International Review of Financial Analysis, 38, 29-43.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), 383-417.

Fama, E. F. (1995). Random walks in stock market prices. Financial analysts journal, 51(1), 75-80.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. the Journal of Finance, 47(2), 427-465.

Foster, F. D., & Viswanathan, S. (1990). A theory of the interday variations in volume, variance, and trading costs in securities markets. *The Review of Financial Studies*, *3*(4), 593-624.

French, K. R. (1980). Stock returns and the weekend effect. *Journal of financial economics*, *8*(1), 55-69.

Gayaker, S., Yalcin, Y., & Berument, M. H. (2020). The day of the week effect and interest rates. *Borsa Istanbul Review*, *20*(1), 55-63.

Grobys, K., & Sapkota, N. (2019). Cryptocurrencies and momentum. *Economics Letters*, *180*, 6-10.

Hensel, C. R., & Ziemba, W. T. (1996). Investment results from exploiting turn-of-the-month effects. *Journal of Portfolio Management*, *22*(3), 17-23.

Jagannathan, R., & Wang, Z. (1996). The conditional CAPM and the cross-section of expected returns. The Journal of Finance, 51(1), 3-53.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance, 48(1), 65-91.

Kaiser, L. (2019). Seasonality in cryptocurrencies. Finance Research Letters, 31.

Kaustia, M., & Rantapuska, E. (2016). Does mood affect trading behavior? *Journal of Financial Markets*, *29*, 1-26.

Keim, D. B., & Stambaugh, R. F. (1984). A further investigation of the weekend effect in stock returns. The journal of finance, 39(3), 819-835.

Kinateder, H., & Papavassiliou, V. G. (2021). Calendar effects in bitcoin returns and volatility. *Finance Research Letters*, *38*, 101420.

Kiymaz, H., & Berument, H. (2003). The day of the week effect on stock market volatility and volume: International evidence. *Review of financial economics*, *12*(4), 363-380.

Koenker, R., & Bassett Jr, G. (1978). Regression quantiles. *Econometrica: journal of the Econometric Society*, 33-50.

Lakonishok, J., Shleifer, A., Thaler, R. H., & Vishny, R. W. (1991). Window dressing by pension fund managers.

Lakonishok, J., & Maberly, E. (1990). The weekend effect: Trading patterns of individual and institutional investors. The Journal of Finance, 45(1), 231-243.

Lloyd, R., Zhang, C., & Rydin, S. (2017). The Halloween Indicator is more a treat than a trick.

Lo, A. W., & MacKinlay, A. C. (2011). A non-random walk down Wall Street. In A Non-Random Walk Down Wall Street. Princeton University Press.

Lucey, B. M., & Zhao, S. (2008). Halloween or January? Yet another puzzle. International Review of Financial Analysis, 17(5), 1055-1069.

Ma, D., & Tanizaki, H. (2019). The day-of-the-week effect on Bitcoin return and volatility. *Research in International Business and Finance*, *49*, 127-136.

Marquering, W., Nisser, J., & Valla, T. (2006). Disappearing anomalies: a dynamic analysis of the persistence of anomalies. *Applied financial economics*, *16*(4), 291-302.

McGuinness, P. B., & Harris, R. D. (2011). Comparison of the 'turn-of-the-month' and lunar new year return effects in three Chinese markets: Hong Kong, Shanghai and Shenzhen. *Applied financial economics*, *21*(13), 917-929.

Mei Hui, P. (2019). 'Chinese New Year Effect' in BTC Market. Retrieved from https://medium.com/tech4she/chinese-new-year-effect-in-btc-market-ab4bd3136199

Nadarajah, S., & Chu, J. (2017). On the inefficiency of Bitcoin. Economics Letters, 150, 6-9.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. Decentralized business review, 21260.

Osborne, M. F. (1962). Periodic structure in the Brownian motion of stock prices. Operations Research, 10(3), 345-379.

Penman, S. H. (1987). The distribution of earnings news over time and seasonalities in aggregate stock returns. Journal of financial economics, 18(2), 199-228.

Phillip, A., Chan, J. S., & Peiris, S. (2018). A new look at cryptocurrencies. *Economics Letters*, *163*, 6-9.

Plastun, A., Drofa, A. O., & Klyushnik, T. V. (2019). The month of the year effect on the cryptocurrency market and portfolio management. European Journal of Management Issues, 27(1-2), 29-35.

Plastun, A., Sibande, X., Gupta, R., & Wohar, M. E. (2020). Historical evolution of monthly anomalies in international stock markets. *Research in International Business and Finance*, *52*, 101127.

Pontoh, S. C., & Rizkianto, E. (2020, June). Asset pricing analysis of 18 cryptocurrencies. In *23rd Asian Forum of Business Education (AFBE 2019)* (pp. 279-282). Atlantis Press.

Qadan, M., Aharon, D. Y., & Eichel, R. (2022). Seasonal and calendar effects and the price efficiency of cryptocurrencies. Finance Research Letters, 46, 102354.

Rahman, M. S. (2020). The advantages and disadvantages of using qualitative and quantitative approaches and methods in language "testing and assessment" research: A literature review.

Reinganum, M. R. (1983). The anomalous stock market behavior of small firms in January: Empirical tests for tax-loss selling effects. Journal of financial economics, 12(1), 89-104.

Reilly, F. K., & Brown, K. C. (2011). *Investment analysis and portfolio management*. Cengage Learning.

Robins, R. P., & Smith, G. P. (2016). No more weekend effect. *Critical Finance Review*, *5*(2), 417-424.

Robiyanto, R., Susanto, Y. A., & Ernayani, R. (2019). Examining the day-of-the-week-effect and the month-of-the-year-effect in the cryptocurrency market. Jurnal Keuangan dan Perbankan, 23(3), 361-375.

Rogalski, R. J. (1984). New findings regarding day-of-the-week returns over trading and non-trading periods: a note. *The Journal of Finance*, *39*(5), 1603-1614.

Rozeff, M. S., & Kinney Jr, W. R. (1976). Capital market seasonality: The case of stock returns. Journal of financial economics, 3(4), 379-402.

Selvarani, M., & Jenefa, L. (2009). Calendar anomalies in National stock exchange indices. IUP Journal of Applied Finance, 15(1), 56.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The journal of finance, 19(3), 425-442.

Shen, D., Urquhart, A., & Wang, P. (2020). A three-factor pricing model for cryptocurrencies. *Finance Research Letters*, *34*, 101248.

Stoffels, J. (2017). Asset pricing of cryptocurrencies and momentum based patterns. *Erasmus School of Economics working paper*.

Strong, N. (1992). Modeling abnormal returns: A review article. Journal of Business Finance & Accounting, 19(4), 533-553.

Urquhart, A. (2016). The inefficiency of Bitcoin. Economics Letters, 148, 80-82.

Wachtel, S. B. (1942). Certain observations on seasonal movements in stock prices. The journal of business of the University of Chicago, 15(2), 184-193.

Witte, H. D. (2010). Outliers and the Halloween effect: comment on Maberly and Pierce. Econ Journal Watch, 7(1), 91.

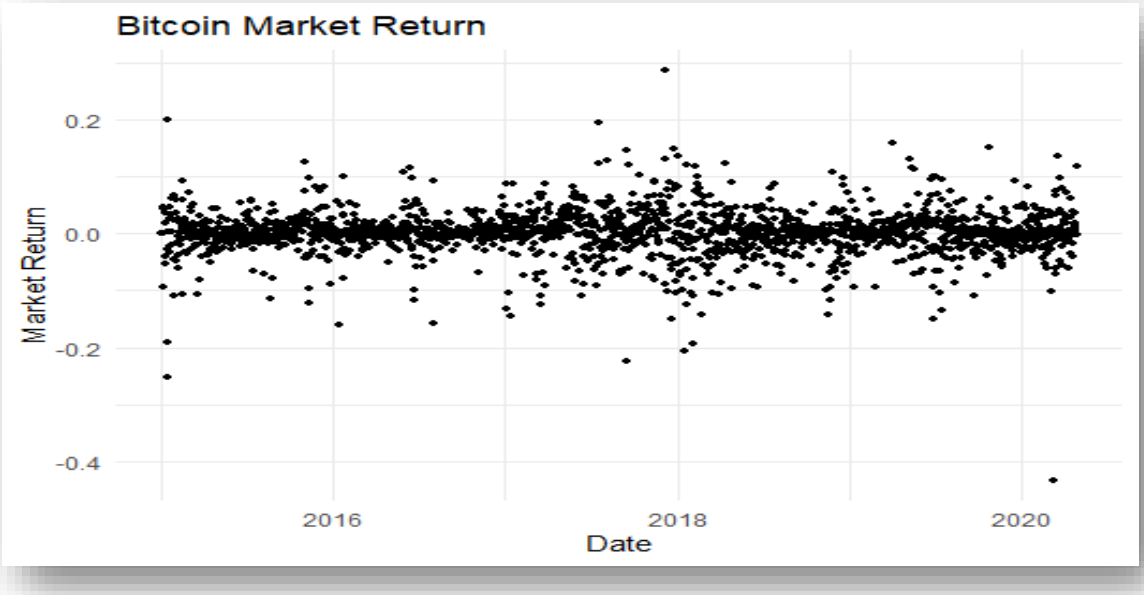
Samuelson, P.A. (1965). Proof that Properly Anticipated Prices Fluctuate Randomly, Industrial Management Review, 6.2;

Saunders, M., Lewis, P. H. I. L. I. P., & Thornhill, A. D. R. I. A. N. (2007). Research methods. *Business Students 4th edition Pearson Education Limited, England*, *6*(3), 1-268.

7 Appendix:

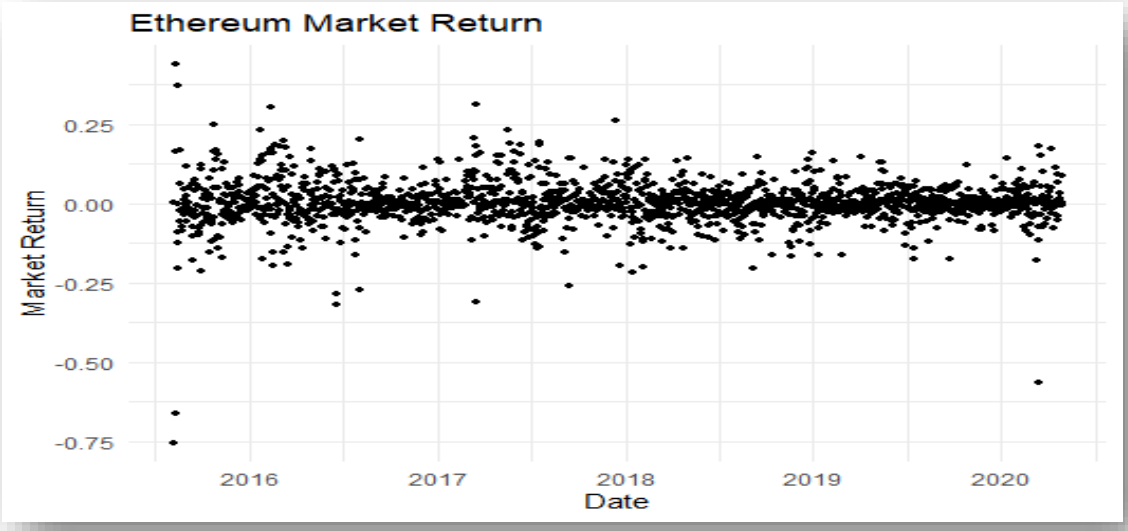
Appendix 1: Bitcoin (Bit) close price in (USD) from 01-01-2015 to 30-04-2020. Source: Author

Appendix 2: Bitcoin (Bit) return in (USD) from 01-01-2015 to 30-04-2020. Source: Author

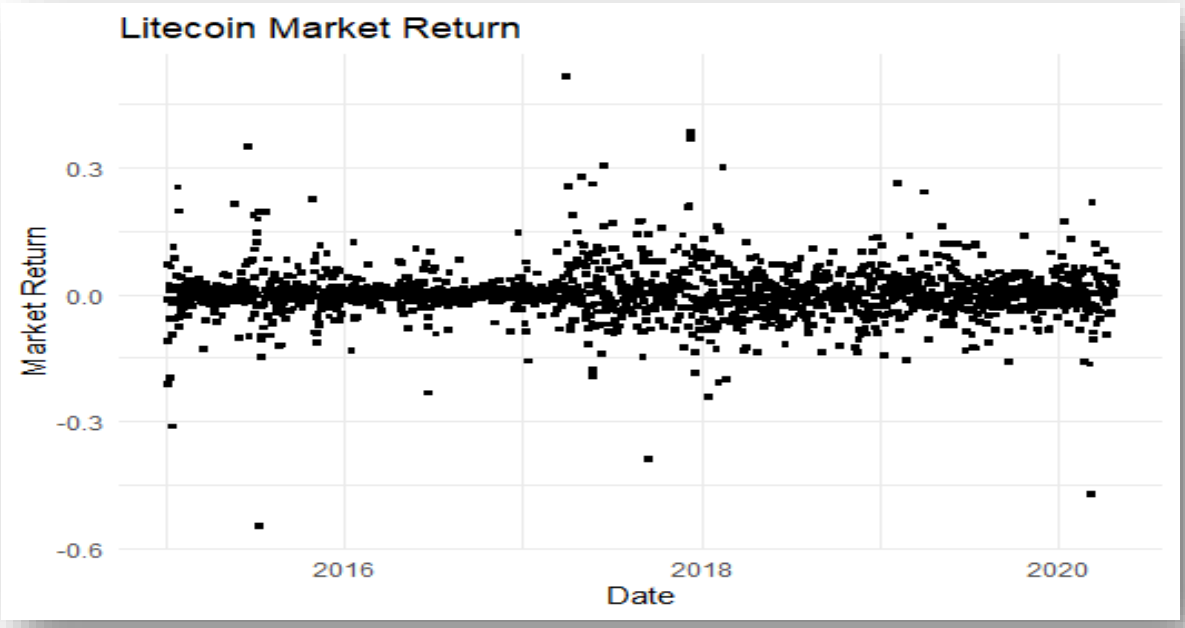


Appendix 3: Ethereum (Eth) close price in (USD) from 08-07-2015 to 30-04-2020. Source: Author

Appendix 4: Ethereum (Eth) return in (USD) from 08-07-2015 to 30-04-2020. Source: Author

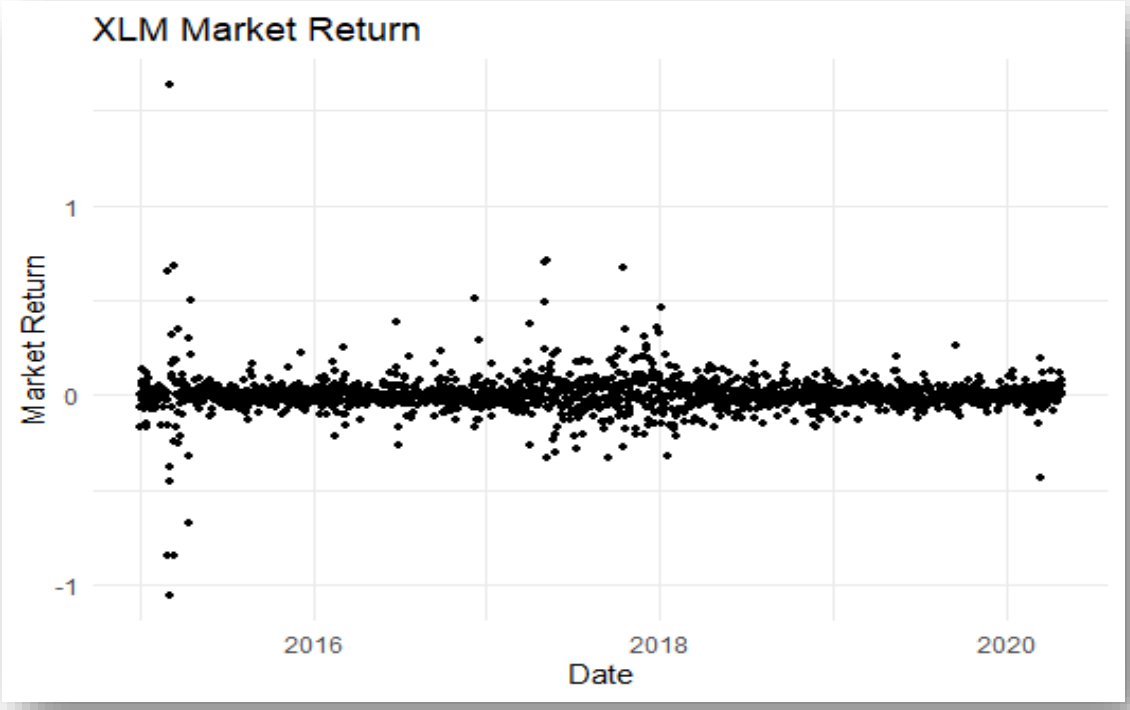


Appendix 5: Litecoin (Lit) return in (USD) from 01-01-2015 to 30-04-2020. Source: Author



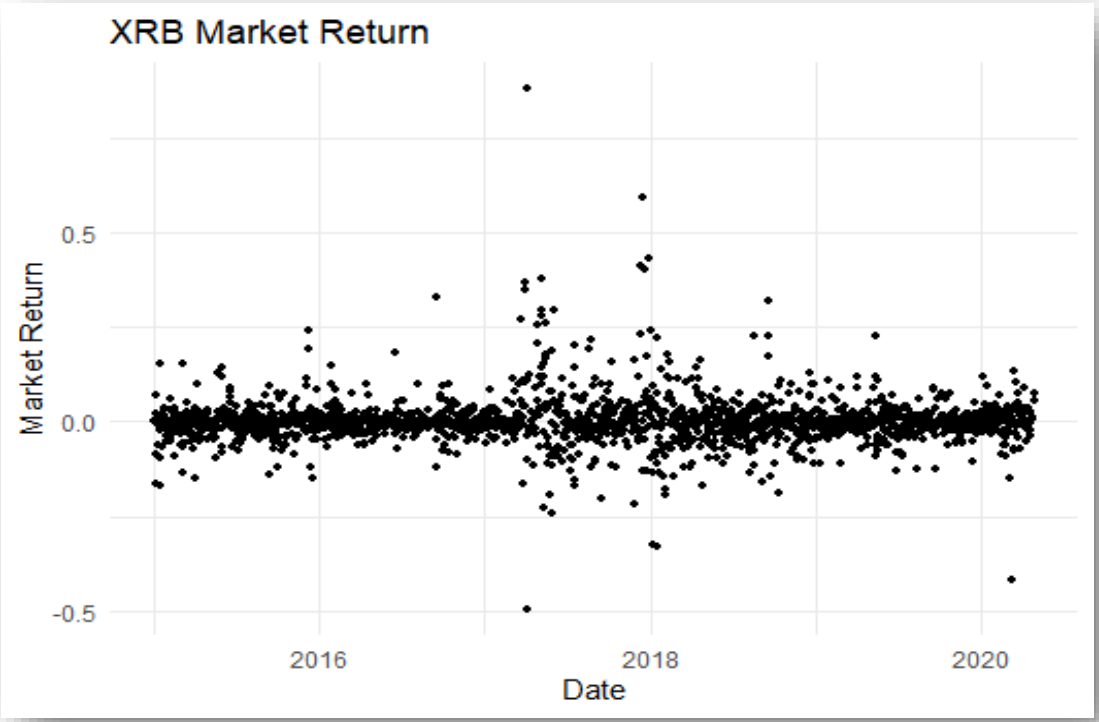
Appendix 6: Litecoin (Lit) close price in (USD) from 01-01-2015 to 30-04-2020. Source: Author

Appendix 7: Stellar (XLM) close price in (USD) from 01-01-2015 to 30-04-2020. Source: Author



Appendix 8: Stellar (XLM) return in (USD) from 01-01-2015 to 30-04-2020. Source: Author

Appendix 9: **XRB return in (USD) from 01-01-2015 to 30-04-2020. Source: Author**



Appendix 10: **XRB close price in (USD) from 01-01-2015 to 30-04-2020. Source: Author**