CALENDAR ANOMALIES ON BITCOIN RETURNS AND EFFECTS THE COVID-19 CRISIS HAD ON THEM

Lappeenranta–Lahti University of Technology LUT

School of Business and Management

Master's Programme in Strategic Finance and Analytics (MSF), Master's Thesis

2023

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Examiner(s): Post-doctoral researcher, D.Sc. (Econ. & BA), Docent, Mariia Kozlova

University Lecturer, Ph.D., Roman Stepanov

ABSTRACT

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64 pages, 5 figures and 9 tables

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Keywords: anomalies, calendar anomalies, day-of-the-week, month-of-the-year, cryptocurrencies, Bitcoin, efficient market hypothesis, Covid-19

The aim of this research is to investigate whether two certain calendar anomalies, namely, the day-of-the-week and month-of-the-year effects, are found in the returns of Bitcoin during the period spanning from October 2014 to September 2022. Additionally, the goal is to study whether Covid-19 crisis had any effect on these two calendar anomalies. To achieve this, the data was studied in two subperiods on top of the whole period: The first subperiod contained data from the period before Covid-19; and the second subperiod contained data from the period during and after the Covid-19 crisis.

There are two research questions that the study aims to answer: The first research question is, "Can the day-of-the-week and month-of-the-year effects be identified in the returns of Bitcoin?" and the second research question is, "Did the Covid-19 crisis and the economic shock it caused affect these anomalies significantly?" The research for this study was done by using linear regression on the daily returns of Bitcoin, which were transformed from the daily closing prices of Bitcoin from one of the largest crypto exchanges, CoinMarketCap. In total, there were six linear regression models built, and all models used either daily or monthly dummies.

According to the linear regression analysis, there was not enough evidence of either of the anomalies existing as all the models turned out to be insignificant. However, on single t-test levels for predictors, there were some differences between the returns on different weekdays and months, indicating some possible differences between the returns depending on the day or the month. This was not enough to claim that these anomalies can be found in Bitcoin returns. This also means that there does not seem to be a significant difference in the anomalies caused by the Covid-19 crisis.

TIIVISTELMÄ

Lappeenrannan–Lahden teknillinen yliopisto LUT

LUT-Kauppakorkeakoulu

Kauppatieteet

Ville Seppälä

Kalenterianomaliat Bitcoinin tuotoissa ja Covid-19 kriisin vaikutukset niihin

Kauppatieteiden pro gradu -tutkielma

2023

64 sivua, 5 kuvaa and 9 taulukkoa

Tarkastajat: Tutkijatohtori, D.Sc. (Econ. & BA), Dosentti, Mariia Kozlova

Yliopisto-opettaja, Ph.D, Roman Stepanov

Avainsanat: anomaliat, kalenterianomaliat, viikonpäiväanomaliat, kuukausianomaliat, kryptovaluutat, Bitcoin, tehokkaiden markettien hypoteesi, Covid-19

Tämän tutkimuksen tavoitteena on selvittää, löytyykö viikonpäivä- ja kuukausianomalioita Bitcoinin tuotoista lokakuun 2014 ja syyskuun 2022 välillä. Tämän lisäksi tavoitteena on tutkia, oliko Covid-19 kriisillä vaikutusta näihin kahteen kalenterianomaliaan. Tätä varten tietoja tutkittiin koko periodin lisäksi kahden alaperiodin osalta: Ensimmäinen alaperiodi sisälsi ajan ennen Covid-19 kriisiä; Toinen osa taas sisälsi Covid-19-kriisin ajanja sen jälkeisen ajanjakson.

Tutkimuksella pyritään vastaamaan kahteen eri tutkimuskysymykseen: Ensimmäinen tutkimuskysymys on, "Voivatko viikonpäivä- ja kuukausianomalian vaikutukset havaita Bitcoinin tuotoissa?" ja toinen tutkimuskysymys on, "Vaikuttiko Covid-19 ja sen aiheuttama talouskriisi näihin anomalioihin merkittävästi?" Tätä tutkimusta varten käytettiin lineaarista regressiota Bitcoinin päivittäisistä tuotoista, jotka muunnettiin Bitcoinin päivittäisistä päätöshinnoista yhdeltä suurimmista kryptovaluuttapörsseistä, CoinMarketCapista. Yhteensä tutkimusta varten käytettiin kuutta eri lineaarista regressiomallia, ja kaikki mallit käyttivät joko päivittäisiä tai kuukausittaisia muuttujia.

Lineaarisen regressioanalyysin tuloksien perusteella kummastakaan anomaliasta ei ollut riittävästi näyttöä, koska kaikki mallit osoittautuivat tilastollisesti merkityksettömiksi. Kuitenkin yksittäisillä ennustajamuuttujien t-testeillä oli joitakin eroja eri viikonpäivien ja kuukausien tuottojen välillä, mikä viittaa mahdollisiin eroihin tuotoissa riippuen päivästä tai kuukaudesta. Tämä ei kuitenkaan riittänyt todistamaan, että näitä anomalioita voitaisiin löytää Bitcoinin tuotoista. Tämä tarkoittaa myös, että Covid-19-kriisin vaikutus näihin anomalioihin ei näytä olevan merkittävä, koska kumpaakaan anomaliaa ei löydetty kummaltakaan alaperiodilta.

AKNOWLEDGMENTS

Time at LUT has been quite different from what I initially expected, as was the case for everyone in the past few years. I did not get to spend much of a normal student life in Lappeenranta. Instead, I spent most of my years studying remotely from some other place, be it a couple hundred kilometers away in Helsinki, or multiple thousand kilometers away during my exchange. However, the time in LUT has helped me understand that a sense of community does not necessarily require people to be physically nearby, as long as the mindsets and the values of people meet.

I would like to give special thanks to my parents, who have always supported me and believed in me, helping me through every step of my life and enabling me to be in a position where I’m able to write these finishing words for this thesis. Secondly, I’d like to thank my girlfriend, who supported me during the whole process, giving me energy and motivation to finish my final chapter in LUT. I’d also like to thank my friends, who have listened without complaints of their own to my own complaints about the thesis process. My final show of gratitude goes to the supervisor of my thesis, Mariia, who helped me push this thesis out and especially for helping me during the last couple of weeks to finalize the process in such a quick manner.

On 20th of September 2023 in Espoo

Ville Seppälä

Abbreviations

EMH	Efficient market hypothesis
DOW	Day-of-the-week
MOY	Month-of-the-year
OLS	Ordinary least squares
SAD	Seasonal affective disorder

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1 INTRODUCTION

For decades, the efficient market hypothesis, introduced by Fama in 1970, was the driving force in financial decision theory. According to it, an ideal market would be one where all the actors in the market had complete information all the time and acted rationally, using all the available information, which in return would reflect in the stock prices on the market. This, of course, would mean that no investor can outperform the markets consistently, as there can be no private information to give an edge compared to the market. According to the efficient market hypothesis, the only way to outperform the market is by luck.

However, even though the current empirical evidence from literature is somewhat mixed, it can be said that there is a wide array of studies that do not support the efficiency of markets even on the weakest form of efficiency, as they provide evidence of different anomalies continuously existing. De Bondt & Thaler (1985) found evidence in their study that markets tend to overreact to past performance and prior “losers” would consistently outperform prior “winners”.

One new asset class, of which efficiency has been an interest to researchers since it was introduced, is cryptocurrencies. The first cryptocurrency, Bitcoin, was introduced in 2008 in an article which was written by a person or a group under the alias, Satoshi Nakamoto. It was the first decentralized digital currency, designed for secure, peer-to-peer transactions using blockchain technology. Despite being a relatively new asset class, cryptocurrencies have steadily gained popularity and market share among investors. They are known to be a highly speculative and unregulated asset class, making it challenging to accurately value them due to a lack of financial fundamentals. However, their potential for short-term volatility in the market can make Bitcoin and other cryptocurrencies a very tempting investment opportunity for those seeking high-risks and high-rewards. (Yang 2019)

As cryptocurrency markets are still quite young, and the research about them is quite limited, it would be interesting to see whether the markets seem to be acting in an efficient way. One way to do this is through research into known anomalies that are known to exist in inefficient markets. For this reason, this study will be focusing on calendar anomalies to see if there is evidence of certain calendar anomalies in Bitcoin returns. In case these anomalies are found in Bitcoin returns, it would mean that the traditional thought of efficient markets would not hold, as investors could use these anomalies to predict Bitcoin prices using historical prices and benefit from them.

1.1 Purpose of the study

The purpose of this study is to explore the existence of certain calendar anomalies in Bitcoin, namely, the day-of-the-week (DOW) and month-of-the-year (MOY) effect. The secondary goal is to find whether the Covid-19 crisis had any effect on these anomalies. The research questions in the study are formulated as follows:

1. ***Can day-of-the-week and month-of-the-year effects be identified in the returns of Bitcoin?***
2. ***Did Covid-19 crisis and the economic shock it caused affect these anomalies significantly?***

The null hypothesis of the study is that the Bitcoin markets are efficient, and as such, there are no anomalies visible in the returns of Bitcoin. Because of the same expectation, it is also naturally expected that the Covid-19 crisis had no effect on these anomalies. These results could also be quite relevant for investors, because if any evidence of such anomalies is found, it would mean that it might be possible for investors to exploit them.

1.2 Limitations of the study

To start off with the limitations, the used data in the study only contains the price of only one single cryptocurrency, which is Bitcoin. While a multitude of other cryptocurrencies could also be studied, it is still reasonable to limit the study to Bitcoin, as it is by far the most traded cryptocurrency, if not counting stable coins, which are cryptocurrencies pegged to a reference asset like the US Dollar, and many cryptocurrencies are at least somewhat correlated with the price of Bitcoin. It is also the oldest cryptocurrency, and all this combined makes it quite a natural choice for it to be selected for this study.

Another limitation is the timeframe of the study. As cryptocurrencies are a relatively new asset class and only date back to 2009, there is a limited timeframe that could be studied. It is even further limited because the availability of historical Bitcoin prices is quite poor in the early years of its existence. The data for this study is gathered from CoinMarketCap, which only offers data from mid-September 2014. Taking this into account, the period chosen for this study is from October 2014 to September 2022, which leaves approximately the first five years of historical data from Bitcoin out of the study. This period is selected so there is the same amount of data for each month, so the analysis of the MOY effect is fairer.

Lastly, another limitation is that since cryptocurrency trading is unregulated, there are multiple crypto exchanges that offer trading of them, and as so, there might be single digital assets like Bitcoin trading at two or more slightly different prices simultaneously. However, this should not make a big real-world difference, as any differences would be corrected by the markets almost instantly.

1.3 Structure of the study

The study is divided into six different chapters. After the introduction, the theoretical background is explored, and the reader is introduced to topics like efficient market hypothesis, behavioral finance, cryptocurrencies, and finally, Covid-19 and the economic crisis it caused.

In the third chapter, the relevant previous studies about calendar anomalies are introduced to the reader. On top of that, theory about these anomalies is introduced for the reader using these studies combined with relevant financial literature. The fourth chapter introduces the data used in this study along with the methodology, which is used to test the hypotheses of the study.

Chapter five goes over the results of the study in detail, focusing on the different calendar anomalies on top of the possible effects the Covid-19 crisis might have had on them. Finally, chapter six presents a summary and conclusion for the study and introduces some possible further research topics that rose while writing this thesis.

2 THEORETICAL BACKGROUND

The idea of this chapter is to introduce the reader to the relevant theoretical background regarding this study. First, the efficient market hypothesis by Fama (1970) is introduced. Afterwards, the chapter introduces the reader to the behavioral finance theory, which is highly relevant to the topic of this study. The chapter also provides information about cryptocurrencies, and especially Bitcoin, before finally delving shortly into the Covid-19 crisis and the financial crisis caused by it.

2.1 Efficient market hypothesis

After Fama introduced the efficient market hypothesis (EMH) over 50 years ago in 1970, it’s been an essential component of research that concerns financial markets. According to Fama (1970), markets are effective when all available information is always fully reflected in prices, and the fluctuations in the prices are random. Fama (1970) introduced three levels of market efficiency: weak-form, semi-strong form, and strong-form. The different levels of market efficiency come down to what information is reflected in the stock prices. In a market that is weak-form efficient, only the historical prices are reflected in stock prices. Secondly, in a market that is semi-strong form efficient, all obviously publicly available information, like annual earnings, is also reflected in stock prices on top of the historical data being already reflected. Lastly, in strong-form efficient markets, all the relevant information, whether it be private or public, is reflected in stock prices. (Fama 1970; Niroomand, Metghalchi & Hajilee 2020)

According to Fender (2019), the efficient market hypothesis will hold if there are no costs of gathering information or transaction costs and all the agents in the market act rationally out of self-interest, and the agents are homogenous. One prerequisite for the EMH to hold is that the stock prices move unpredictably and randomly. This so-called random walk process ensures that it’s impossible to predict the future prices using only public information. For calendar anomalies to be present in the Bitcoin markets, it would mean that this random walk cannot exist simultaneously in the Bitcoin markets. However, this randomness in the price changes should not be confused with irrationality in the level of the prices. A random walk is the natural consequence of rational investors trying to react to new information, which itself is random. In efficient markets, new information is the only reason for rational change in the price level. This means that a random walk is a result of prices that always reflect all information available at the current time. (Bodie, Kane & Marcus 2014, 350-351)

Over the last decades, there has been a wide array of research on the accuracy of EMH. Research about the weak-form efficiency has been the most comprehensive out of all three forms, and mostly the results seem to support the theory regarding markets being weak-form efficient. Still, there exists research with differing results. In support of the efficiency of markets, Kawakatsu and Morey (1999) found in their study that emerging stock markets like Asia and Latin America were both weak-form efficient. Additionally, Hudson, Dempsey, and Keasey (1996) write in their article that the results of their research provide evidence to support the notion of markets being weak-form efficient, at least in the UK.

However, there has also been criticism against EMH, and some studies have rejected even the simplest weak-form efficiency completely. Al-Loughani and Chappell (1997) claim that British stock markets don't seem to be weak-form efficient as they do not follow the random walk. This differs drastically from the study of Hudson et al. (1996), which were published just a year before the study of Al-Loughani and Chappell. Even though the efficient market hypothesis is over half a century old, it is still being actively studied and discussed. There are those who completely dismiss the efficient market hypothesis and claim that markets don't follow even the simplest weak-form efficiency. Even though it has its critics, EMH still remains as one of the most important building blocks of modern financial theory.

2.2 Behavioral finance

According to Barberis & Thaler (2002), the problems in traditional finance theory stem from trying to understand financial markets using rational agents in the models. According to them, traditional finance assumes that these rational agents update their beliefs correctly once they receive new information, and the agents also make normatively acceptable choices with this information. Barberis & Thaler (2002) describe that the idea behind behavioral finance is the argument that some phenomena in the world of finance can be better understood using models in which at least some of the agents act in a way that is not fully rational. According to Birnberg (2012), behavioral research aims to study the way individuals make decisions and the way those choices influence other individuals, markets, or organizations.

So, behavioral finance stems from the idea that not all agents act rationally 100% of the time, and one of the earlier research papers delving into the effects of risk on decision-making was written by Kahneman and Tversky (1979). In the paper, they introduced the so-called "prospect theory," which led to a rising interest in behavioral finance. According to their paper, utility theory, which states that the value function of individuals is concave for both gains and losses, is partly incorrect as the prospect theory states it is concave for gains, but for losses, it can also be convex. In Kahneman and Tversky paper published in 1992, which is a continuation of this theory, they introduced the fourfold structure of risk attitudes in decision-making. In the paper they claim that individuals tend to exhibit risk aversion for gains and risk-seeking in high-probability situations. On the contrary, individuals tend to exhibit risk-seeking for gains and risk aversion for losses of low probability.

Ritter (2003) describes behavioral finance as a study of financial markets using models that are less narrow than the utility theory and arbitrage assumptions. He describes behavioral finance as being composed of two fundamental components: cognitive psychology and the limits to arbitrage. Limits to arbitrage argues that undoing the disruptions caused by less rational traders can pose difficulties for the rational ones, according to Barberis and Thaler (2002). They also describe cognitive psychology as a study focusing on cataloging the kinds of deviations from rationality which irrational traders might be expected to exhibit.

2.2.1 Cognitive Biases

Behavioral finance is a study that combines psychology, sociology, and finance, according to Ricciardi & Simon (2000). Cognitive biases fall mostly under the category of psychology and have been studied exclusively regarding trading, and this has led to conclusions that there are some established biases that seem to be persistent for a large percentage of traders. In this subchapter, some of these biases will be introduced.

Ritter (2003) describes one cognitive bias as heuristics, or so-called rule of thumb. When an investor is faced with N number of choices on how to divide their investments, a large percentage tends to allocate the investments using the 1/N rule. According to Ritter (2003), this rule might lead to biases on allocations of investments, especially during change periods in the market. In their study, Benartzi and Thaler (2001) find proof that many people seem to follow the 1/N rule to ease them navigate the complex task of selecting a portfolio for their retirement funds. According to them, the use of heuristics in determining a portfolio doesn't automatically make a portfolio unreasonable, but it doesn't assure in a sufficient way that the decision-making regarding the portfolio will be coherent and sensible.

Overconfidence is the second cognitive bias that is worth introducing. It is especially interesting, as Barber and Odean (2001) claim in their study that overconfident investors tend to trade too much and that men are much more prone to overconfidence than women. Hasso, Pelster, and Breitayer (2019) write in their study that men are more likely to engage in cryptocurrency trading and, additionally, they're more likely to trade them more actively and hold positions shorter than women. According to Ritter (2003), overconfidence in trading might manifest itself in a multitude of different ways, one being insufficient diversification.

According to Hirshleifer (2001), the disposition effect refers to people's tendency to avoid realizing losses and end up holding investments that have declined in value, and instead, investors are more likely to sell their "winner" investments. Avoiding realizing losses may help investors sidetrack themselves from the unpleasant feelings that come from observation of losses. This goes against traditional financial theory, according to Shefrin and Statman (1985), who claim that a rational investor should hold on to the winners on their portfolio to maximize potential gains and sell losers so further losses can be avoided. However, in the real world, investors tend to behave in the opposite way, as they do not feel comfortable realizing their losses.

Lastly, another cognitive bias related to investing is representativeness. Ritter (2003) claims that investors tend to overestimate the importance of recent experience and, for example, when equity returns have been higher than normal for some time, investors begin to believe that high returns are the new norm instead of it being just a limited period of higher returns. Hirshleifer (2001) writes in his study that people, in general, tend to rely too weightily on small sample sizes while simultaneously rejecting the importance of large sample sizes.

2.2.2 The limits to arbitrage

Ritter (2003) describes misevaluations of financial assets as a common occurrence but simultaneously admits that it’s not an easy feat to reliably profit from those misevaluations. He recognizes two types of misevaluations: First, the recurrent or arbitrageable misevaluations, and secondly, misevaluations that are, by nature, non-repeating and long-term. Out of these two types of arbitrages, only the first ones are the type of misevaluations that investors could theoretically reliably make money from, according to Ritter. This is because for the second type, it is impossible to identify the peaks in real-time until after they’ve passed. Shleifer and Vishny (1997) argue that textbook arbitrage, in which an investor would not need any capital and would not entail any risk, is not a realistic description of arbitrage trades. They argue that even the simplest real-world arbitrages are more complex than the most complicated textbook definitions of arbitrages.

According to Shleifer and Vishny (1997), their study describes real-world markets where specialized arbitrageurs, like certain hedge funds, use the capital of outside investors, and other investors use the ability and resources of these arbitrageurs to discover profitable investment strategies. Their study shows that some arbitrages, in certain cases, may not be completely effective in bringing security prices back to their fundamental values, especially since many professional arbitragers might avoid volatile arbitrage positions. Lam and Wei (2011) claim in their study that due to real-world arbitrages being risky and costly, the correction of mispricing will take longer than in the theoretical world where arbitrages would be able to be exploited without any risk or cost.

2.3 Cryptocurrency and blockchain

When the first cryptocurrency, Bitcoin, was introduced back in 2009, it came along with a completely new technology called blockchain, on which it relies. Blockchain in cryptocurrencies is used to secure transactions. When both were first introduced, blockchain technology was overshadowed by Bitcoin itself, according to Ali, Ally, Clutterbuck, and Dwivedi (2020). The real use cases for cryptocurrencies are discussed a lot, but according to Sauer (2016), cryptocurrencies are mainly a means of exchange.

For others, it might also be an interesting way to link virtual life with the real world, and for other people, cryptocurrencies represent speculative investment tools that are aiming for the highest possible returns. The first application of blockchain was to serve as a distributed ledger so each Bitcoin transaction could be tracked, but after its emergence, a lot of different real-world use cases have been identified, and it's becoming one of the core technologies in the financial technology family. (Du, Pan, Dorothy, Leidner & Yinga 2019; Ølnes, Ubacht, & Janssen 2017)

Blockchain technology allows cryptocurrencies to work in a decentralized manner, where transactions are secured on a peer-to-peer network, which means that there's no need for a third centralized party to secure and manage transactions. Instead, transfers occur directly between users, almost in real-time, independent of location and time. Since there is no centralized authority for cryptocurrencies, the value of them relies completely on supply and demand. (Nakamoto 2008; Bollen 2013)

2.3.1 Blockchain as technology

Iansiti and Lakhani (2017) describe blockchain as "an open, distributed ledger that can record transactions between two parties efficiently and in a verifiable and permanent way." Blockchain is a chain of data blocks, which get info added to them during each new transaction, and each block has four components. The main component records the most crucial information of the transaction. In the case of payments, this would include the payer's ID, the receiver's ID, and the transaction amount. The hash function takes this information and returns a hash number, which can be used to validate the transaction because each transaction record modification leads to a different hash number. The hash number also helps in the formation of the actual chain part of blockchain, since each block contains the preceding block's hash number, which is also presented on the simplified example of blockchain in Figure 1. (Du et al. 2019; Nofer, Gomber, Hinz & Schiereck 2017)

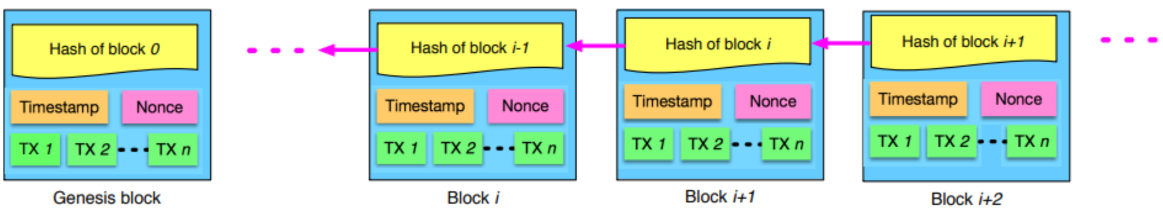

Figure 1. Blockchain example (Zheng et al. 2018, 355).

Blockchain's use cases nowadays are not limited to just cryptocurrencies. According to Zheng, Xie, Dai, & Wang (2018), blockchain technology is used in a multitude of fields, and examples of these are finance, security and privacy, public and social services, and the internet of things. When focusing on the financial field, Peters, Panayi, and Chapelle (2015) discuss in their paper that blockchain, as a technology, would have the potential to disrupt the whole world of banking. Some of the possible applications in banking would be the clearing and settlement of financial assets. On top of having the potential to make changes in traditional banking, blockchain technology also creates opportunities for a peer-to-peer financial market. Noyes (2016) explored ways of combining peer-to-peer and multiparty computation protocols to create a peer-to-peer financial multiparty computation market, which would allow offloading the computational tasks to a wide network of anonymous peer-processors instead of a centralized entity. Lastly, Pilkington (2016) provided another use case for blockchain in his paper, in which it was used in risk management. According to him, in the modern investment environment, securities are often maintained through a series of custodial entities. Since there's a risk associated with any of these entities failing, blockchain technology offers an alternative solution: it allows for quicker decision-making regarding investments and collaterals, bypassing the lengthy chain of custodial entities.

2.3.2 Bitcoin

Böhme, Christin, Edelman, & Moore (2015, 213) describe Bitcoin as "an online communication protocol that facilitates the use of a virtual currency, including electronic payments." Bitcoin was first introduced in 2009 by an anonymous entity which used the name Satoshi Nakamoto. The identity of the original group or person behind the creation of Bitcoin remains unknown to this day. Nakamoto (2008) describes the technology as a pure peer-to-peer version of electronic cash that allows online payments to be sent directly without interference or aid from any financial institution.

The original article delves into the challenges of so-called traditional digital money and suggests a system for electronic transactions which would eliminate the requirement of any trust between its users. One major flaw of traditional digital money is described as the necessity for financial institutions to validate electronic payments. While traditional digital money has its merits in ensuring strong ownership, it cannot prevent double spending the digital money without the involvement of financial institutions. To address this issue, Nakamoto introduced a peer-to-peer system that uses a public transaction history to verify the authenticity of a payment, eliminating the need for financial institutions acting as a middleman. (Nakamoto, 2008; Böhme et al. 2015)

The premise behind Bitcoin is a completely anonymous transaction chain, meaning the buyer and seller in the transaction cannot identify each other just by the information of the transaction. Even though the parties in a transaction do not know each other, each transaction is visible to everyone on the network in a sort of a ledger as public information. This means the origin of every individual Bitcoin can be traced, and intermediaries through which it ended up in the current digital wallet can be identified. (Dion, 2013) This idea of an anonymous transaction has been discussed long before the rise of Bitcoin and other cryptocurrencies. For example, Milton Friedman talked about the idea of electronic currency, which would be decentralized, and the transactions would be anonymous in a way that no party of the transaction would know each other in an interview as early as 1999 (Hanke, 2014).

One subject of debate after the rise of Bitcoin and other cryptocurrencies has been whether they should be classified as currencies or not. Yermack (2015) argues in his early study about the topic that Bitcoin does not meet the qualifications to be classified as money. This is mainly because it is an unstable measure and store of value according to his article. However, other research papers have argued the opposite, and for example, Hazlett & Luther (2020) argue that Bitcoin and other cryptocurrencies should be classified as money as they fit the definition of money (i.e., a commonly-accepted medium of exchange), which according to them is proved by the large demand and routine use as a medium of exchange in digital transactions, which makes Bitcoin worthy of the label of money. The European Central Bank (2018) has also weighed in on the classification of cryptocurrencies, and according to them, Bitcoin and other cryptocurrencies should not be classified as money as they aren't widely accepted, their value is highly volatile, and no official centralized entity oversees or issues them. Consequently, even stablecoins, which are cryptocurrencies that are tied to other currencies such as USD or EUR to minimize the volatility in price, should not be considered currencies and instead, Bitcoin and other cryptocurrencies are categorized as a speculative asset (European Central Bank, 2018; Grobys, Junttila, Kolari, & Sapkota, 2021). While the debate whether cryptocurrencies should be classified as money continues, one thing that has been pivotal in studies regarding it is the acknowledgment that Bitcoin is challenging to fit within the traditionally defined boundaries of finance due to its unique nature.

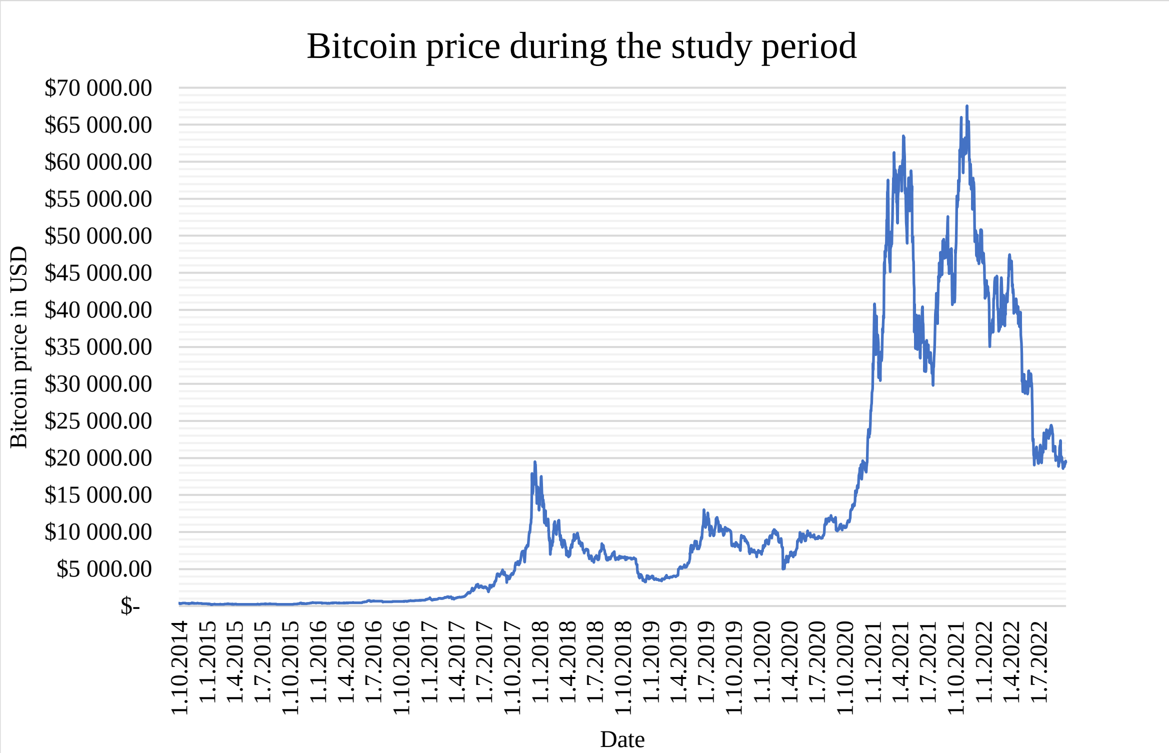

Figure 2. Bitcoin USD price during the study period

Figure 2 shows the price movements of Bitcoin during the study period. Especially interesting is that, sometime after the COVID-19 crisis started, there was a huge rise in the value of Bitcoin, which was followed by a large drop a couple of years later, at the end of the study period. The high volatility of Bitcoin is also quite well represented just by this figure, but it will be explored more in the coming chapters.

The large volatility of Bitcoin leads to a situation where it is difficult to be used as a medium of exchange, because it would not be convenient to display any prices of items in Bitcoin. The value of one Bitcoin could drastically change just hours or minutes after the price was originally set, meaning that the value of the item compared to fiat money would drastically change due to the changes in Bitcoin price (Segendorf, 2014). This high volatility in price also makes Bitcoin an unsafe medium to store value, but it might possibly also give it a feature as a great, although risky, short-term and speculative investment according to Arias and Shin (2013). Segendorf (2014) claims that one of the main reasons for the high volatility in Bitcoin price is the relatively small user base compared to other currencies. However, the user base has significantly grown in the past 10 years, while the volatility still has shown to stay high.

2.4 COVID-19

Covid-19 is an infectious disease caused by the SARS-CoV-2 virus. The World Health Organization indicates that the majority of people infected show mild to moderate respiratory symptoms and can recuperate without intensive care. However, older individuals, or those with pre-existing health issues such as heart diseases, diabetes, or cancer, are at higher risk for severe complications from Covid-19. It's still essential to note that people of all ages, regardless of their health status, can exhibit extreme respiratory symptoms and even death. (WHO 2020a)

On December 31, 2019, WHO's office in China was notified of cases of "viral pneumonia" in the city of Wuhan. That same day, in the same city, WHO's Epidemic Intelligence from Open Sources identified and reported a cluster of pneumonia cases, which were caused by an unknown virus. Ten days later, on January 10th, WHO announced that these cases were caused by a new coronavirus, marking the onset of the outbreak. The first case outside of China was reported on January 13th in Thailand, and by February 11th, WHO officially named the virus Covid-19. The rise in case numbers accelerated quickly: 100,000 cases were reported by March 7th, 2020, and in under a month from that, the number of cases exceeded a million by April 4th. Covid-19 was officially declared a pandemic by WHO on March 13th. (WHO 2023b)

According to He, Sun, Zhang, and Li (2020), the effect of Covid-19 on stock markets could be seen in China already at the start of January 2020. In China, the biggest initial negative impact was on sectors such as travel and beverage industries, while sectors like medicine manufacturing and IT seemed to benefit from the initial shock (Al-Awadhi, Alsaifi, Al-Awadhi, and Alhammadi 2020). Meanwhile, the effect on US markets came later, and the real crash of stock markets in the US was in March 2020, according to Mazur, Dang, and Vega (2021), as the virus was introduced to the US later. However, just like in China, in the US, the effects were also tied tightly to sectors. Mazur et al. (2021) demonstrated in their study that sectors like healthcare, food, IT, and natural gas performed abnormally well during the initial crash, while other sectors like travel, real estate, and crude petroleum sectors plummeted.

3 Calendar anomalies

For decades, the EMH of Fama (1970) has been one of the driving forces in financial decision theory. According to EMH, a strong-form efficient market would be one where all the actors in the market had complete information all the time and acted rationally using all this information, which in return would fully reflect in the stock prices on the market. This situation would mean that no investor can consistently outperform the markets, as there can be no private information to give an edge compared to the market. However, the efficiency of the markets has been challenged in a multitude of studies, and many studies have found empirical evidence of different anomalies continuously existing, which underlines doubts about the efficiency of the markets.

According to Frankfurter and Mcgoun (2001), anomalies are “an irregularity, a deviation from the common or natural order, or an exceptional condition.”. Anomalies can be related to firm characteristics, fundamentals, or even time. In this thesis, the focus will be on the anomalies related to time, which are called calendar anomalies or calendar effects. These calendar anomalies imply that market returns are systematically either lower or higher upon a specific time, day, month, or some other period. The study regarding calendar anomalies has been comprehensive, as they were first reported over 80 years ago by Wachtel (1942) in his study. But, as Bitcoin and cryptocurrencies overall are a relatively young asset class, there is still room for more research regarding the existence of these anomalies in the world of cryptocurrencies.

3.1 Monday effect and day-of-the-week effect

One of the most studied calendar anomalies is the Monday effect, and it refers to situations where Mondays consistently offer lower returns in the market when compared to other days returns. In addition to the Monday effect, other DOW effects have been studied, and it can be used to describe a wider array of anomalies where certain days of the week produce higher returns on a constant basis, while others produce constantly lower returns. One of the first mentions of consistently lower returns on Monday was made in an article by Cross (1973) in which he found evidence that in the US stock markets, Fridays consistently have higher returns than other days, while Mondays, oppositely, tend to consistently have lower returns. Another early study about the Monday effect was published by French in 1980, in which he presented evidence that not only were the stock returns consistently lower for Mondays during the study period from 1953 to 1977 in the US markets, but also, in cases where the market open would fall on a different day from Monday due to holidays, only on Tuesday openings, the returns on stock market were consistently lower. If the market opening fell on any day other than a Monday or Tuesday, the stock returns weren't significantly different from the returns on the US stock market on other days. French (1980) argued that this shows proof that the lower returns on stock markets were not caused by the general ‘closed market’ effect but were instead caused by the effect of the weekend and starting a new week. This is extremely important for the Monday effect to also exist in the world of cryptocurrencies because the market for them does not close over the weekend or any other period, as it is an unregulated market with no centralized trading place. Later, Keim and Barmstaugh (1984) would confirm the results of French of the consistently lower returns on Mondays on the sample S&P 500 index using an extended period by adding more data compared to French’s original study. Their research covered the time between the years 1928 and 1982. Gibbons and Hess (1981) also studied weekday anomalies on the US markets, and their study covered the years between 1962 and 1978. They also found evidence of consistently lower returns on Mondays on the S&P 500 index, while simultaneously, Wednesday and Friday seemed to produce significantly higher returns than on average.

The effects have also been studied on other markets, and Jaffe and Westerfield’s (1985) study on the DOW effect included the markets of Australia, Canada, Japan, and the UK, on top of the US market. Using data from the period from 1950 to 1983, they observed distinct differences in the daily returns between the countries. For instance, Mondays typically yielded negative returns in the US, UK, and Canada. Meanwhile, in Japan and Australia, the lowest returns were typically seen on Tuesdays instead of Mondays. Condoyanni, O’Hanlon, and Ward (1987) also analyzed stock exchanges from several countries, including Australia, Canada, France, Japan, Singapore, and the US, between 1969 and 1984. Their findings showed a distinct Monday effect, particularly in the US markets. The Canadian stock exchange presented negative returns, not just on Mondays, but also on Tuesdays too. The trend of higher negative returns on Tuesdays instead of Mondays also appeared in Australia, France, Japan, and Singapore, meaning that the results of Condoyanni et al. (1987) aligned with the results of Jaffe and Westerfield (1985).

On some markets, the evidence points to completely different DOW effects than the traditional Monday effect. Selvarani and Jenefan (2009), who claim that calendar anomalies are among the most recognized instances of market inefficiency, focused on the Indian stock markets. In their study, they observed that five out of the included six indices on the Indian stock exchange produced results of significantly higher returns on Thursdays when compared to average. On the other hand, the returns of those indices were significantly lower on Tuesdays between their study period of 2002 and 2007. Only the one remaining index had the highest returns occurring on Friday, while the lowest returns occurred on Monday. This evidence challenges the traditional understanding of the DOW effect as the traditional view is that the lowest returns would be on Mondays and highest on Fridays, which did not seem to be the case on most indices on Indian markets. Another study by Raj and Kumari (2006), which focused on the DOW effect on Indian markets also supports this view. The study used data of different Bombay stock exchange indices during a period from 1987 to 1998. Raj and Kumari couldn't find evidence of the traditional Monday effect on either index, and instead of consistently lower profits on Monday, they found evidence of consistently higher profits on Mondays when compared to other days returns. These two studies combined imply that on Indian stock markets, the traditional Monday effect does not hold, but instead, other DOW effects exist. Raj and Kumari (2006) offered a possible explanation in which they thought that the reason for this lies in the unique way the Indian stock exchange was constructed, where the trades had a 14-day settlement period until the year 1996. These settlement periods would end on Fridays and start on Mondays, meaning that low closing prices at the end of the settlement period on Fridays, coupled with high opening prices at the start of the settlement period on Mondays, would lead to high Monday returns when comparing to other days. However, this would not explain why Selvarani and Jenefan's (2009) results would still be inconsistent with the traditional Monday effect as the study focused on period after change to this 14-day settlement period.

In addition to differences in the prevalence of the Monday effect and other DOW effects between different countries, differences in the prevalence of these calendar effects have also been detected between firms with differing fundamentals. Athanassakos and Robinson (1994) found that for large companies, stock returns typically were negative on Mondays, while for smaller companies, stock returns were typically lowest on Tuesdays. They speculated that this might be due to a delay for smaller companies, where adverse information takes more time to reflect on their stock values. Athanassakos and Robinson

(1994) claim that since smaller firms' stocks are traded far less frequently than those of larger firms, changes in average returns tend to take longer to manifest compared to the stocks of big firms, which are more actively traded. Choy and O'Hanlon (1989) also found in their study that in the UK, the DOW effect is more likely to be present for large companies with frequently traded stocks than for smaller firms' less traded stocks.

There are also some studies where the DOW effect seemed to have disappeared over time. Connolly (1989) speculated that the anomalies noted in some research might be due to the methodologies and testing methods employed. In his own study, he found that the DOW effect vanished after 1975 in the US markets, where he studied the effect using three different major indices. Maheran and Naziman (2010) also found that in the Malaysian stock market, the DOW effect disappeared after the Asian financial crisis. In their study, they considered the effects of the financial crisis by dividing the data into two sub-periods. The first period encompassed the years during the financial crisis from 1999 to 2002, and the second sub-period covered the post-crisis years from 2003 to 2006. When analyzing the entire period, they observed the occurrence of the traditional Monday effect, with average returns on Mondays being significantly lower than on Fridays. However, when the data was split into the two sub-periods, the significant differences disappeared completely during the second period, meaning there was no longer enough evidence of any DOW effect. Bassiouny, Kiryakos, and Tooma (2023) studied the calendar anomalies over an extensive period spanning multiple decades, with the exact years depending on the available data for each market in their study. They based their study on adaptive market hypothesis, which according to Bassiouny et al. (2023) utilizes principles from evolutionary biology. This approach provides a fresh perspective on financial markets. It offers a novel framework to elucidate the presence of calendar irregularities and suggests a dynamic, non-binary version of market efficiency, presenting an alternative to the EMH. In their study, they found that calendar effects typically emerged on different trading days within the sample and then faded as time progressed. They also found that the Monday effect reappeared across most markets in their study in the period overlapping the COVID-19 outbreak and disappeared as the initial shock caused by the start of the crisis was over. Both studies seem to have implications that crisis might affect the appearance of the Monday and other DOW effects. Bassiouny et al. (2023) speculated that one reason for the initial reappearing of these anomalies was caused by markets becoming less efficient during the initial impact of Covid-19, which caused the largest impact on stock markets. They also speculated that as the time went by, the markets again became gradually more efficient as the initial shock was over. This is particularly interesting regarding the second research question of this thesis.

3.2 January effect and month-of-the-year effect

Another calendar anomaly explored in this thesis is the MOY effect. Ever since the boom of anomaly research in the 70s and 80s, monthly return differences have been well-studied, especially in the traditional stock markets. Among all calendar anomalies, monthly variations in returns are particularly captivating for investors since they can benefit from them without resorting to day trading, which often leads to higher overall fees than relatively long-term holding of investments. The most widely recognized pattern in the monthly returns is December's negative returns followed by January's positive returns, which has been named the January effect. So, in contrast to the Monday effect, the returns are typically higher in the month after which the anomaly is named. One of the first studies written about the January effect was published by Rozeff and Kinney as early as 1976. They analyzed the NYSE index during a period ranging from 1904 to 1974, and the index showed an average January return of 3.48 percent, compared to 0.42 percent for the other months on average. More proof of the existence of the January effect in the US markets was provided in a study written by Mehdian and Perry in 2002. They analyzed data from 1964 to 1998, and their research included three major US indices: Dow Jones Composite, NYSE Composite, and S&P 500. Their paper provided evidence of the traditional MOY effect in all the above indices from the start of the study period until 1987. However, after 1987, while January returns remained positive, they lacked statistical significance, meaning that, like in the case of the Monday effect, it seems like this anomaly also might disappear during some periods, either permanently or temporarily.

In studies focusing on other parts of the world, Tonchev and Kim (2004) explored monthly variations in the returns of stock markets in the Czech Republic, Slovakia, and Slovenia between 1999 and 2003. Their findings highlighted small but significant monthly differences in the first of the three, where January and May had the largest returns and June the lowest one, with all these being significant differences. In the latter two markets, however, they did not find any substantial evidence of the January effect or any other MOY effect. Additionally, Ho (1990) examined ten different Asian Pacific stock markets between the years 1975 and 1987. Out of the ten markets, there was a significant noticeable January effect in seven out of the ten markets during the period. However, there was no such significant effect noticeable for the markets of Australia, New Zealand, and Thailand. Both of these studies seem to suggest that some markets might be more prone to having a significant MOY effect than others. However, neither of the studies provided any possible reasons for this difference between different markets.

One possible explanation given for the January effect is that investors would realize tax benefits by selling off their loss-making investments towards the end of the year in December. Reinganum and Shapiro (1987) claim that in the UK, the MOY effect did not exist before the year 1965, which is a year when the capital gains tax was introduced in the UK. According to their study, the MOY effect emerged on the market after the introduction of capital taxes, and significantly high returns could be seen both for January and April after 1965, which would seem to support the notion of the effect being caused by investor behavior aiming to maximize tax benefits. However, as British people close their tax year at the start of April, and most corporations in the UK close their tax year at the end of December, Reinganum and Shapiro (1987) write that only positive returns in April can be fully explained by the behavior of people trying to maximize tax benefits. Meanwhile, the January effect in the UK cannot be attributed to this phenomenon, but instead, according to them, one possible explanation is that it is caused by the behavior of corporations instead of investors. Fountas and Segredakis (2002) studied the January effect on multiple emerging markets including South Korea, Argentina, India, Mexico, and many others. They present evidence of monthly seasonality in stock returns but fail to present evidence of the January effect and write that the results of their study do not support the hypothesis of tax-loss selling in most of the markets they studied. One other possible reason for the existence of the January effect is highlighted by Hertzel, Lemmon, Linck, and Rees (2002) in their study. They claim that it is caused by institutional and individual investors often displaying an overly positive view of their chances to replicate past success, especially in times when market sentiment remains high. This overconfidence might be linked to the observation that many investors reassess their portfolio distribution in January, which might be a key factor causing this anomaly according to them.

3.3 Previous evidence of day-of-the-week and month-of-the-year effects in cryptocurrencies

Research into the effects of calendar anomalies in cryptocurrency is still somewhat limited, as the asset type is still relatively new. However, previous research has found some evidence of both DOW and MOY effects in Bitcoin and other cryptocurrencies.

Aharon & Qadan's (2019) study focuses on investigating the DOW effect in Bitcoin using linear regression and GARCH models during the period spanning from 2010 to 2017. Unlike most studies in traditional markets, their study presents proof of reverse Monday effect in Bitcoin returns, as Mondays would typically yield significantly higher returns during the period of their study compared to other days, while simultaneously having higher volatility. Caporale and Plastun (2019) also find evidence of a reverse Monday effect in Bitcoin returns in their study, meaning that the Bitcoin returns were significantly higher instead of lower. In their study, they use the more traditional regression analysis method for data collected between a period from 2013 to 2017. However, none of the other cryptocurrencies that they included in their analysis showed any sign of any kind of DOW effect in their study. This is very interesting since it seems like many studies have Bitcoin behaving in a completely opposite way when compared to the traditional stock markets.

However, not all studies focused on the DOW effect in cryptocurrencies have found evidence of the reverse Monday effect. Khuntia & Pattanayak (2022) used multiple different methods in their study to test whether any calendar anomalies exist on the cryptocurrency market. Instead of the traditional EMH approach, Khuntia & Pattanayak (2022) used the adaptive market hypothesis as the foundation of their study. They claim that this approach interprets shifts in efficiency better than the traditional EMH approach. In their study, they found evidence of fluctuating calendar effects on the prices in a multitude of different cryptocurrencies but could not find any evidence of a DOW effect in Bitcoin returns. Baur, Cahill, Godfrey, and Liu (2019) also conclude in their study that no persistent DOW effect could be found in the returns of any of the cryptocurrencies included in their study for any prolonged time. They also claim that any sign of a Monday effect in Bitcoin prices would be the result of high returns in particular years rather than Monday returns being consistently higher than the returns of other days. Kinateder and Papavassiliou (2021) also only found weak evidence of a slight DOW effect as returns seemed to be abnormally low on

Wednesdays at a 0.10 confidence level and no evidence of the reverse Monday effect. They also claim that the evidence in their study points to Bitcoin returns still being mostly weak-form efficient towards calendar anomalies, as for example, proof of any kind of reverse January effect was not found.

It seems like most evidence pointing to any kind of DOW effect existing in cryptocurrency is mostly in favor of a reverse Monday effect, especially in Bitcoin returns. However, as there are still some studies that only find weak evidence of any kind of DOW effect, and some found no evidence at all, it is interesting to see whether evidence is found during the period of this study. This is especially fascinating since most studies on the topic only have data until 2018, so it is going to be interesting to see if evidence of such an anomaly can still be found in this study where the data spans years past this.

Regarding the MOY effect on Bitcoin returns, there have been fewer studies on the topic, and the evidence provided by them has also been quite conflicting. Kinateder and Papavassiliou (2021) could only find weak evidence at a 0.10 confidence level of a reversed January effect, which means that the returns in January were on average negative during their period of the study instead of being positive. Additionally, their study showed evidence of the daily returns in March being significantly lower than the average daily returns. Khuntia and Pattanayak (2022) also found evidence of such a reverse January effect in their study, but they did note that in the case of Bitcoin, the January effect seemed to be weakening over time, which according to them would be in line with the adaptive market hypothesis. On the other hand, similarly as in the case of the DOW effect, Baur et al. (2019) found no evidence of persistent MOY effects in their study.

Overall, it seems that the findings of previous research on the existence of these two anomalies are not conclusively leaning in any specific direction. It is quite interesting to see what kind of results this study yields as most studies that were discussed in this subchapter only include data until 2018 at most, while this study includes much more recent data. It also seems like Bitcoin behaves in a completely opposite way to traditional stock markets, as the results of prior research show that both Monday and January effects seem to be reversed when compared to the traditional ones in cases where they are visible in especially the Bitcoin returns.

3.4 Other calendar anomalies

Another calendar anomaly in normal stock markets was presented by Kamstra et al. in their study in 2003. Their idea for the study was that in stock markets, which are physically located on areas where seasonal affective disorder (SAD) and its milder forms are prominent, there might exist an anomaly of abnormally low returns before the winter solstice, while the day is shortening, followed by abnormally high returns afterwards, as the day starts to lengthen again. Kamstra et al. (2003) hypothesized that there is an effect on the stock markets related to SAD and its milder form, “winter blues.” They provided evidence in their study that the SAD anomaly has a significant effect on market returns around the world. Furthermore, they found evidence that the SAD effect is stronger on higher latitude markets. According to Kamstra et al. (2003), the effect of SAD in the Southern Hemisphere is happening six months out of phase compared to the Northern Hemisphere, and since the seasons are reversed, this was more proof of such an anomaly existing, according to them. After the original study, there have been multiple other studies that have provided evidence of the SAD effect on different stock markets. Murgea (2016) provides evidence in her study that there is a significant SAD effect visible in the Romanian stock market, even when controlling for the January effect. Furthermore, Škrinjarić (2018) provides evidence of the SAD effect in Serbian, Hungarian, Croatian, Slovakian, Romanian, and Ukrainian stock markets.

However, there has also been criticism of the SAD effect. Jacobsen & Marquering (2008) challenge the results of the study, as they claim that there was not enough proof provided in the study to link SAD to stock returns. They do note that they find strong evidence of seasonality between summer and winter in stock returns and that their criticism is more towards the conclusion of this being caused by mood changes related to the weather. Jacobsen & Marquering (2008) claim that the conclusions that Kamstra et al. (2003) reach in their study could be data-driven inference based on misleading correlation. To answer this criticism, Kamstra et al. (2009) claim that to support their hypotheses of the SAD effect, there is also an opposing seasonal pattern in low-risk assets such as Treasury bonds. Kamstra et al. (2009) also claim that there’s evidence of seasonal patterns in accordance with SAD between low- and high-risk categories of mutual funds. However, Jacobsen & Marquering (2009) criticize in their response that Kamstra et al. (2009) failed to answer the main criticism of their original article, which is that there is not enough proof that SAD is causing the seasonal effect instead of some other effect.

Another well-studied anomaly is the turn-of-the-month effect, which is one of the oldest price anomalies in the financial markets. The anomaly means that returns seem to be significantly higher on the last few days of the month and the first few of the next one, compared to other days' returns. Irtiza, Khan, Baig, Tirmizi, and Ahmad (2021) noticed in their study that in the Pakistani stock market, the effect was significant during a period from 2013 to 2016, while it vanished for the years 2017 and 2018. Vasileiou (2018) also finds evidence of such effect in his study in almost all the eleven different European stock markets included in his study during the period from 1999 to 2016. He also claims in his study that the optimal dates for this effect seem to be dependent on the market and, while the effect is visible during normal time periods, it seems to disappear during crisis. In the world of cryptocurrencies, Kumar (2022) focused on the turn-of-the-month effect in his study and found out that during the period spanning from August 2015 to August 2021, all cryptocurrencies included in his study, one of them being Bitcoin, had significantly higher returns on the last few days of the month as well as on the first few days of the month, indicating that the turn-of-the-month effect also exists in cryptocurrency returns.

Another calendar anomaly is called the holiday effect. The existence of this anomaly implies that the returns are significantly higher than average on the day before a holiday. One possible explanation given for this effect is that investors tend to buy more shares before a holiday because of “high holiday spirits” according to Marrett and Worthington (2009). In their study, they studied the existence of this effect in the Australian stock market during the period from 1996 to 2006 using data from 12 different stock indices. They found evidence of significantly higher returns on the day before the holiday when looking at the overall market level, but the anomaly mostly disappeared when studying at a sub-market level. According to Marrett and Worthington (2009), the most likely reason for this is the high holiday seasonality in the retail industry, which led to the overall market having significantly higher returns on the day before a holiday, instead of the seasonality being a result of “high holiday spirits”. McGuinness (2005) also found evidence of the holiday effect in the Hong Kong stock exchange between the years from 1995 to 2005. He also claims that the effect seems to be more stable than other existing calendar anomalies, such as the DOW effect, for example. In his paper, McGuinness (2005) provides evidence that the biggest driving factor for this effect in the Hong Kong market is the Chinese Lunar New Year, which is one of the most important holidays in Hong Kong.

4 DATA AND METHODOLOGY

This chapter will introduce the reader to the data used in this study and the methods that are used to analyze the data. The original data used in this study are the daily closing prices of Bitcoin during the period of October 2014 to September 2022. There are in total, a little bit under 3,000 observations. The method to analyze the data will be linear regression.

4.1 Period of the study

Even though Bitcoin dates to 2009, the data used in this study will be the daily closing values of Bitcoin from October 2014 to September 2022. The reason for this is that CoinMarketCap, which will be the data source for the study, does not provide earlier data for Bitcoin prices. Bitcoin price data prior to that through other sources is also quite limited, as for a long time, there was no real reasonable value to be presented for Bitcoin as its use and trading volume were so low. The selected period is the longest available period for this study, cut in a way that there is the same amount of data for each month, which makes studying the MOY effect fairer to get approximately the same amount of data included for each month. It could also have been possible to choose data from the start of 2015 to the end of 2022, to achieve the same, but the earlier start point was chosen so data would start from the earliest possible time and the effect of Covid-19 would be easier to intercept. The period overall is quite interesting as it includes the corona crisis, which started at the beginning of 2020, so it can be researched whether it has any effect on the prevalence of calendar anomalies on Bitcoin. Overall, for the purpose of the study, 8 years of data should be sufficient as the returns used are the daily returns so there will be sufficient number of observations to make reasonable conclusions.

The data in this study will be studied in three different periods. Firstly, the prevalence of calendar anomalies will be examined during the whole period. In addition, two subperiods will be constructed: the first containing data from August 2014 to the end of 2019 and the second containing data from 2020 to September 2022. This will allow us to study whether there is any change between the reasonably stable period in financial markets from 2014 to 2019 and the period affected by the Covid-19 crisis from 2020 to 2022. One notable thing is that 2022 also includes the Russia-Ukraine war, which may or may not have had an effect in the price of Bitcoin. However, I decided to include the data until September 2022, so there would be an approximately same amount of data for each month, and additionally, I believe the one extra year of data is more important than what possible effect the Ukraine crisis might have on the results. However, this should be considered when interpreting the results, especially in interpreting the results between the two subperiods.

4.2 Data and Descriptive Statistics

In financial studies, it's typical to compute daily returns using continuous compounded returns, often referred to as logarithmic returns. Logarithmic returns offer a more accurate representation of an asset's statistical progression over time than simple returns and also take the properties of time-series into account in a more suitable manner. (Campbell 1997, 9-11). The study uses logarithmic daily returns for the analysis to, which are calculated from daily closing prices of Bitcoin using the following formula 1:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{1}$$

Where r_t is the change in the Bitcoin price, P_t is the last value of Bitcoin on day t, and P_{t-1} is the last value of Bitcoin on day t - 1.

Table 1 presents descriptive statistics of the study's dataset. In addition to the mean, standard deviation, skewness, and kurtosis, the Shapiro-Francia value, used for measuring normality, is included in the table, as well as the first-order autocorrelation. The number of observations is also mentioned in the table. These statistics were derived using MATLAB. The data spans from October 2nd, 2014, to September 30th, 2022. Additionally, the table provides a breakdown of the statistics for two sub-periods: Time before the COVID-19 crisis (October 2nd, 2014, to December 31st, 2019) and after the COVID-19 crisis (January 1st, 2020, to September 30th, 2022).

Table 1. Descriptive statistics of the logarithmic returns for the different periods, ** indicates statistical significance at the 0.01 level and * at 0.05.

Period	Min	Max	Mean	Std. Dev	Skewness	Kurtosis	Bera-Jarque	Autocorrelation	N
Whole Period 2014-2022	-0.4647	0.2251	0.0013	0.0389	-0.7730	13.8360	14582.00**	-0.0208	**2921**
Period 1 2014-2020	-0.2376	0.2251	0.0015	0.0386	-0.2829	8.3206	2286.70**	0.0051	**1917**
Period 2 2020-2022	-0.4647	0.1718	0.0010	0.0397	-1.6307	23.1540	17420.00**	-0.0678	**1004**

From Table 1, the first noticeable thing is the minimum value of logarithmic returns, which is approximately -46.47%. This means that, during the study period, there has been a day on which Bitcoin has lost nearly half of its value in a single day. This gives some display of the riskiness of Bitcoin as an asset, since, at least, the extreme values seem to be truly extreme. This is also supported by the standard deviation being quite high and nearing almost 4% during the whole period. Noteworthy is also the fact that the standard deviation seems to stay consistent during both periods, indicating that the Covid-19 crisis didn’t have a very large effect on the volatility of Bitcoin price.

Additionally, as seen on Table 1, the data paints a very vivid picture of Bitcoin's non-normality. Especially the highly negative values skewness, particularly for datasets containing the whole period and second subperiod, leans left. This suggests that negative Bitcoin returns tend to be more severe compared to the positive ones. The first subperiod, while somewhat more balanced, also tilts slightly left. Such leanings, combined with sudden drops like the sharp 46.47% decline, emphasize Bitcoin's riskiness and erratic behavior.

Kurtosis also tells the same story, as the elevated values across all datasets hint at a distribution that deviates from normal, marked by fatter tails. This means abrupt and large price shifts in Bitcoin are more common than we would expect from the standard curve. Finally, this is also supported by the Jarque-Bera test. Its high values for all our datasets, paired with the significance at a 1% significance level, reinforce the point that Bitcoin returns are not normally distributed. This can also be observed in Figure 3, which presents the distributions of the logarithmic returns during the different periods of the study.

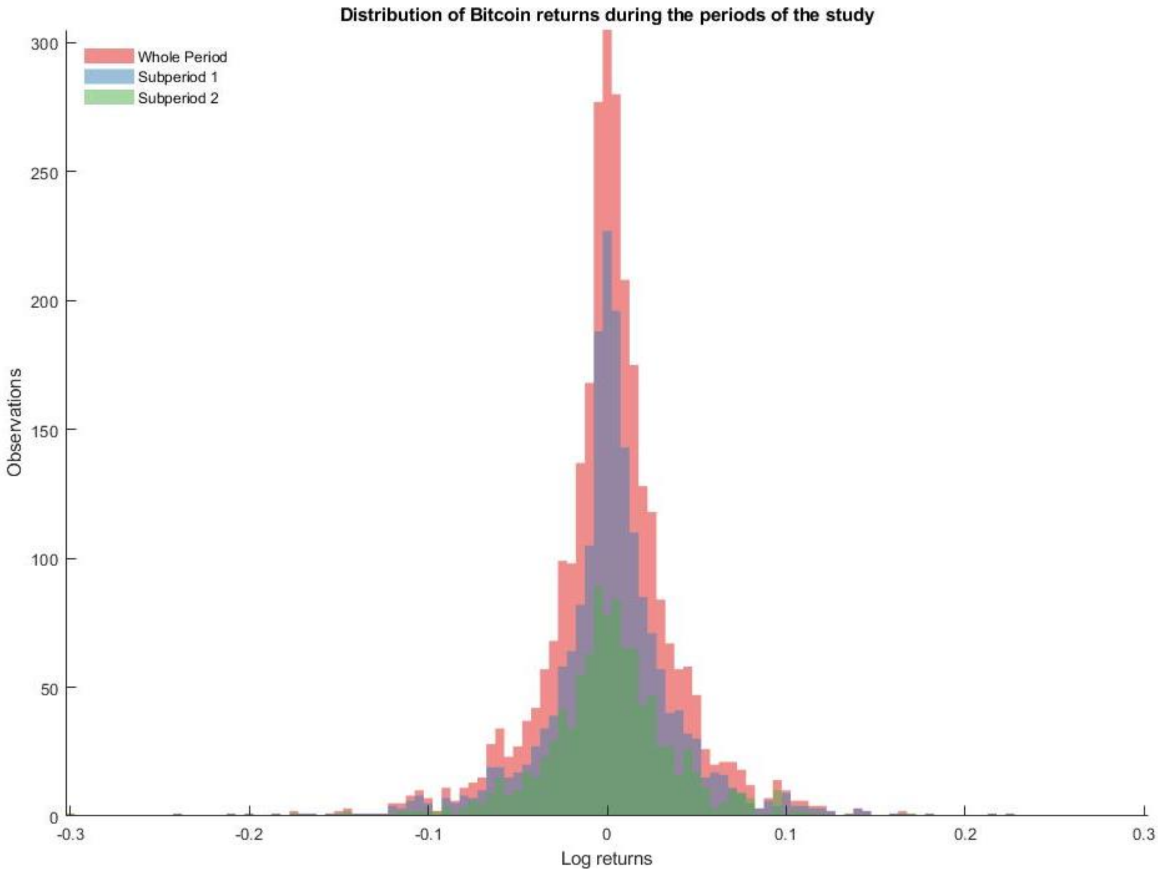

Figure 3. Distribution of Bitcoin logarithmic returns during the different periods of the study.

In essence, Bitcoin's volatility is clear from both its standard deviation and its non-standard distribution, making it worthy of the title of an unpredictable high-risk asset that some people call it. Finally, Table 1 also shows that the autocorrelation in the data remains near zero, indicating that the returns on Bitcoin do not seem to be dependent on the previous date's returns.

Table 2. Descriptive statistics of the logarithmic returns for each day, ** indicates statistical significance at the 0.01 level and * at 0.05.

Day	Min	Max	Mean	Std. Dev	Skewness	Kurtosis	Bera-Jarque	Autocorrelation	N
Monday	-0.174	0.172	0.005	0.041	-0.063	5.999	156.49**	-0.002	**417**
Tuesday	-0.2016	0.160	0.000	0.039	-0.813	7.771	441.46**	-0.056	**417**
Wednesday	-0.238	0.182	0.001	0.042	-0.439	7.653	389.63**	-0.004	**417**
Thursday	-0.465	0.225	0.000	0.049	-1.821	25.240	8845.70**	-0.118	**418**
Friday	-0.166	0.145	0.002	0.037	-0.161	5.758	134.28**	0.046	**418**
Saturday	-0.124	0.122	0.002	0.031	-0.276	6.596	230.02**	-0.060	**417**
Sunday	-0.106	0.120	0.000	0.030	-0.320	5.533	118.55**	0.006	**417**
Whole period	-0.465	0.225	0.001	0.039	-0.773	13.836	14582.00**	-0.021	**2921**

In Table 2, the same statistics can be found for each separate weekday during the whole study period. Notably, both the steepest daily drop in price, as well as the highest daily rise, happened on Thursday. Each day exhibits negative skewness, flagging a more pronounced tendency for extreme negative returns, especially on Thursdays. Additionally, the by far highest kurtosis value (25.240) is also for the Thursdays, which signals extreme price variations on this day compared to others. The Jarque-Bera test again further echoes the departure from normality for each day on the dataset, which is shown in skewness and kurtosis, and again it’s particularly pronounced on Thursdays. The standard deviation also shows the same story: that returns on Thursdays seem to be especially volatile compared to other weekdays. On the other hand, looking at the standard deviation, the returns on weekends seem to be less volatile compared to the weekdays.

Autocorrelation trends also shed some light on Bitcoin’s daily patterns. Though most days hover close to zero, Thursday stands out with a slight negative trend. This might hint at a possible pattern where a high return on Wednesday might lead to a contrasting trend on Thursdays, or vice versa.

In conclusion, while Bitcoin displays distinctive daily patterns, Thursdays emerge as especially intriguing. Whether it's the pronounced negative returns, the stark deviations from normal distributions, or its slightly negative autocorrelation, Thursdays, in the world of Bitcoin, seem to come with a higher risk when compared to other days.

Table 3. Descriptive statistics of the logarithmic returns for each month, ** indicates statistical significance at the 0.01 level and * at 0.05.

Month	Min	Max	Mean	Std.Dev	Skewness	Kurtosis	Bera-Jarque	Autocorrelation	N
January	-0.238	0.164	-0.003	0.050	-0.956	6.710	180.05**	-0.003	**248**
February	-0.174	0.172	0.004	0.040	0.032	6.329	104.42**	-0.068	**226**
March	-0.465	0.167	-0.002	0.048	-3.627	37.903	13132.00**	-0.110	**248**
April	-0.092	0.160	0.004	0.030	0.873	7.652	246.89**	-0.090	**240**
May	-0.148	0.122	0.002	0.039	-0.213	5.112	47.99**	-0.062	**248**
June	-0.174	0.109	0.000	0.042	-0.662	5.165	64.40**	-0.060	**240**
July	-0.139	0.215	0.003	0.037	0.771	8.489	335.91**	-0.049	**248**
August	-0.201	0.116	0.000	0.032	-1.014	9.521	481.87**	-0.087	**248**
September	-0.208	0.142	-0.002	0.034	-0.976	11.119	697.33**	-0.069	**240**
October	-0.089	0.145	0.005	0.027	0.702	7.400	219.51**	0.112	**247**
November	-0.144	0.141	0.002	0.039	-0.126	5.121	45.62**	0.136	**240**
December	-0.133	0.225	0.002	0.042	0.868	7.779	267.13**	0.092	**248**

Finally, we investigate Table 3, which portrays the same statistics, divided for each separate month. What is interesting is that, in previous tables, skewness was constantly negative, but now, looking at the data divided by month, it seems like there is also some positive skewness in the data. Additionally, the skewness seems to be more significant among the monthly statistics, but it might also be because there are fewer observations, which leads to high skewness if, for example, January has a rising price trend even for one or two years during the period.

It is also noticeable that now some months have negative means, while previously all the means were above zero. Especially interesting is that the lowest mean and highest standard deviation happens to be in January, as the January effect would suggest the exact opposite to be the case if it existed in Bitcoin returns.

Similarly, elevated kurtosis values across all months suggest that Bitcoin's return distribution is characterized by fatter tails than what a normal distribution would predict. This means that Bitcoin, more frequently than anticipated, undergoes sizable price changes. The Jarque-Bera test results also seem to imply this abnormal distribution, since the daily returns for each month, once again, are not normally distributed at the 0.01 confidence level.

To sum up, all the tables discussed display the volatile nature of Bitcoin through both its pronounced standard deviation and its departure from normal distribution. This further shows an indication of Bitcoin being a high-stakes, high-reward asset. Furthermore, the near-zero autocorrelation in each table seems to suggest that Bitcoin's returns don't rely too much on its past performance.

4.3 Methodology

When studying calendar anomalies, the goal is to determine whether abnormal returns exist on certain days, weeks, months, or other selected periods that are statistically significant. Brooks (2008, 457) suggests, for this purpose, using linear regression analysis of the ordinary least squares (OLS) combined with the use of dummy variables. It has also been commonly used in similar studies (e.g., Gibbons et al. 1981; Tonchev & Kim 2004). Since the same method is quite widely used previously to study DOW and MOY effects, the result obtained in this study will be relatively comparable with previous studies on the matter.

When examining the DOW effect, a multivariate regression model is used to test unrestricted regression, which can be presented in the following form (Brooks 2008, 457):

$$R_t = y_1 D_{1t} + y_2 D_{2t} + y_3 D_{3t} + y_4 D_{4t} + y_5 D_{5t} + y_6 D_{6t} + y_7 D_{7t} + \varepsilon_t \tag{2}$$

In formula 2, R_t represents the return on Bitcoin price at time t. Each day of the week is represented by dummy variable from D_{1t} to D_{7t}. Dummy variable is used to transfer a qualitative variable into a dichotomous variable, so the variable gets the value of 1 when the feature is present and otherwise it gets the value of 0. In this case the qualitative variable in question is the day of the week, so on Mondays the D_{1t} gets the value of one and on other days zero. Similarly, on Tuesdays the D_{2t} gets the value of one and otherwise zero and so on for the rest of the weekdays. The estimated coefficients in formula 2 represent the average return for each day of the week based on the sample data and the ε_t is a normally distributed error term with an expected value of zero and with variance σ^2. The null hypothesis for the test can be presented according to formula 3.

$$H_0 = y_1 = y_2 = y_3 = y_4 = y_5 = y_6 = y_7 (= 0) \tag{3}$$

The null hypothesis is that the returns do not differ statistically significantly on different weekdays. If the returns differed significantly depending on the day, it would suggest that there exists a DOW effect on Bitcoin prices.

Exploring the monthly data, the method would be the same otherwise, but instead of day dummy there is a month dummy, which would work in a similar manner to the day dummy in earlier regression. The regression model for monthly exploration would be as follows in formula 4.

$$R_t = y_1 M_{1t} + y_2 M_{2t} + y_3 M_{3t} + y_4 M_{4t} + y_5 M_{5t} + y_6 M_{6t} + y_7 M_{7t} + y_8 M_{8t} + y_9 M_{9t} + y_{10} M_{10t} + y_{11} M_{11t} + y_{12} M_{12t} + \varepsilon_t \tag{4}$$

In this case the regression model is interpreted in similar way as the one for examining DOW effect, but now instead of D_1 to D_7 there is M_1 to M_{12}, which presents the month instead of day. So, in case the return is from January the M_1 gets a value of 1 and otherwise 0 and this continues for each month separately. The null hypothesis to explore the MOY effect can be presented according to formula 5.

$$H_0 = y_1 = y_2 = y_3 = y_4 = y_5 = y_6 = y_7 = y_8 = y_9 = y_{10} = y_{11} = y_{12} (= 0) \tag{5}$$

It is also important to consider the dummy variable trap when using regression analysis and dummy variables. Dummy variable trap means, that if all categories are included in the dataset, their sum is equal to 1, representing perfect multicollinearity and none of the coefficients could be estimated. Therefore, not all categories can be considered, and one must be left out as a reference group. However, this does not mean that one day or month would be left completely out of the analysis, but instead other days or months' returns will be compared to this group's returns, meaning that the results will still be valid representation of all months and days. In this study, Monday and January returns are used as reference groups, meaning that all other days and months are compared to returns during them respectively. This way, the obtained results indicated a difference from the reference group.

Finally, taking the dummy variable trap into account the final regression model to explore the DOW effect is presented in formula 6.

$$R_t = \alpha + y_2 D_{2t} + y_3 D_{3t} + y_4 D_{4t} + y_5 D_{5t} + y_6 D_{6t} + y_7 D_{7t} + \varepsilon_t, \tag{6}$$

Where α is the intercept and represents the average logarithmic returns on Mondays. Similarly, the regression to explore the MOY effect can be presented as in formula 7.

$$R_t = \alpha + y_2 M_{2t} + y_3 M_{3t} + y_4 M_{4t} + y_5 M_{5t} + y_6 M_{6t} + y_7 M_{7t} +$$
$$y_8 M_{8t} + y_9 M_{9t} + y_{10} M_{10t} + y_{11} M_{11t} + y_{12} M_{12t} + \varepsilon_t, \tag{7}$$

Where α is the intercept and represents the average logarithmic returns in January.

5 RESULTS

Chapter 6 consolidates the research findings. This chapter is subdivided based on the type of anomaly. Firstly, we delve into the results of the DOW effect, followed by the findings on the MOY effect. In each section, the data is analyzed in three periods: first for the full study period, second for the first subperiod before the COVID-19 crisis, and lastly for the second subperiod during and after the COVID-19 crisis.

5.1 Day-of-the-week effect results

Figure 4 represents the average daily returns presented for each weekday during the whole period of study from 2014 to 2022, for subperiod 1 from 2014 to 2019, and subperiod 2 from 2020 to 2022. Looking at the graph, Mondays seem to consistently have the highest average returns during almost all the three periods, with the only exception being the second subperiod where Wednesday has a slightly higher average return. Mondays, having consistently higher average returns compared to other weekdays, which could imply the existence of the reverse Monday effect, but the data needs to be studied more to draw any further conclusions.

Another interesting thing is the difference between the returns on the two different subperiods, and especially the Wednesday and Thursday returns, which seem to have the biggest differences. Again, this might give some implication that Covid-19 might have influenced the returns of Bitcoin, but this conclusion cannot be confirmed just by looking at the graph. It is also interesting that the average returns seem to be either negative or only slightly positive just a day before and after Mondays, which could also support the existence of the reverse Monday effect, but again, more thorough study is needed to come to that conclusion.

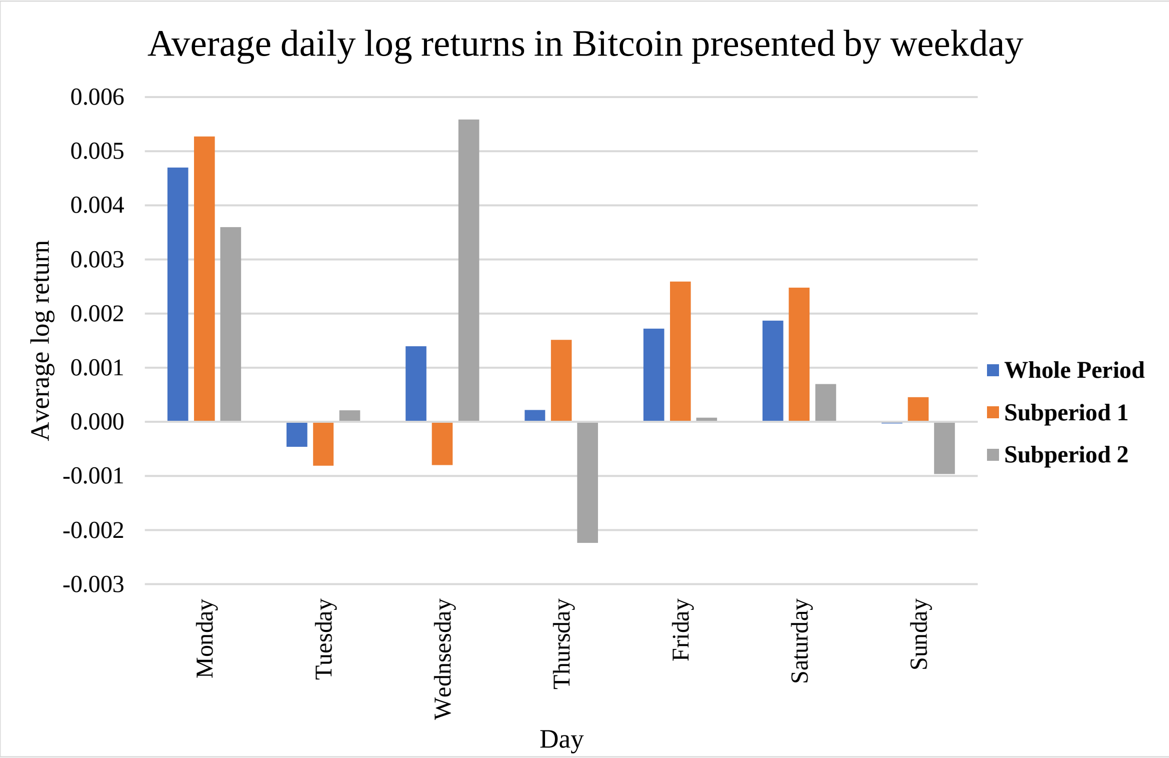

Figure 4. Average daily log returns in Bitcoin presented by weekday.

Table 4 presents the collected results of regression analysis for the whole study period regarding the DOW effect. The first notable thing in the table is that the t-test for the intercept, which represents the logarithmic returns on Monday, is significantly positive at the 0.05 level. This is quite interesting, as this would imply that, instead of the traditional Monday effect where Mondays have lower returns than other days, the opposite seems to be the more likely case for Bitcoin. Additionally, when looking at the estimates that compare the returns of other weekdays to Monday returns, all of them seem to be negative. This would suggest that other weekdays underperform when compared to Monday. However, upon closer examination of the p-values of the t-tests for the coefficients, it appears that only Wednesdays are significantly underperforming when compared to Mondays at the 0.05 level at the single coefficient level. However, the high value for the overall F-statistics means that the model itself is not statistically significant, as it exceeds the accepted level of 0.05 (0.3840). To reject the null hypothesis, there would need to be statistical significance between the returns of weekdays. But since the F-statistic is not significant, having a single coefficient with a p-value under 0.05 is not enough to reject the null hypothesis, as the whole model is insignificant. One possible reason for the insignificant model might be the huge overall volatility of Bitcoin.

Table 4. Regression analysis results for the whole period (10/2014-09/2022), day-of-the-week effect. ** indicates statistical significance at the 0.01 level and * at 0.05.

	Estimate	SE	tStat	pValue
Monday (Intercept)	0.0066	0.0028	2.3821	0.0174*
Tuesday	-0.0056	0.0039	-1.4177	0.1566
Wednesday	-0.0090	0.0039	-2.2862	0.0225*
Thursday	-0.0023	0.0039	-0.5957	0.5515
Friday	-0.0053	0.0039	-1.3541	0.1760
Saturday	-0.0061	0.0039	-1.5601	0.1191
Sunday	-0.0048	0.0039	-1.2181	0.2235
Overall F-statistic			1.0600	0.3840

Looking next at Table 5, which presents the results of regression analysis for the first subperiod from 2014 to 2019, we can immediately see that, again, Mondays seem to have statistically significant positive returns at the 0.05 level when looking at the p-value for the t-test of the intercept. Just looking at the estimates, it again seems like the other weekdays underperform compared to Mondays, but this time it is notable that none of the differences are statistically significant when compared to Monday returns. Closest to statistical significance are Tuesday and Wednesday, as their p-value is just a bit over 0.06, but it is still over the accepted level for statistical significance.

However, for subperiod 1, the p-value for the overall F-statistic, being grossly over the significance level of 0.05 (0.5220), means that again the results do not offer enough evidence to reject the null hypothesis and the data does not seem to support the existence of any DOW effect in Bitcoin returns during 2014-2019.

Table 5. Regression analysis results for the first subperiod (10/2014-12/2019), day-of-the-week effect. ** indicates statistical significance at the 0.01 level and * at 0.05.

	Estimate	SE	tStat	pValue
Monday (Intercept)	0.0053	0.0023	2.2624	0.0238*
Tuesday	-0.0061	0.0033	-1.8463	0.0650
Wednesday	-0.0061	0.0033	-1.8406	0.0658
Thursday	-0.0037	0.0033	-1.1131	0.2658
Friday	-0.0027	0.0033	-0.8143	0.4156
Saturday	-0.0028	0.0033	-0.8478	0.3967
Sunday	-0.0048	0.0033	-1.4611	0.1442
Overall F-statistic			0.8620	0.5220

Table 6 shows the regression analysis results for the second subperiod, which contains data from the period during and after the Covid-19 crisis. The first interesting thing is that even the positive Monday returns are no longer statistically significant, which means that the returns no longer significantly deviate from zero even on the simple t-test level on Mondays. Additionally, now the Wednesday estimate is positive, which could give some very slight implication that after the Covid-19 crisis, the returns on Wednesdays were better than on Mondays. However, during the other periods, it always seemed that Mondays would have the highest returns when looking just at the estimates. However, again, the p-values suggest that none of the differences are significant this time even on the simple t-test level. They are also all quite far away from significance level as the lowest single p-value is ~0.23 for Wednesday, meaning that any true interpretations cannot be made from this data.

For the second subperiod, the data again supports that the null hypothesis remains valid, and there does not seem to be any DOW effect in Bitcoin prices during the period of 2020-2022, especially since the F-statistic is very clearly over the 0.05 level (0.6970). This is quite interesting, as when looking at the whole period from 2014-2022, there was still some slight implication differences between the returns for separate weekdays, although it was not statistically significant, and there was not enough evidence to reject the null hypothesis for any period. However, when the whole period was broken down into subperiods to accommodate the investigation of the difference the Covid-19 crisis made, and during the second subperiod even the slightest possible implication of a DOW effect disappeared completely.

Table 6. Regression analysis results for the second subperiod (1/2020-9/2022), day-of-the-week effect. ** indicates statistical significance at the 0.01 level and * at 0.05.

	Estimate	SE	tStat	pValue
Monday (Intercept)	0.0036	0.0033	1.0832	0.2790
Tuesday	-0.0034	0.0047	-0.7205	0.4714
Wednesday	0.0020	0.0047	0.4232	0.6722
Thursday	-0.0056	0.0047	-1.2001	0.2304
Friday	-0.0035	0.0047	-0.7511	0.4528
Saturday	-0.0029	0.0047	-0.6170	0.5374
Sunday	-0.0046	0.0047	-0.9715	0.3316
Overall F-statistic			0.6410	0.6970

When comparing the differences between the first and second subperiod these results do not provide evidence of any kind of effect caused by the Covid-19 crisis on the DOW effect or Monday effect on Bitcoin prices. The data supported null hypotheses for both subperiods used for the regression, meaning that the data did not indicate enough evidence of the existence of DOW effect during either subperiod. Even for the whole period of the study, the data seems to support the null hypothesis that returns do not differ statistically significantly on different weekdays. However, this does not completely shut down the possibility of DOW effect in Bitcoin returns, but the results in this study are not conclusive enough to warrant the rejection of null hypothesis meaning that no hard evidence of such anomaly was found. One thing that is clear from the results is that the traditional Monday effect, which is found in stock markets where Mondays seem to present significantly lower returns, does not seem to exist in the world of Bitcoin as all the evidence points away from it.

5.2 Month-of-the-year effect results

Figure 5 represents the average daily returns presented for each month for the whole period of study. Again, Figure 4 presents data for the whole period of the study, in addition to the two subperiods. Looking at the graph, the first thing that is noticeable is that the graph itself seems to give the implication that the January effect could not be found in Bitcoin returns, as January returns on average seem to be negative during the whole period, and especially during the first subperiod. However, this must be confirmed by the regression analysis, but just looking at the graph, it seems highly unlikely that the traditional January effect would exist in bitcoin prices during the period of this study.

It is also noteworthy that there seems to be more negative average returns for individual months than there were for weekdays. This, however, is quite logical, as there might be rising or falling trends which will affect the average presented by month more easily. A falling trend of three weeks might only affect the January average, while it will affect the average presented by weekday in a more even manner.

Again, there seems to be quite striking differences between the two subperiods, especially in May, which was the highest average for the first subperiod but the second lowest average for the second subperiod. This can be attributed to the sudden trends being more visible on the data when presented by month, and especially since the subperiods are quite short. A rising or falling trend lasting for a whole month during a single year might have a huge impact on the total average of that subperiod. This possibility of a rally to the top or bottom should also be remembered when interpreting the regression results, as there is a higher possibility of such a trend affecting the overall results in regression for the MOY effect than it has for the DOW effect.

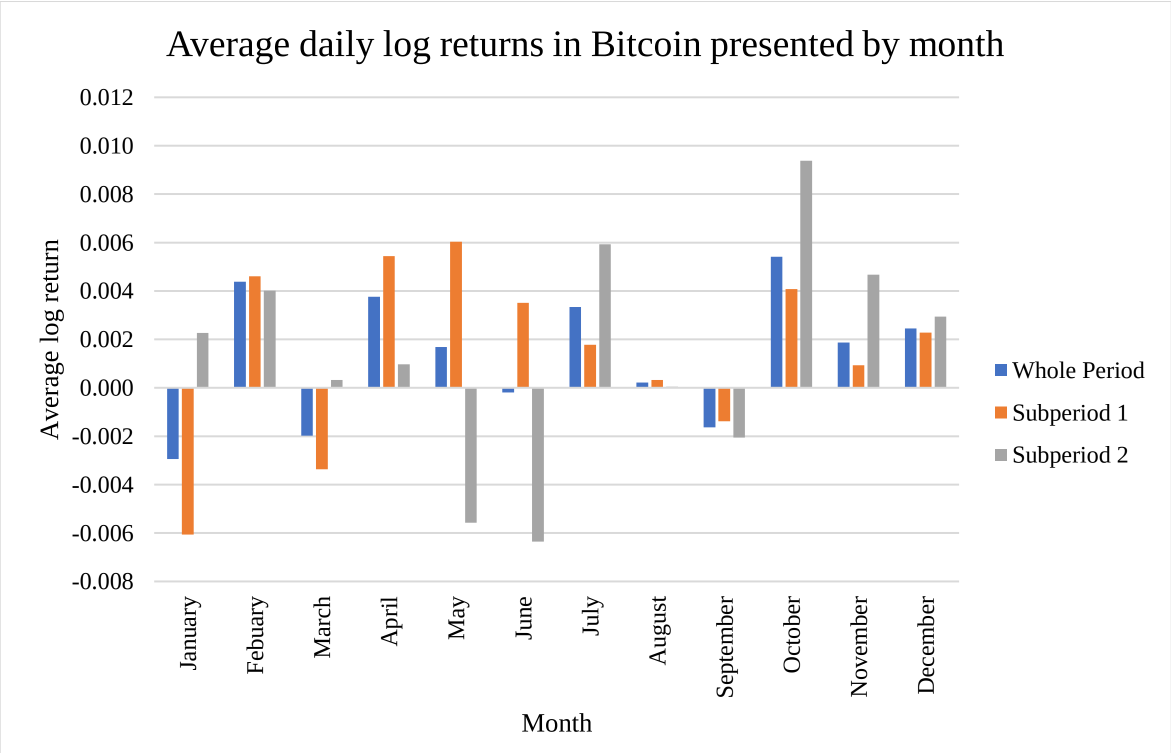

Figure 5. Average daily log returns in Bitcoin presented by month.

Table 7 shows the regression results for the MOY effect for the whole period of the study. The first noticeable thing about the results is that, just looking at the estimates, January seems to have the worst returns, as all the other months have a positive estimate, which would mean that their returns compared to January are higher. It is also noteworthy that the estimate for January is negative. However, the p-value for January, which is also an intercept value, is over 0.05, which means that the intercept is not statistically significantly different from zero. Luckily, this does not mean that the results of the whole model could not be interpreted, as it is still possible for other months to have significant differences when compared to January. These results confirm what the previous graph already implied: that the traditional January effect does not seem to exist in Bitcoin prices during the study period.

Looking at the other p-values in Table 7, it is notable that there are three months which have significantly higher returns than January. First, May has the highest expected value of 0.130 relative to January out of all months and is also statistically significant at the level of 0.01 on the simple t-test level. On top of that, February and June both have a significantly higher expected value relative to January at the 0.05 level at the t-test level, with both having an expected value of over 0.01 higher than January. These results could imply that Bitcoin prices see hikes especially during the early summer months, after at best, just adequately performing in January.

However, similarly to the DOW regression results, it seems like the model itself is not significant for the MOY regression, as the p-value for the whole F-statistic is over 0.05 (0.2230). As such, there is not enough evidence to reject the null hypothesis. It should also be noted again that, even though the data size itself is the same size as for the DOW regression, the results for the MOY regression are more prone to being affected by localized trends in the data, which could skew these results of the single coefficients to seem more significant than they actually are. Still, it is noteworthy that, just looking at the p-values of single coefficients, they would seem to show more support to differences between months in Bitcoin prices, but it is still not enough to reject the null hypothesis. Therefore, it’s fair to say that there does not seem to be a MOY effect during the whole period of the study.

Table 7. Regression analysis results for the whole period (10/2014-09/2022), month-of-the-year effect. ** indicates statistical significance at the 0.01 level and * at 0.05.

	Estimate	SE	tStat	pValue
January (Intercept)	-0.0058	0.0034	-1.6728	0.0947
February	0.0119	0.0050	2.3930	0.0169*
March	0.0038	0.0049	0.7726	0.4400
April	0.0087	0.0049	1.7818	0.0751
May	0.0130	0.0049	2.6707	0.0077**
June	0.0108	0.0049	2.1971	0.0282*
July	0.0058	0.0054	1.0693	0.2852
August	0.0010	0.0054	0.1829	0.8550
September	0.0071	0.0055	1.3013	0.1935
October	0.0093	0.0049	1.9004	0.0577
November	0.0097	0.0049	1.9799	0.0480*
December	0.0081	0.0049	1.6746	0.0943
Overall F-statistic			1.2900	0.2230

In Table 8, similar regression results are presented for the first subperiod in the study. It is notable that again, while the intercept is negative, the p-value of it is just barely over the limit of 0.05, and as so, January returns do not significantly differ from zero. First, focusing on the months which had significantly differing estimates from January, the chart shows that February, May, and June again have significantly higher returns, and on top of that, now also returns of April, October, and December are significantly higher on simple t-test level. Out of these months, April and May have significance at level 0.01 according to the t-tests, while the rest have statistical significance at level 0.05. The highest estimated difference out of these months is again in May, for which the estimate is ~0.012 higher than for January. It is interesting to see that the same months, February, May, and June, are all significant on t-test level during both periods studied so far.

However, once again, the overall F-statistics tells a story of an overall insignificant model as the p-value for it is again over the level of 0.05 (0.1610), meaning that the significance of the single t-tests are again irrelevant regarding the hypothesis. It seems like there just is not enough evidence of MOY effect in the data to reject the null hypothesis, and so far, it looks like the Bitcoin pricing is efficient, at least against these calendar anomalies.

Table 8. Regression analysis results for the first subperiod (10/2014-12/2019), month-of-the-year effect. ** indicates statistical significance at the 0.01 level and * at 0.05.

	Estimate	SE	tStat	pValue
January (Intercept)	-0.0061	0.0031	-1.9600	0.0501
February	0.0107	0.0045	2.3797	0.0174*
March	0.0027	0.0044	0.6161	0.5379
April	0.0115	0.0044	2.6062	0.0092**
May	0.0121	0.0044	2.7646	0.0058**
June	0.0096	0.0044	2.1710	0.0301*
July	0.0078	0.0044	1.7930	0.0731
August	0.0064	0.0044	0.4605	0.1443
September	0.0047	0.0044	1.0619	0.2884
October	0.0103	0.0042	2.4503	0.0144*
November	0.0070	0.0042	1.6566	0.0978
December	0.0083	0.0042	1.9932	0.0464*
Overall F-statistic			1.4100	0.1610

Finally, looking at Table 9, which presents the same regression results for the second subperiod, the first notable thing is that the p-value is no longer significant even for the intercept or any of the coefficients, and in fact, the p-values seem quite high. This can simply be because of the reduced sample size in this subperiod compared to the first one. The overall F-statistic is also getting higher, as now it is 0.3810, meaning that once again the null hypothesis is not rejected.

Table 9. Regression analysis results for the second subperiod (1/2020-9/2022), month-of-the-year effect. ** indicates statistical significance at the 0.01 level and * at 0.05.

	Estimate	SE	tStat	pValue
January (Intercept)	0.0026	0.0042	0.6319	0.5276
February	0.0014	0.0060	0.2322	0.8164
March	-0.0023	0.0058	-0.3943	0.6935
April	-0.0017	0.0059	-0.2804	0.7792
May	-0.0082	0.0058	-1.4023	0.1611
June	-0.0090	0.0059	-1.5241	0.1278
July	0.0033	0.0058	0.5650	0.5722
August	-0.0026	0.0058	-0.4415	0.6589
September	-0.0047	0.0059	-0.7949	0.4269
October	0.0068	0.0065	1.0342	0.3013
November	0.0020	0.0066	0.3106	0.7562
December	0.0003	0.0065	0.0486	0.9612
Overall F-statistic			1.0700	0.3810

Overall, the regression results for the MOY effect tell a similar story compared to the results for the results regarding the DOW effect. The data does not provide enough support to reject the null hypothesis for any of the periods for this anomaly either. However, it is notable that there were still more significant coefficient values on t-test level, especially in the first subperiod, but due to the overall models being insignificant during all periods, it must be said that the Bitcoin markets seem to be efficient against MOY effect. Since the null hypothesis was not rejected for any of the periods, it also cannot be said that Covid-19 would have had any effect on the MOY effect either.

6 Conclusions and discussion

The aim of this chapter is to go over the progress of this study and highlight the results and their conclusions. The chapter summarizes the key research results and the conclusions that can be drawn based on these results. In addition, possible topics for further research are reviewed at the end of the chapter.

6.1 Conclusions

This study focused on two different calendar anomalies, namely, DOW and MOY effects in Bitcoin returns during the period from October 2014 to September 2022, and the data used in this study was built from the closing prices from CoinMarketCap, which is one of the largest trading exchanges for Bitcoin. Logarithmic returns were used for the data to be better applicable for the purpose of the study.

The theoretical background focused on introducing the reader to relevant financial theories and cryptocurrencies and gave some slight background on Covid-19 and the economic crisis it caused. This was supplemented by a literature review on previous studies of calendar anomalies on both stock exchanges and research focusing on calendar anomalies in cryptocurrencies. The previous research was not all consistent in one way or another, but at least in the case of Bitcoin, there was quite a bit of research that found some evidence of the existence of DOW and MOY effects, even if the traditional Monday and January effects did not seem to exist in light of previous research.

The research method was linear regression, which is an established and common way to conduct research about such anomalies both in normal stock markets and in cryptocurrencies. Linear regression was used to see if there were any significant differences between the returns on different weekdays or months.

When considering the first research question, *“Can day-of-the-week and month-of-the-year effects be identified in the returns of Bitcoin?”* along with the results of this study, it must be said that for the two calendar anomalies researched in this study, there was not enough evidence to support the claim that either of them could be identified for Bitcoin returns in any of the periods that were studied.

Regarding the second question, *"Did the Covid-19 crisis and the economic shock it caused affect these anomalies significantly in Bitcoin returns?"* The answer is again that there is not enough evidence to support any claim that there would be a significant effect on these anomalies caused by Covid-19, as there were no calendar anomalies found in either study period. This means that Covid-19 and the economic crisis it caused did not seem to have a significant effect on Bitcoin returns. In light of these results the Bitcoin returns seem to be at least weak-form efficient related to these two calendar anomalies during the period of the study.

6.2 Discussion

While the results failed to show any evidence of significant DOW or MOY effects, the slight implications of differences in the Bitcoin returns between months and days pointed more towards the same direction as previous research that has often found a reversed effects compared to stock markets. This has been especially the case with the DOW effect, where many studies have found evidence of a reverse Monday effect in Bitcoin returns. However, no real explanation for this has been speculated on the studies of Aharon & Qadan's (2019) or Caporale and Plastun's (2019). One possible explanation for this could be that the markets for cryptocurrencies do not close during the weekend, which could potentially imply that the normal Monday effect in stock markets is caused by a close-week effect. However, this would not explain why the effect seems to be the exact opposite in many studies regarding Bitcoin returns.

There were also some very light implications of differences between weekdays and months in the form of significant t-test results between them, which pointed in the same direction. Still, there was not enough evidence to reject any of the null hypotheses for the study, as the overall F-statistics remained insignificant in all models. The slight implications could also be entirely due to luck, as erroneous inferences become more likely as more inferences are added. However, there is a slight possibility that these implications could be an actual sign of differences between the returns on different days and months, especially since they are pointing in the same direction as previous research, for example, in the case of the reverse Monday effect.

Overall, these results are quite interesting, as a lot of previous research on the topic has found evidence of these anomalies of which no evidence was found during this study period. However, this study contains data from a period where the price of Bitcoin rose and fell rapidly, meaning a high likelihood for a higher volatility than before the year 2018, on which year most previous studies ended. One possible explanation for the seemingly disappearing DOW effect might be the heightened swings in the price of Bitcoin.

Another possibility could be that the markets have “fixed” this anomaly over time, thus becoming efficient again. It is the basis of EMH that efficient markets will lead to the disappearance of such anomalies, but since previous studies have often found evidence of such anomalies, it would mean that the market was not effective during those times. However, as the market for Bitcoin is still quite young, it might be possible that it has taken some time for the market to fix itself regarding this certain anomaly. This would at least be supported by the adaptive market hypothesis that Khuntia & Pattanayak (2022) based their study on and found evidence that the calendar anomalies on Bitcoin returns were changing over time. Wong & Agarwal (2006) also claim that in most cases, anomalies diminish and eventually disappear over time, as their discovery leads to more and more investors exploiting them, leading to the anomalies disappearing over time. However, all this is still just discussion about possible reasons for such results, but without further research, it is impossible to say for sure what has been the reason that these anomalies do not seem to be prevalent during the period of this study, while most previous studies have found at least some evidence of such anomalies.

The results of this study left many possible future research topics on the table. First, it would be interesting to do separate research on the effect of the Covid-19 crisis on the returns of Bitcoin instead of just on the effects it had on these anomalies. Additionally, it would be quite interesting to extend this research into other cryptocurrencies to see if these calendar anomalies still exist on the returns of them. This could be coupled with the addition of different calendar anomalies, such as the Halloween effect, SAD effect, Holiday effect, etc. Another possible topic would be to dig deeper into the reverse effects in Bitcoin compared to traditional stock markets, to see if any possible reasons for them being visible on some research could be found through further research.

Since these results also differed from most of the previous results on the topic, it would be interesting to extend the study back some years and study more different subperiods to see if there could be found any difference between some other subperiods than just the ones I chose for my study. It would also be interesting to return to the topic once markets for Bitcoin and other cryptocurrencies have had more time to mature, as they are still young as far as different asset classes are concerned. Previous research on stock markets has given some implications that the younger the stock markets are, the more likely they are to have such anomalies, so it would be very interesting to see if this will be the case with Bitcoin and other cryptocurrencies. This could mean that the initial results of these anomalies existing were just a result of young markets, which would fix themselves as time goes by, like this study might suggest. However, to get a more conclusive idea about this, it would be necessary to give more time for the markets to mature before they can be properly studied.

References

Aharon, D. Y. & Qadan, M., 2019. Bitcoin and the day-of-the-week effect. *Finance research letters,,* Vol 31.

Al-Awadhi, A. M., Alsaifi, K., Al-Awadhi, A. & Alhammadi, S., 2020. Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. *ournal of behavioral and experimental finance,* Vol 27.

Ali, O., Ally, M., Clutterbuck & Dwivedi, Y., 2020. The state of play of blockchain technology in the financial services sector: A systematic literature review. *International journal of information management,* Vol 54.

Al-Loughani, N. & Chappell, D., 1997. On the validity of the weak-form efficient markets hypothesis applied to the London stock exchange. *Applied financial economics,* 7(2), pp. 173-176.

Arias, M. A. & Shin, Y., 2013. There Are Two Sides to Every Coin-Even to the Bitcoin, a Virtual Currency. *Regional Economist,* pp. 1-.

Athanassakos, G. & Robinson, M. J., 1994. THE DAY-OF-THE-WEEK ANOMALY: THE TORONTO STOCK EXCHANGE EXPERIENCE. *Journal of business finance & accounting,* 21(6), pp. 833-856.

Barber, B. M. & Odean, T., 2001. Boys will be Boys: Gender, Overconfidence, and Common Stock Investment. *The Quarterly journal of economics,* 116(1), pp. 261-292.

Barberis, N. & Thaler, R., 2002. A Survey of Behavioral Finance.. *NBER Working Paper Series,* p. 9222–..

Bassiouny, A., Kiryakos, M. & Tooma, E., 2023. Examining the adaptive market hypothesis with calendar effects: International evidence and the impact of COVID-19. *Global finance journal,* Vol 56, p. 100777.

Baur, D. G., Cahill, D., Godfrey, K. & Liu, Z., 2019. Bitcoin time-of-day, day-of-week and month-of-year effects in returns and trading volume. *Finance research letters,* Vol 31, pp. 78-92.

Benartzi, S. & Thaler, R. H., 2001. Naive Diversification Strategies in Defined Contribution Saving Plans. *The American economic review,* 91(1), pp. 79-98.

Birnberg, J. G. & Ganguly, A. R., 2012. Is neuroaccounting waiting in the wings? An essay. *Accounting, organizations and society,* 37(1), pp. 1-13.

Bodie Z., Kane A., Marcus A.J., 2014. *Investments.* 10th edition. New York: McGraw-Hill Education.

Bollen, R., 2013. The legal status of online currencies: Are Bitcoins the future?. *Journal of Banking and Finance Law and Practise.*

Brooks, C., 2008. *Introductory econometrics for finance.* 2nd edition. Cambridge: Cambridge University Press.

Brusa, J. & Liu, P., 2004. The Day-of-the-Week and the Week-of-the-Month Effects: An Analysis of Investors' Trading Activities. *Review of quantitative finance and accounting,* 23(1), pp. 19-30.

Böhme, R., Christin, N., Edelman, B. & Moore, T., 2015. Bitcoin: Economics, Technology, and Governance. *The Journal of economic perspectives,* 29(2), pp. 213-238.

Campbell, J. Y., Lo, A. W. & MacKinlay, A. C., 1997. *The econometrics of financial markets.* Repr. with corr. toim. Princeton (NJ): Princeton University Press.

Caporale, G. M. & Plastun, A., 2019. The day of the week effect in the cryptocurrency market. *Finance research letters,* Vol 31.

Chainalysis, 2020. *The 2020 Geography of Cryptocurrency Report,* p.l-.

Choy, A. & O'hanlon, J., 1989. Day of the Week Effects In the Uk Equity Market: A Cross Sectional Analysis. *Journal of business finance & accounting,* 16(1), pp. 89-104.

Condoyanni, L., O'HANLON, J. & WARD, C., 1987. Day of the Week Effects On Stock Returns: International Evidence. *Journal of business finance & accounting,* 14(2), pp. 159-174.

Connolly, R. A., 1989. An Examination of the Robustness of the Weekend Effect. *Journal of financial and quantitative analysis,* 24(2), pp. 133-169.

Cross, F., 1973. The Behavior of Stock Prices on Fridays and Mondays. *Financial analysts journal*, 29(6), pp. 67-69.

De BONDT, W. F. M. & THALER, R., 1985. Does the Stock Market Overreact?. *The Journal of finance (New York),* 40(3), pp. 793-805.

Dion, D., 2013. I'll gladly trade you two bits on Tuesday for a byte today: Bitcoin, regulating fraud in the e-conomy of hacker-cash. *Journal of Law, Technology & Policy,* Vol 1, pp. 166-197.

Du, W. (., Pan, S. L., Leidner, D. E. & Ying, W., 2019. Affordances, experimentation and actualization of FinTech: A blockchain implementation study. *The journal of strategic information systems,* 28(1), pp. 50-65.

Fama, E. F., 1965. The Behavior of Stock-Market Prices. T*he Journal of business,* 38(1), pp. 34-105.

Fama, E. F., 1970. EFFICIENT CAPITAL MARKETS: A REVIEW OF THEORY AND EMPIRICAL WORK. *The Journal of finance,* 25(2), pp. 383-417.

Fender, J., 2020. Beyond the efficient markets hypothesis: Towards a new paradigm. *Bulletin of economic research,* 72(3), pp. 333-351.

Fountas, S. & Segredakis, K. N., 2002. Emerging stock markets return seasonalities: the January effect and the tax-loss selling hypothesis. *pplied financial economics,* 12(4), pp. 291-299.

Frankfurter, G. M. & Mcgoun, E. G., 2001. Anomalies in finance: What are they and what. *International Review of Financial Analysis,* 10(4), pp. 407-429.

French, K. R., 1980. Stock returns and the weekend effect. *Journal of Financial,* Vol 8, pp. 383-417.

Gibbons, M. R. & Hess, P., 1981. Day of the Week Effects and Asset Returns. *The Journal of business,* 54(4), pp. 579-596.

Grobys, K., Junttila, J., Kolari, J. W. & Sapkota, N., 2021. On the stability of stablecoins. *Journal of empirical finance,* Vol 64, pp. 207-223.

Hanke, S. H., 2014. Bitcoin: Milton Friedman saw it coming. *National post (Toronto).*

Hasso, T., Pelster, M. & Breitmayer, B., 2019. Who trades cryptocurrencies, how do they trade it, and how do they perform? Evidence from brokerage accounts. *Journal of behavioral and experimental finance,* Vol 23, pp. 64-74.

Hazlett, P. K. & Luther, W. J., 2020. Is bitcoin money? And what that means. *The Quarterly review of economics and finance,* Vol 77, pp. 144-149.

He, P., Sun, Y., Zhang, Y. & Li, T., 2020. COVID-19's Impact on Stock Prices Across Different Sectors-An Event Study Based on the Chinese Stock Market. *Emerging markets finance & trade,* 56(10), pp. 2198-2212.

Hertzel, M., Lemmon, M., Linck, J. S. & Rees, L., 2002. Long-Run Performance following Private Placements of Equity. *The Journal of finance (New York),* 57(6), pp. 2596-2617.

Hirshleifer, D., 2001. Investor Psychology and Asset Pricing. *The Journal of finance,* 56(4), pp. 1533-1597.

Ho, Y.-K., 1990. Stock Return Seasonalities in Asia Pacific Markets. *Journal of international financial management & accounting,* 2(1), pp. 47-77.

Iansiti, M. & Lakhani, K. R., 2017. The truth about blockchain. *Harvard business review,* 95(1), pp. 118-127.

Irtiza, M. S., Khan, S., Baig, N., Tirmizi. S. M. A., Ahdmad, I., 2021. The turn-of-the-month effect in Pakistani stock market. *Future business journal,* 7(1), pp. 1-11.

Jacobsen, B. & Marquering, W., 2008. Is it the weather?. *Journal of banking & finance,* 32(4), pp. 526-540.

Jaffe, J. & Westerfield, R., 1985. The Week-End Effect in Common Stock Returns: The International Evidence. *The Journal of finance (New York),* 40(2), pp. 433-454.

Kahneman, D. & Tversky, A., 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica,* 47(2), pp. 263-291.

Kamstra, M. J., Kramer, L. A. & Levi, M. D., 2003. Winter Blues: A SAD Stock Market Cycle. *The American economic review,,* 93(1), pp. 324-343.

Kamstra, M. J., Kramer, L. A. & Levi, M. D., 2009. Is it the weather? Comment. *Journal of banking & finance,* 33(3), pp. 578-582.

Karacaer, S., Kapusuzoglu, A. & Bozkurt, F. G., 2010. From the Anomalies of the Days of the Week Point of View Testing of the Validity of Efficient Market Hypothesis: Evidence from Istanbul Stock Exchange. *Banking and Finance Letters*, 2(1), pp. 215-.

Kawakatsu, H. & Morey, M. R., 1999. AN EMPIRICAL EXAMINATION OF FINANCIAL LIBERALIZATION AND THE EFFICIENCY OF EMERGING MARKET STOCK PRICES. *The Journal of financial research*, 22(4), pp. 385-411.

Keim, D. B. & Stambaugh, R. F., 1984. A Further Investigation of the Weekend Effect in Stock Returns. *The Journal of finance (New York)*, 39(3), pp. 819-835.

Khuntia, S. & Pattanayak, J., 2022. Adaptive calendar effects and volume of extra returns in the cryptocurrency market. *International journal of emerging markets*, 17(9), pp. 2137-2175.

Kinateder, H. & Papavassiliou, V. G., 2021. Calendar effects in Bitcoin returns and volatility. *Finance research letters*, Vol 38.

Kumar, S., 2022. Turn-of-the-month effect in cryptocurrencies. *Managerial finance*, 48(5), pp. 821-829.

Lam, F. E. C. & Wei, K. J., 2011. Limits-to-arbitrage, investment frictions, and the asset growth anomaly. *Journal of financial economics*, 102(1), pp. 127-149.

Lopez-Martin, C., 2022. Ramadan effect in the cryptocurrency markets. *Review of behavioral finance*, 14(4), pp. 508-532.

Magnusson, A., 2000. An overview of epidemiological studies on seasonal affective disorder: Overview of studies on SAD. *Acta psychiatrica Scandinavica*, 101(3), pp. 176-184.

Maheran, M. & Naziman, A. R., 2010. Efficient Market Hypothesis and Market Anomaly: Evidence from Day-of-the Week Effect of Malaysian Exchange. *International Journal of Economics and Finance*, 2(2). pp. 35-42.

Mangram, M. E., 2013. A Simplified Perspective of the Markowitz Portfolio Theory. *Global Journal of Business Research*, 7(1), pp. 59-70.

Markowitz, H., 1952. Portfolio Selection. *The Journal of Finance*, 7(1), pp. 77-91.

Marrett, G. J. & Worthington, A. C., 2009. An empirical note on the holiday effect in the Australian stock market, 1996-2006. *Applied economics letters*, 16(17), pp. 1769-1772.

Mazur, M., Dang, M. & Vega, M., 2021. COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. *Finance research letters,* Vol 38.

McGuinness, P. B., 2005. A re-examination of the holiday effect in stock returns: the case of Hong Kong. *Applied financial economics,* 15(16), pp. 1107-1123.

Mehdian, S. & Perry, M. J., 2002. Anomalies in US equity markets: A reexamination of the January effect. *Applied financial economics,* 12(2), pp. 141-.

Murgea, A., 2016. Seasonal affective disorder and the Romanian stock market. *Economic research - Ekonomska istraživanja,* 29(1), pp. 177-192.

Nakamoto, S., 2008. *Bitcoin: A Peer-to-Peer Electronic Cash System,* s.l.: s.n.

Niroomand, F., Metghalchi, M. & Hajilee, M., 2020. Efficient market hypothesis: a ruinous implication for Portugese stock market. *Journal of economics and finance,* 44(4), pp. 749-763.

Nofer, M., Gomber, P., Hinz, O. &. Schiereck, D., 2017. Blockchain. *Business & Information Systems Engineering,* 58(3), pp. 183-187.

Noyes, C., 2016. Efficient Blockchain-Driven Multiparty Computation Markets at Scale.

Peters, G. W., Panayi, E. & Chapelle, A., 2015. Trends in crypto-currencies and blockchain technologies: A monetary theory and regulation perspective. *A Monetary Theory and Regulation Perspective.*

Pilkington, M., 2016. Does the FinTech Industry Need a New Risk Management Philosophy? A Sequential Blockchain-based Typology for Virtual Currencies and e-Money Services in Luxembourg. *Social Science Research Network.*

Raj, M. & Kumari, D., 2006. Day-of-the-week and other market anomalies in the Indian stock market. *nternational journal of emerging markets,* 1(3), pp. 235-246.

Reinganum, M. R. & Shapiro, A. C., 1987. Taxes and Stock Return Seasonality: Evidence from the London Stock Exchange. *The Journal of business (Chicago, Ill.),* 60(2), pp. 281-295.

Ricciardi, V. &. Simon, H. K., 2000. What Is Behavioral Finance?. *Business, Education & Technology Journal,* Vol 2, pp. 1-9.

Ritter, J. R., 2003. Behavioral finance. *Pacific-Basin finance journal,* 11(4), pp. 429-437.

Rozeff, M. S. & Kinney, W., 1976. Capital Market Seasonality: The Case of Stock. *Journal of Financial Economics,* Vol 3, pp. 379-402.

Rubinstein, M., 2002. Markowitz's 'Portfolio Selection': A Fifty-Year Retrospective. *The Journal of finance,* 57(3), pp. 1041-1045.

Sauer, B., 2016. Virtual Currencies, the Money Market, and Monetary Policy. *International advances in economic research,* 22(2), pp. 117-130.

Segendorf, B., 2014. What is Bitcoin?. *Sveriges Riksbank,* pp. 71-87.

Selvarani, M. & Jenefa, L., 2009. Calendar Anomalies in National Stock Exchange Indices. *The ICFAI journal of applied finance,* 15(1), p. 56.

Shefrin, H. & Statman, M., 1985. The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence. *The Journal of finance (New York),* 40(3), pp. 777-790.

Shleifer, A. & Vishny, R. W., 1997. The Limits of Arbitrage. *The Journal of finance (New York),* 52(1), pp. 35-55.

Škrinjarić, T., 2018. Testing for Seasonal Affective Disorder on Selected CEE and SEE Stock Markets. *Risks (Basel),* 6(5), p. 140.

Tonchev, D. & Kim, T.-H., 2004. Calendar effects in Eastern European financial markets: evidence from the Czech Republic, Slovakia and Slovenia. *Applied financial economics,* 14(14), pp. 1035-1043.

Tversky, A. & Kagneman, D., 1992. Advances in Prospect Theory: Cumulative Representation of Uncertainty.. *Journal of risk and uncertainty.,* 5(4), pp. 297-323.

Vasileiou, E., 2018. Is the turn of the month effect an "abnormal normality"? Controversial findings, new patterns and...hidden signs. *Research in international business and finance,* Vol 44, p. 153.

Wachtel, S. B., 1942. Certain Observations on Seasonal Movements in Stock Prices. *The Journal of business of the University of Chicago,* 15(2), pp. 184-193.

Wing-Keung, W., Aman, A., Nee-Tat & Wong, 2006. The Disappearing Calendar Anomalies in the Singapore. *The Lahore Journal of Economics,* 11(2), pp. 123-139.

World Health Organization, 2023a. *Coronavirus disease (COVID-19).* [Online] Available at: https://www.who.int/health-topics/coronavirus#tab=tab_1 [Accessed 16 October 2023].

World Health Organization, 2023b. *Timeline: WHO's COVID-19 Response.* [Online] Available at: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/interactive-timeline?gclid=CjwKCAjw8-78BRA0EiwAFUw8LNs_WmsLL8rGpqjlnc1xAV55XxoYglmSjV62cN0gyP8hiOhFO9plVxoCNY0QAvD_BwE
[Accessed 16 October 2023].

Yang, H., 2019. *Behavioral Anomalies in Cryptocurrency Markets,* Switzerland: University of Zurich.

Yermack, D., 2015. Is Bitcoin a Real Currency? An Economic Appraisal. *Handbook of Digital Currency,* pp. 31-43.

Zheng, Z., Xie, S.,Dai, H-N., Chen, X. and Wang, H, 2018. Blockchain Challenges and Opportunities: A Survey. *International Journal of Web and Grid Services,* 14(4), pp. 352-375.

Ølnes, S., Ubacht, J. & Janssen, M., 2017. Blockchain in government: Benefits and implications of distributed ledger technology for information sharing. *Government information quarterly,* 34(3), pp. 355-364.