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Negative Bitcoin Sentiment and Its Effects on the Stock Market

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Abstract

This research aims to identify the effect of negative sentiment of the Bitcoin market on the stock market. The research question is formulated as follows: '*What is the effect of negative sentiment of Bitcoin on the stock market?'*. Based on a quantitative and qualitative analysis, it can be concluded that sentiment has a significant effect on stocks that are correlated and uncorrelated to the returns of Bitcoin. However, causality is not proven in this research. No significant spillover effect has been found between forecasts of analysts on uncorrelated stocks during periods of negative sentiment on Bitcoin. This research is useful for investors who would like to adopt a strategy based on the negative sentiment on Bitcoin. The models used in this research could be improved by using a larger sample, making the models more reliable. An avenue for future research would be to investigate the effect of positive sentiment of Bitcoin.

Contents

1 Introduction

In 2008 an anonymous group, or figure, under the pseudonym of Satoshi Nakamoto posted a paper online that offset the rapid rise in crypto currencies and laid the foundation of the ongoing hype surrounding digital currencies. The paper titled “Bitcoin: A Peer-to-Peer Electronic Cash System” was the start of the first peer-to-peer digital currency: Bitcoin. Ever since the launch of this new form of payment, the world has been the witness of an increasing interest in the digital currency (Giudici, Milne, & Vinogradov, 2020). Bitcoin has had, practically, no value for years. The first Bitcoins were auctioned in 2010 for $50. Ten years later this same auction would be worth $600 million. With that, Bitcoin has been one of the most volatile securities, which is often attributed to speculative mania and fueled by news messages and social media (Peterson, 2020). The rise of Bitcoin can be partially attributed to its innovative design. Bitcoin eliminates the need for a trusted third party, allows for irreversible transactions and has a public transaction history, all while transactions remain anonymous. Anyone can create a Bitcoin account, without charge and without any centralized vetting procedure—or even a requirement to provide a real name (Böhme, Christin, Edelman, & Moore, 2015). Over the past few years, researchers have been divided about Bitcoin’s value. Some researches argue in favor of Bitcoin to be a viable alternative of fiat currencies (Cermak, 2017; Nguyen Trinh, 2018). Other articles suggest that Bitcoin is mere foolery, because there is no guaranteed payment and argue that it should be treated as a speculative instrument instead (Baur, Hong, & Lee, 2018; Bradbury, 2013; Yermack, 2015).

Several researchers have developed different metrics to predict the price of Bitcoin, for example with machine learning (Mallquia & Fernandes, 2019; McNally, Roche, & Caton, 2018). Another form of predictive models is through social media and web searches. Matta, Lunesu & Marchesi investigated in 2015 if the spread of the Bitcoin’s price is related to the volumes of tweets or Web Search media. They find significant cross correlation values, especially between the price of Bitcoin and Google Trends data, making web searches a predictor of the price of Bitcoin (Matta, Lunesu, & Marchesi, 2015). Mai et al. took this a step further in 2018 by analyzing sentiment on social media as a predictor of the future value of Bitcoin. They find that social media sentiment is an important predictor in determining Bitcoin’s valuation. However, not all social media messages are of equal impact; messages on internet fora have a stronger impact than tweets.

Literature on news analytics has been growing fast over the years; the works provide evidence that financial markets are partially driven by sentiments (Audrino & Tetereva, 2019). Research in the field of behavioral finance has shown that prices of financial assets are not only based on intrinsic values and rational expectations, but are also driven by irrational factors such as investor sentiment (Su & Li, 2020). Investor sentiment is defined as a belief about future cash flows and investment risks. This reflects the investor’s emotional changes in speculative demand and has gained recognition as a new behavioral driving factor of financial asset price movements (Baker & Wurgler, 2006). Many existing studies have found that investor sentiment can serve as a price-discovery indicator to predict stock returns (Brown & Cliff, 2015); Su & Li, 2020). In other words, investor sentiment belongs to the field of behavioral research and analyzes it's effect to the financial markets. Investors tend to speculate on future prices with use of the overall optimism or pessimism about an asset (Baker & Wurgler, 2006) which can often lead to erroneous beliefs about a market or asset, which causes mispricing. More recent research incorporates the sentiment indicator to predict returns of Bitcoin and find that Twitter sentiment, by using a cryptocurrency-specific lexicon-based sentiment analysis approach, can be used to predict price returns for the nine largest cryptocurrencies: Bitcoin, Ethereum, XRP, Bitcoin Cash, EOS, Litecoin, Cardano, Stellar and TRON (Kraaijeveld & De Smedt, 2020).

Research has shown that sentiment of a certain sector can cause excess return in another sector, this is referred to as sentiment spillover. This sentiment spillover has proven to exist in different markets: from Chinese stock market to stock index futures (Yang & Gao, 2014), between different types of institutional investors (Tsai, 2017), from the US market to G7 countries equities (Bathia, Bredin, & Nitzsche, 2016) and between cryptocurrencies (Bouri, Gabauer, Gupta, & Tiwaride, 2021; Chen & Hafner, 2019). It has been found that Bitcoin is the most connected cryptocurrency contributing heavily to the spillover risk in the cryptocurrency market, meaning that Bitcoin sends market shocks to other cryptocurrencies (Moratis, 2021). In other words, a positive shock in the price of Bitcoin can lead to a positive shock in the price of other cryptocurrencies. This raises the question whether shocks in the Bitcoin market can lead to spillover in other asset classes. The paper by Su and Li (2020) investigates this sentiment spillover among gold, oil and the Bitcoin market. They find that the total sentiment spillover among crude oil, gold and Bitcoin markets is time-varying and is greatly affected by major market events. On average, the Bitcoin market is the major transmitter of directional sentiment spillovers, whereas the crude oil and gold markets are the major receivers. The sentiment spillover from Bitcoin to other asset markets, like the stock market, is yet to be discovered. Furthermore, prior research finds that that pessimistic views weight harder than optimistic views; negative sentiment has a stronger effect on stock prices than positive sentiment (Denk, Huang, Sinha, & Zhao, 2017). This research aims to discover the effect of sentiment of Bitcoin on the stock market and investigate whether negative Bitcoin sentiment will lead to negative sentiment spillover to (un)correlated assets and the forecasts of analysts. This research abstains from incorporation co-movements between Bitcoin and other assets and will concentrate on the spillover impacts of sentiment, returns and forecasts. In order to elaborate on the findings brought to the surface by this research an extensive literature review will be conducted to explore sentiment spillover interconnectedness and providing a roadmap for further research. The research question is as follows:

What is the effect of negative sentiment of Bitcoin on the stock market?

This research question will be answered with help of three hypotheses. First, this research will explore the effect of sentiment on correlated stocks. This will indicate to what extent sentiment of Bitcoin has an effect on stocks that show a linkage with Bitcoin during periods of negative sentiment. The first hypothesis is as follows:

Hypothesis 1: *Bitcoin causes sentiment spillover to correlated stocks*

Secondly, in order to fully capture the effect of negative sentiment this research will focus on forecasts of analysts. Financial analysts forecast prices of stocks one year ahead; the Target Price (TP). This hypothesis will focus on the difference between forecasts during period of negative sentiment and neutral sentiment, specifically between analysts who track stocks already correlated to Bitcoin and analysts who do not track that same correlated stock. A difference in target price might indicate an effect from sentiment of the Bitcoin market, no difference might indicate that sentiment towards Bitcoin has no effect on the behavior of analysts. The second hypothesis is as follows:

Hypothesis 2: *Negative Bitcoin sentiment has a negative effect on analysts' forecasts*

Lastly, this research will explore the effect of sentiment on uncorrelated stocks. This will indicate to what extent sentiment of Bitcoin has an effect on stocks that show no linkage with Bitcoin during periods of negative sentiment. The expectation is that if hypothesis 2 does not document a difference then this hypothesis might also show no spillover; investors do not bring the negative sentiment across markets. The third hypothesis is as follows:

Hypothesis 3: *Bitcoin causes sentiment spillover to uncorrelated stocks*

The research will increase the understanding of sentiment in the Bitcoin market, with respect to the stock market as other asset class. This research will be relevant for investors who would like to adopt a strategy based on Bitcoin sentiment. The results of a possible spillover effect could result in future strategies that can obtain better portfolio value over time compared to basic benchmark strategies (Škrinjarić, Golubić, & Orlović, 2020). This research also contributes to the field of work of behavioral finance with respect to the bias of investor sentiment and sentiment spillover. The following chapters will be structured as follows: the literature review will define important concepts, increase the rationale behind the research and investigate the historical value and sentiment of Bitcoin; the chapter will lay the foundations of the research that will follow. Thereafter, the methodology of the research will be discussed and the data will be specified. This will be followed by the chapter with results and, thereafter, the chapter will follow with conclusion, discussion and avenues for future research.

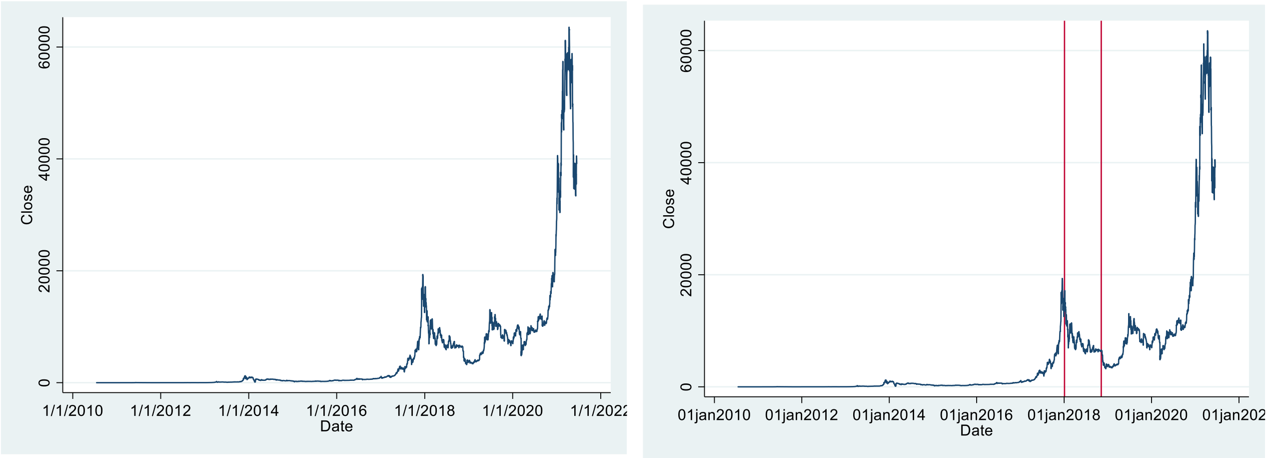
2 Literature review

2.1 History of Bitcoin

The firsts fundamentals of Bitcoin were laid down in 1998. Wei Dai, a Chinese computer scientist, placed a key precursor proposition for Bitcoin. He proposed a design of a 'distributed and anonymous electronic cash system' and called this B-money. In the same year, Nick Szabo also proposed a mechanism for a decentralized digital currency: Bit Gold. Both currencies are seen as the first ever cryptocurrencies, even though they both have never been implemented. However, they are fundamental for Bitcoin's architecture. Satoshi Nakamoto, a pseudonym, introduced Bitcoin in a paper in 2008 called: "Bitcoin: A Peer-to-Peer Electronic Cash System". The paper describes a platform where digital payments could be made and where the payment would flow from payer to receiver without any intermediaries (Nakamoto, "Bitcoin: A Peer-to-Peer Electronic Cash System", 2008). In 2009 Nakamoto mined (See section 2.2.3) the first Bitcoin block: the genesis block. Early adopters of Bitcoin were members of a community called 'Cypherpunk' of which Nakamoto, but also Wei Dai and Nick Szabo were members. The first Bitcoin transaction took place in 2010 when somebody ordered two pizzas for ฿10,000. This same order would be now worth over $550 million. Nakamoto disappeared in 2010 after he mined 100 million Bitcoins. His anonymity is easy to explain: with his disappearance Bitcoin lost the figure that could have be seen as the 'leader', his disappearance makes Bitcoin completely decentralized.

Bitcoin's value has been as low as $0.09. The first big jump in price was in 2013: Bitcoin's price jumped from a little over $13 to $946, but quickly fell back to $400 (Coinmarketcap, 2021). It took four years for Bitcoin to reach $900 again, in 2017, in this same year the price rose to over $13.412. This peak also caused the biggest fall: Bitcoin came down with almost 300% to $3468 over the year 2018. This period of time implies a negative sentiment towards Bitcoin. After 2019, we can see an upward trend to the current value of a Bitcoin; almost breaking the $60.000 mark (Figure 1).

Figure 1: Historical Bitcoin prices, bear market accentuated on right side



The left panel of Figure 1 shows the historical price of bitcoin over the 2010-2021 period. The right panel shows the same, but the bear market is accentuated.

Multiple cryptocurrencies have been invented over the years. These alternative cryptocurrencies are referred to as Altcoins. The most popular Altcoin is Ethereum with a market value of almost $350 million, which is over a third of Bitcoin's total market value (Coinmarketcap, 2021). Altcoins usually have small differences from Bitcoin. For example, Litecoin, which has been created in 2011, creates blocks every two and a half minutes, whereas Bitcoin creates a block every ten minutes. This makes transactions with Litecoin faster than transactions with Bitcoin (Ciaian, Rajcaniova, & Kancsa, 2018). This same research finds that Bitcoin and Altcoins are highly interdependent; similar price developments can be found with Bitcoin and Altcoin. Even with the rise of Altcoins, Bitcoin remains the most popular cryptocurrency with a market value of over $1 trillion (Coinmarketcap, 2021), accounting for over 50% of the total cryptocurrency market capitalization (Figure 2). Kyriazis (2019) conducted a research about the interconnectedness and co-movement of Bitcoin with other cryptocurrencies. The author revealed that Bitcoin is the most dominant cryptocurrency and is the most influential giver as concerning virtual coins and receiver of spillover impacts as regards high-capitalization cryptocurrencies and other assets. Currencies such as Ethereum, Litecoin, and Ripple are found to be in tight relation to Bitcoin mainly as receivers of its spillovers (Kyriazis, 2019).

Figure 2: Total Market Capitalization Dominance in percentages, (Tradingview, 2021)

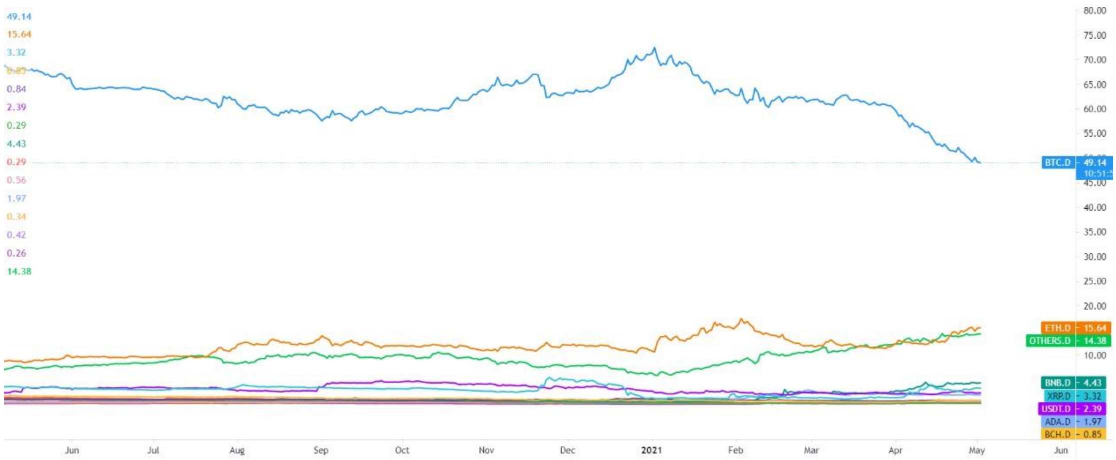


Figure 2 shows the total market capitalization of the cryptocurrency market. The blue line is the percentual market capitalization of Bitcoin, the orange line is the percentual market capitalization of Ethereum, the green line is the percentual market capitalization of Altcoin.

2.2 Mechanism behind Bitcoin

The founder(s) of Bitcoin describe the need of a decentralized way of payment. The purely peer-to-peer version of electronic cash would allow online payments to be sent directly from one party to another without going through a financial institution. All transactions online rely almost exclusively on financial institutions serving as trusted third parties to process electronic payments, which suffers from the weakness of the trust-based model (Nakamoto, 2008). Bitcoin stepped in as electronic payment system based on cryptographic proof instead of trust. This allows two parties to make a transaction directly without the need of a trusted third party. The following sections will explain the design and mechanism behind Bitcoin.

2.2.1 Blockchain

A blockchain is a specific database that stores all information. It is essentially a distributed database of records, or public ledger of all transactions or digital events that have been executed and shared among participating parties. The databases consist of blocks which, when filled with data, are linked to a previously data-filled block. This makes the blocks 'chained' in chronological order, all the way back to the 'genesis block'; the first block created by Satoshi Nakamoto. The blockchain is the full history of every transaction ever made with Bitcoin. Each transaction in the public ledger is verified by consensus of a majority of the participants in the system. In other words: not one single person controls the information, but every user in the blockchain controls it. Lastly, once information has entered the blockchain, it can never be erased (Crosbyet et al., 2016). This means that the blockchain contains information on every transaction ever made. Every ten minutes a new block is created containing new transactions, the mechanism works without intervention of a third party. The blocks make sure that Bitcoins are only spend once and users are not trying to double-spend a Bitcoin. To verify a transaction the consensus of the majority of participants is needed, this is done through mining.

2.2.2 Mining

A Bitcoin miner is part of Bitcoin's peer-to-peer network that collects recent transactions and aims to complete a proof of work scheme (O'Dwyer & Malone, 2014). It is the role of miners to confirm and secure transactions. Practically, this mining process consists of solving a mathematical problem and spreading the result to the Bitcoin network for it to reach consensus. The first miner to solve the mathematical problem gets his block included in the blockchain (Houy, 2014). To control the monetary base, mining is a complex process that requires extensive computational resources. The probability for each miner to solve a mining problem depends on the computational power of his equipment and the complexity of mining is dependent on the total computational power of all miners. Because of the need for certain resources, miners will be compensated in form of new Bitcoins or transaction fees that Bitcoin users can add to their transaction. The complexity of the process is dynamically adjusted so that a block solving and hence a creation of Bitcoins occurs every ten minutes, even when the computational power has increased over time (Houy, 2014). The mathematical problem that is solved by miners is a form of a proof-of-work puzzle: a computation that is thought to be difficult to perform but whose result is easy to verify (Kroll, Davey, & Felten, 2013). To prevent Bitcoin from having an infinite flow of Bitcoins appearing on the market, the reward per mined block is halved after every 210.000 blocks mined. In 2009 the reward per block was 50 Bitcoin, after four years the first 210.000 blocks were mined and the reward was cut in half to 25 Bitcoins. The reward for mining a block is currently 6.25 Bitcoins. This process will continue until 21 million Bitcoins are on the market, approximately, in the year 2140.

2.3 Critique

Bitcoin has shown to have several benefits. Due to its decentralized nature, there is no third party risk and all transactions are tax free. This also means that there are no third parties who can trace back who made a transaction, making a transaction completely anonymous and private. However, Bitcoin is also a subject of criticism. Bitcoin aims to be a replacement of fiat currency, but a currency functions as a medium of exchange, a store of value and a unit of account. Bitcoin largely fails to satisfy these criteria (Yermack, 2015). Yermack who argues against Bitcoin as bona vide currency also argues that Bitcoin faces daily hacking and theft risks, lacks access to a banking system with deposit insurance, and is not used to denominate consumer credit or loan contracts. Furthermore, research by Foley at al. (2019) finds that a quarter of all Bitcoin transactions are involved in illegal activities because of the unregulated nature of Bitcoin (Foley, Karlsen, & Putniņš, 2019). It has also been found that Bitcoin's annual electricity consumption adds up to 45.8 TWh, which is produced by the participants in the mining process. This level sits between the carbon footprint of the nations of Jordan and Sri Lanka (Stoll, Klaaßen, & Gallersdörfer, 2019). This carbon footprint is expected to increase even more over time, because the computational power will be extended to fulfil the mining process.

2.4 Bitcoin as investment

Even though Nakamoto intended Bitcoin to be an alternative currency and to be used as electronic cash system, many see Bitcoin as an alternative investment security and the amount of Bitcoins used as investment cannot be overlooked (Hong, 2017). Hong finds in his research that a combined portfolio of S&P500 and Bitcoin momentum strategy results in a higher expected return, making Bitcoin a viable asset to include in portfolio strategies. Moreover, empirical findings find that the price of Bitcoin is affected by returns on the S&P500 and sentiment indicators like Google searches (Kjærland et al, 2018; López-Cabarcosa et al., 2021). The research of Lòpez-Cabarcose et al. (2021) concludes that financial markets and social network sentiment influence Bitcoin volatility. Bitcoin shows different behaviors depending on market conditions. Thus, Bitcoin could act as a safe haven, implying that investors could use Bitcoin as refuge asset when the Bitcoin market is stable. Or when the Bitcoin market has high volatility, and stock markets have low volatility, investors could use Bitcoin as a speculative asset. This makes Bitcoin a viable investment vehicle.

3 Data

This chapter outlines the data that will be used for the empirical research. Firstly, this chapter will describe the dataset that will be used to explore the hypothesis. Thereafter, section 3.1 until 3.3 will explain the choice and further exploration of certain data.

The dataset includes daily logarithmic returns of Bitcoin, daily logarithmic returns of stocks considered correlated with Bitcoin, as explained in section 3.1, and daily logarithmic returns of stocks uncorrelated to Bitcoin, as explained in section 3.2. Bitcoin prices are retrieved from CoinDesk, which calculates and publishes the average price of Bitcoin in major Bitcoin exchanges. Daily data on the stocks are extracted from WRDS (CRSP) and include daily prices which are then transformed to logarithmic returns. The descriptive statistics of the daily stock prices and Bitcoin prices can be found in appendix A. Bitcoin had an average price of $7540 over the year 2018, with the lowest price $3200 and highest price of almost $17000, making it the year with one of the fastest price drops in the history of Bitcoin. The data time period available for Bitcoin is 19 July 2010 to June 2021, where the starting date is determined by the availability of Bitcoin data. Furthermore, the database Thomson Reuters I/B/E/S provides estimates featuring 26 forecast measures for more than 70,000 companies. Specifically for this research, the target price (TP) of assets (un)correlated to Bitcoin will be used from several different analysts. The analysts and stocks will be chosen, based on availability of analysts that make forecasts for both a correlated and an uncorrelated stock. The data projects price levels as forecasted by analysts within a specific time horizon. Analysts chose to adjust their forecast when they believe it has changed, which might happen monthly or bi-monthly. This chapter will be structured as follows: first assets correlated and uncorrelated with Bitcoin will be specified, then this correlation will be checked and, lastly, the sentiment data will be explained.

3.1 Database

3.1.1 Assets correlated with Bitcoin

This section will explore which assets are correlated with the movement of Bitcoin, specifically the correlation in a bearish market of Bitcoin; the Bitcoin market has seen its longest bear market between the beginning of 2018 until the end of 2018, where the coin dropped 70%. Based on commonly used statistical measures, a correlation of zero means the performance of one asset is uncorrelated to the other, while a correlation of one indicates that the asset moves in lockstep—in the same direction, and by the same degree. A positive correlation could imply co-movement with a certain asset, which means that stock returns can be predicted by the negative market sentiment towards Bitcoin. The most correlated asset is, presently, the Grayscale Bitcoin Trust (GBTC) with a correlation of 0.81 meaning that the trust moves nearly in lockstep with the crypto, as noted by a news platform (DeCambre, 2021). Multiple research papers have investigated the correlation of Bitcoin with various asset classes. Symitsi and Chalvatzisb (2019) estimate with use of a multivariate GARCH model the dynamic conditional correlations between Bitcoin and other asset classes. They find positive correlation, albeit low, between Bitcoin and the S&P500 index and Dow Jones index (Symitsia & Chalvatzisb, 2019). Klein et al. (2018) use a k-dimensional conditional mean structure and also find a correlation between Bitcoin and the S&P500 index, but also with the MSCI World Index and MSCI Emerging Market index between the period 2011-2017. In addition, by estimating the quantile correlation coefficient using logarithmic returns, Kristoufek (2020) finds a positive correlation between Bitcoin and the S&P500 and the Nikkei 225 index based on the 2014 to 2020 period. Therefore, the database used will include the S&P500 index, Dow Jones index, NASDAQ-100 index and the Nikkei 225. Stocks from these indices will be selected based on market capitalization, because these stocks are well-known stocks and traded frequently. Then, the stocks are checked on their correlation with Bitcoin in 2018. Stocks that show no correlation might then be excluded or moved to the other database: assets uncorrelated to Bitcoin. The selected stocks are shown in Appendix A.

3.1.2 Assets uncorrelated to Bitcoin

This section will explore which assets are uncorrelated with the movement of Bitcoin, specifically the uncorrelation in a bearish market of Bitcoin. If a positive correlation implies co-movement with a certain asset, then a negative correlation implies the opposite; a perfect negatively correlated asset will move in the exact opposite direction. This means no correlation implies that Bitcoin can be used for hedging purposes in a stock portfolio to diversify away the risk that comes with a certain asset. Stocks have been found to have a, albeit small, positive correlation with Bitcoin. Therefore, other assets need to be explored to find assets that do not move or move inversely to Bitcoin. It has been known that bonds, sovereigns as well as corporates, have not moved or moved inversely with stock prices; this means that a bond price will go up if the stock price goes down or shows no significant effect. Ram (2019) researched this relation between ALBI (All Bond Index), S&P International Corporate Bond and Bitcoin and found negative correlation to no correlation. The author also finds no correlation between Bitcoin and real estate (Dow Jones Global Select Real Estate Securities) and Bitcoin and Gold, the latter has already been known to be negatively correlated to stocks. Bitcoin is also not correlated with the DXY, a dollar index that tracks the dollar's price against a basket of other currencies (Ghorbel & Jeribi , 2021), they find no correlation between Bitcoin and Gold, which is in line with the research of Ram (2019). However, this research focuses on the spillover to stocks. Therefore, the database will include stocks of companies that trade or work with gold and the Dow Jones Global Select Real Estate Securities. Stocks from these indices will be selected based on market capitalization and then checked on their correlation with Bitcoin in 2018. Stocks that show correlation might then be excluded or moved to the other database: assets correlated to Bitcoin. The overview of selected stocks are presented in appendix A.

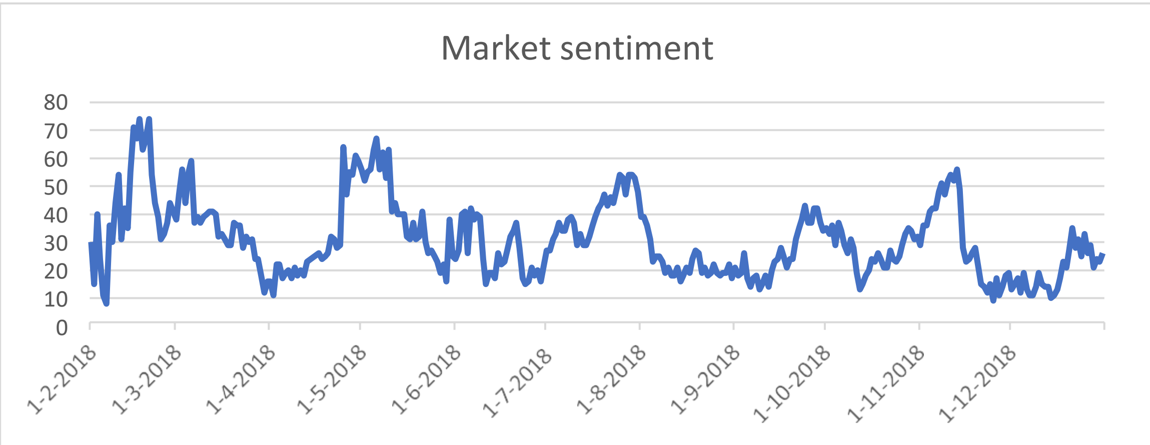
3.2 Correlation check

The correlation between two assets is dynamic and subject to change over time. Therefore, a check is needed to ensure a reliable database for the research. The correlation between the stocks and Bitcoin will be measured over the year 2018, because this period is known to be the longest bear market of Bitcoin. The correlation will also be measured over the year prior to Bitcoin entering the bear market, to grasp the change correlation. The Pearson correlation coefficient is a linear regression performed on Bitcoin's return and the return of a certain stock against each other. The correlation coefficient ranges from −1 to +1, the larger the absolute value of the coefficient, the stronger the relationship between the variables. While the correlation coefficient is a measure of the historical relationship between assets, it may provide insights to the future relationship between the assets. A limitation of modelling correlation through a linear regression is the decreasing predictive power of the correlation coefficient when the time span increases. Therefore, this research focuses on a smaller time span of one year. A correlation between -0.1 and 0.1 will be seen as 'no correlation'. The dataset includes nine positively correlated stocks, eighteen neutral stocks and zero negatively correlated stocks in the year 2018 (Appendix B). The correlations of the positively correlated stocks are all statistically significant at either 5% or 10%. The uncorrelated stocks show no significance, because the correlation coefficient is not significantly different from zero. Correlation between the returns of Bitcoin and the returns of certain stocks has increased from 2017 till 2018. The data from the 2017-period shows only four correlated stocks and the remainders uncorrelated. Of the database, 17 out of 27 have increased in correlation, with five stocks changing from uncorrelated stocks to correlated stocks. This might be in line with the literature of Denk et al. (2017), they had found that pessimistic views weight harder than optimistic views; stock prices are more affected by negative sentiment than positive sentiment resulting in a stronger co- movement with the negative market sentiment of Bitcoin.

3.3 Sentiment indicator

The Bitcoin Fear & Greed Index will be used as a proxy to capture the market sentiment of Bitcoin. The FG index is a tool build to model market behavior based on emotion in the Bitcoin market. People tend to get greedy when the market is rising, which results in fear of missing out. Also, people often sell their coins in irrational reaction of seeing red numbers. With the Fear and Greed Index they model emotional overreactions on a scale from 0 to 100, with 0 as extreme fear and 100 as too greedy. When investors are too greedy, the market has high sentiment, it means the Bitcoin market is rising and the market might be due for a mispricing correction. Extreme fear is a sign of low sentiment; investors are worried and the asset might decline in price. The index is created with the following factors. Volatility (25%): an unusual rise in volatility is a sign of a fearful market. Market Momentum/Volume (25%): high buying volumes is an act of greed. Social media (15%): a Reddit and Twitter analysis with an unusual high interaction resulting in greed. Surveys (15%): a poll asking investors directly their sentiment. Dominance (10%): the market capitalization of Bitcoin. Trends (10%): various Bitcoin related Google search queries, for example, an increase in the query ‘Bitcoin price manipulation’ is a sign of fear in the market (Crypto Fear and Greed index, sd).

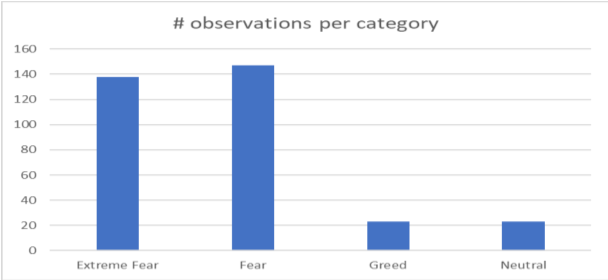
Figure 3. Sentiment distribution in 2018



The Bitcoin Fear & Greed Index gauges investor sentiment and can be a precursor for any market movement (Crypto Fear and Greed index, sd). The sentiment index has historical data as soon as 01-02-2018, there are 331 sentiment observations (Figure 2), where fear and extreme fear are the most dominant categories. This suggests a low market sentiment towards Bitcoin during the bear market (Figure 3).

Figure 3. Sentiment observations per category in 2018

Category	# of observations
Extreme Fear	138
Fear	147
Greed	23
Neutral	23



4 Methodology

This chapter will outline the methodology that will be used for the empirical research. The methodology outline will be provided per hypothesis. The research will use daily log return data to study the sentiment spillover from Bitcoin to other stocks. Bitcoin data has proven to be volatile and sometimes unpredictable, therefore the data will be checked by performing robustness tests. Stationarity will be tested with a Dickey-Fuller test, normality will be tested with a Skewness Kurtosis test for normality and to account for heteroscedasticity and autocorrelation the hypothesis will be tested with a Newey-West robust estimator, with four lags as determined by the rule of thumb proposed by Newey & West (Newey & West, 1987). The results can be found in appendix C.

4.1 Hypothesis *1*

Under the first hypothesis will be tested if Bitcoin causes sentiment spillover to correlated stocks. This will be researched by investigating the effect of a period of negative sentiment in the Bitcoin market on the returns of correlated stocks. To determine this relationship a time series analysis will be conducted and a linear regression analysis (OLS with Newey-West robust estimator). The regression will look as follows:

$$(1)\ y = \beta_0 + \beta_1 x_1 + \varepsilon$$

With the dependent variable (y) the daily log return of correlated stocks and x_1 the day-to-day change in market sentiment of Bitcoin, while controlled for Bitcoin and S&P500 returns. The null hypothesis, as specified below, will be rejected when a significant effect has been found between the return of the stock and the sentiment.

$$H_0: \beta = 0$$

$$H_a: \beta \neq 0$$

4.2 Hypothesis *2*

Under the second hypothesis will be investigated whether negative sentiment of Bitcoin has a negative effect on the forecasts of analysts. To estimate the effect on analysts forecast, a difference-in-difference (DiD) method will be applied. This method involves comparing results from two groups, the control group and treatment group, with data from multiple stocks and multiple analysts. The control group is not exposed to 'treatment' before or during one of the two time periods. The treatment group is exposed to a treatment before or during one of the two time periods. The same amount of observations is made for both groups, over the same period of time. In this research is the treatment group an analysts (A or B) who tracks a stock that is correlated to Bitcoin and makes forecasts of a stock uncorrelated to Bitcoin. The control group is the average forecast price of multiple analysts who track the same uncorrelated stock as Analyst A/B, but who do not track the correlated stock. The two time periods will consist of a period with negative sentiment and a period with neutral sentiment. The period of negative sentiment is the year 2018, where the average sentiment was 30. The period of neutral sentiment is the year 2019, where the average sentiment was 45. The DiD will calculate the difference between the first and second time period and then subtract the average gain or loss in the control group from the average gain or loss in the treatment group. To minimize the effects of a possible unrelated trend, different analysts will be taken into account and multiple uncorrelated stocks will be used. The result will show if negative sentiment of Bitcoin has, to some extent, the same effect on both groups. DiD is usually implemented as an interaction term between time and treatment group dummy variables in a regression model (Childers, 2021; (Columbia, sd). The DiD looks as follows:

$$(2)\ Y = \beta 0 + \beta 1 * [Time] + \beta 2 * [Treatment] + \beta 3 * [Time * Treatment] + \varepsilon$$

The key idea behind the Difference-in-Difference model is the parallel-trend assumption: without the treatment, the treatment group would experience the same change in forecast as the control group. This assumption allows for any additional changes in forecast to be attributed to the treatment; the negative sentiment. The groups and time periods are identified with dummy variables with a value of either zero or one, depending on the existence of negative sentiment. The dummies together create the interaction variable, which shows the effect of the treatment (negative sentiment) on the treatment group (correlated stock). The coefficient β3 is the difference in-difference estimator. This shows the average effect on the treatment group and is the coefficient of interest. β0 is the baseline average of the control group, β1 the time-trend in the control group and β2 the difference between the groups during neutral sentiment.

4.3 Hypothesis *3*

Under the third hypothesis will be tested whether Bitcoin causes sentiment spillover to uncorrelated stocks. To answer this hypothesis the same methodology as proposed under 3.1 will be used. If hypothesis 2 documents no differemce between both groups, then the null hypothesis of no effect is not expected to be rejected.

5 Results

5.1 Hypothesis 1

Under hypothesis 1 will be tested if Bitcoin sentiment has an effect on stocks correlated with Bitcoin. The correlated stocks and robustness tests can be found in appendix B and C. The data is stationary, however, not normally distributed. The key results of the model are presented in Table 1. The model finds a significant effect between Bitcoin sentiment and correlated stocks. When zoomed in on the individual companies in the sample, it has been found that sentiment has a significantly effect on Boeing, Goldman Sachs, NVIDIA Corporation, Tesla, Toyota and UnitedHealth Group. The companies Apple, American Towers and Newmont Mining return no significant effect between sentiment of Bitcoin (Table 2). Therefore, it seems that the returns of these companies are not driven by the market sentiment of Bitcoin. When sorted per industry it has been found that sentiment does not have a significant effect on the gold stocks and real estate stocks, which is in line with the expectations that came forth from the literature. Gold and real estate serve as hedging instrument in investor's portfolio, the correlation that was found between the returns of bitcoin and these specific gold and real estate stocks might have been found by default and random luck.

The robustness tests show no issues other than non-normality. However, daily returns might show more random fluctuations and external factors that are not related to the sentiment leading to noise in the data. This problem is partly solved by using logarithmic data, which removes outliers and lets the data approach normal distribution. However, the problem is still not completely solved, because logarithmic data only approaches normality; the data is still not perfectly normally distributed (appendix C). Because this research focuses on a smaller time period, the initial choice for daily data was for the sake of sufficient observations. To make sure the daily return does not lead to a distorted result, the same regression model has been used with logarithmic monthly return data. This monthly data is normally distributed (appendix C), in contrast to the daily data which is not normally distributed. The model, when monthly data is used, finds significant effect between sentiment and the companies with positive correlation with Bitcoin. When zoomed in on the companies, it is found that all companies show significant results. This means that Apple, American Towers, Newmont Mining and Tesla now also have a significant effect with sentiment of Bitcoin. However, this model uses a small sample of only twelve observations, because the time period covers twelve months. This fact makes the model less reliable. The results of the model with monthly data are added as robustness test in appendix C. The results of the first hypothesis are as follows. The null hypothesis is rejected: an effect of market sentiment of Bitcoin on the return of correlated companies has been found on monthly and daily basis.

Table 1. Newey-West regression of sentiment on stocks

Stock	Coefficient	t	95% Confidence Interval	
Sentiment	0.01*** (0.000)	4.84	0.00	0.01
SP500	0.02* (0.05)	0.44	-0.08	0.12
Bitcoin	0.02** (0.01)	0.16	-0.01	0.04
Constant	0.00 (0.00)	0.13	0.00	0.00
Observations	2.034			
|F| > Probability	0.00			
Maximum Lag	4			

Table 1 provides the results of regression with Newey-West standard errors with collapsed stock data as dependent variable and sentiment as independent variable, the S&P500 and Bitcoin returns are added as control variables*. Standard errors are presented in parenthesis, Inference: *** p<0.01; ** p<0.05; * p<0.1*

Table 2. Newey-West regression of sentiment on stocks

Stock	Coefficient	Standard Error	F-Value
Apple	0.005	0.005	0.79
American Towers	0.004	0.003	1.99
Boeing	0.016***	0.004	9.96
Goldman Sachs	0.011***	0.004	3.48
Newmont Mining	0.002	0.004	0.43
NVIDIA Corporation	0.019***	0.006	5.33
Toyota	0.006*	0.004	1.43
Tesla	0.116*	0.008	1.30
UnitedHealth Group	0.007**	0.003	2.89
Observations	251		
Maximum Lag	4		

*Table 2 provides the combined results of linear regressions with Newey-West standard errors with a certain correlated stock return as dependent and sentiment as independent variable, the S&P500 and Bitcoin returns are added as control variables. Standard errors are presented in parenthesis, Inference: *** p<0.01; ** p<0.05; * p<0.1*

5.2 Hypothesis 2

Under hypothesis 2 will be tested if Bitcoin sentiment has an effect on the forecasts of analysts. This will be tested by comparing the forecasts of uncorrelated stocks of an analyst who tracks a correlated stock and the mean forecasts of analysts who do not track that stock. In this dataset is Boeing the most correlated asset (0.16) and therefore used to find analysts who makes forecasts of both Boeing and an uncorrelated stock from the dataset. Two analysts have been found to track both Boeing and an uncorrelated stock: Analyst A and Analyst B. The uncorrelated stocks are Simon Property Group and UnitedHealth Corporation, respectively. The control group consists of analysts' forecasts on the stock not correlated to Bitcoin. The treatment group consists of either analyst A or B with their monthly forecast of the uncorrelated stock. The treatment group is susceptible for effect of the negative market sentiment towards Bitcoin and possibly takes this sentiment with them when making forecasts of the uncorrelated stock.

The results of the DiD are presented in Table 3 and Table 4. The baseline (t=0) refers to the period with neutral market sentiment and the follow up period (t=1) refers to the period with negative sentiment. Column (2) shows the average forecast price of the analyst who tracks Boeing. Column (3) shows the average forecast price of the remaining analysts. The difference (T-C) is the difference between the treatment and control group for t=0 and t=1. The diff-in-diff estimator is the difference between the two differences (T-C), or in other words, the coefficient of the interaction factor estimated with a regression model. Table 3 displays the results of Analyst A. The difference between the treatment group (correlated) and the control group (uncorrelated) is at t=0 32.756 and the difference between the treatment group (correlated) and the control group (uncorrelated) is at t=1 34.674, both statistically significant at 1%. This means that the forecasts of Analyst A are 17.3% and 18.5% higher than the mean forecast price of the other Analysts. This results in a difference of 1.918 between the forecasts of analyst A and the other analysts between time periods, while a negative difference was expected to be found for a spillover effect. However, this difference-in-difference estimator is not statistically significant (p=0.563). This means that there is no significant effect found of negative Bitcoin sentiment on the forecasts of analysts. Table 4 displays the results of Analyst B. The difference between the treatment group (correlated) and the control group (uncorrelated) is at t=0 6.179 and the difference between the treatment group (correlated) and the control group (uncorrelated) is at t=1 12.080, statistically significant at 10% and 1%, respectively. This means that the forecasts of Analyst B are 4.0% and 8.2% higher than the mean forecast price of the other analysts. This results in a difference of 5.901 between the forecasts of analyst A and the other analysts between time periods, while a negative difference was expected to be found for a spillover effect. However, this difference-in-difference estimator is not statistically significant (p=0.182). This means that there is no significant effect found of negative Bitcoin sentiment on the forecasts of analysts. These results might imply one of the following: the analysts are experienced investors and do not take the negative sentiment with them when making a forecast on an uncorrelated stock, the analysts are all equally affected by the negative sentiment or an effect has not yet been proven. This might be due to the sample, which is rather small. It was a difficult task to identify analysts who make forecasts on a correlated and an uncorrelated stock, with both of them included in the data sample of this research. As a consequence of the lack of observations, this research is not able to provide a more in-depth analysis of the effect of negative sentiment on stock forecasts of analysts. A dataset that includes all stocks and matches all analysts requires a lot of computational power, but will improve the quality of the research. Furthermore, there might be stocks even more correlated than Boeing which one or more or the other analysts follow. This makes it possible that a spillover effect is yet to be proven. The results of the second hypothesis are as follows. The null hypothesis is not rejected: an effect of market sentiment of Bitcoin on the forecasts of analysts has not been found.

Table 3. DIFFERENCE-IN-DIFFERENCES estimation results

	Predicted Sign (1)	Analyst A (2)	Other (3)	Difference (4)
Before (t=0)	o	221.833	189.087	32.756*** (2.329)
After (t=1)	-	222.333	187.660	34.674*** (2.329)
Difference (T-C)	-	0.500	-1.427	1.918 (3,294)
Observations	48			
R-Squared	0.91			

*Table 3 provides the results of the difference-in-difference test with Analyst A as treatment group. Standard errors are presented in parenthesis, Inference: *** p<0.01; ** p<0.05; * p<0.1*

Table 4. DIFFERENCE-IN-DIFFERENCES estimation results

	Predicted Sign (1)	Analyst B (2)	Other (3)	Difference (4)
Before (t=0)	o	160.167	153.988	6.179*** (3.077)
After (t=1)	-	159.333	147.253	12.080*** (3.077)
Difference (T-C)	-	-0.834	-6.735	5.901 (4.532)
Observations	48			
R-Squared	0.34			

*Table 4 provides the results of the difference-in-difference test with Analyst B as treatment group. Standard errors are presented in parenthesis, Inference: *** p<0.01; ** p<0.05; * p<0.1*

5.3 Hypothesis 3

Under hypothesis 3 will be tested if Bitcoin sentiment has an effect on stocks uncorrelated with Bitcoin. The uncorrelated stocks and robustness tests can be found in appendix B and C. The data is stationary, however, not normally distributed. The key results of the model are presented in Table 5. The model finds a significant effect between sentiment and companies with no correlation with Bitcoin. Therefore, it seems that the returns of the companies are driven by the market sentiment of Bitcoin. When zoomed in on the individual companies in the sample, it has been found that sentiment has a significantly effect on Comcast, Disney, Microsoft and Simon Property. The remaining companies return no significant effect between sentiment of Bitcoin (Table 6). Therefore, it seems that the returns of these companies are not driven by the market sentiment of Bitcoin. When sorted per industry, the same results as in 5.1 are found: gold stocks and real estate stocks show no significant results with Bitcoin sentiment.

The robustness tests show no issues other than non-normality. However, daily returns might show more random fluctuations that are not related to the sentiment leading to noise in the data. This problem is partly solved by using logarithmic data, but still not completely gone, since the data is not normally distributed (appendix C). Because this research focuses on a smaller time period, the initial choice of daily data was for the sake of sufficient observations. To make sure the daily return does not lead to a distorted result, the same regression model has been used with logarithmic monthly return data. This regression finds a significant effect between sentiment and companies with positive correlation with Bitcoin. When zoomed in on the results per country, then it is found that all companies show a significant result with the sentiment of Bitcoin. This differs from the model with daily data where only three companies returned significant results. This can be interpretated as follows. The uncorrelated stocks have a weaker link with sentiment on a day-to-day basis, however, might be affected on a longer time period with the monthly average sentiment. In other words, uncorrelated stocks have a weaker link than the correlated stocks, but are equally affected on a longer timer period. However, this model uses only a small sample of twelve observations per company, because the bear market covers twelve months. This fact makes the model less reliable. The results of the model with monthly data are added as robustness test in appendix C. The expectation of these results was that if hypothesis 2 does not document an effect, then the results of this hypothesis will also show no effect. However, where the results of hypothesis 2 did not find an effect, the results of hypothesis 3 did find an effect. This might be explained by the exposure Bitcoin has in media outlets. Fluctuations of Bitcoin are closely followed and given lots of attention, leading to equal spillover to all stocks caused by every analyst. This would lead to an insignificant difference. Another explanation is that the specific stocks investigated under hypothesis 2 (Simon Property and UnitedHealth) are overall unaffected by the negative sentiment. However, Simon Property is among the stocks where a significant effect has been found between the return on sentiment of Bitcoin. Which makes the latter explanation unlikely. The results of the third hypothesis are as follows. The null hypothesis is rejected: an effect of market sentiment of Bitcoin on the return of uncorrelated companies, however for some specific companies only on a monthly basis.

Table 6. Newey-West regression of sentiment on stocks

Stock	Coefficient	t	95% Confidence Interval	
Sentiment	0.004*** (0.001)	3.10	0.001	0.006
SP500	0.078* (0.035)	2.20	0.009	0.147
Bitcoin	0.008** (0.009)	0.92	-0.009	0.025
Constant	-0.001** (0.000)	0.07	-0.001	0.000
Observations	3.616			
|F| > Probability	0.00			
Maximum Lag	4			

Table 6 provides the results of regression with Newey-West standard errors with collapsed stock data as dependent variable and sentiment as independent variable, the S&P500 and Bitcoin returns are added as control variables*. Standard errors are presented in parenthesis, Inference: *** p<0.01; ** p<0.05; * p<0.1*

Table 7. Newey-West regression of sentiment on stocks

Stock	Coefficient	Standard Error	F-Value
Adobe	0.008	0.005	1.40
Amazon	0.003	0.005	0.37
Brookfield	0.005	0.004	0.87
cci	0.004	0.003	2.14
Comcast	0.006*	0.004	1.47
Disney	0.006*	0.003	1.86
Facebook	0.002	0.005	0.31
Google Inc.	0.005	0.005	0.46
Hecla Mining	-0.005	0.008	0.63
Microsoft	0.009*	0.005	1.79
PayPal	0.007	0.005	1.05
Sibanye Gold	-0.005	0.009	1.15
Sony	-0.001	0.004	0.06
Simon Property Group	0.005*	0.003	3.18
United Technology	0.005	0.003	2.57
Observations	251		
Maximum Lag	4		

Table 7 provides the combined results of linear regressions with Newey-West standard errors with a certain uncorrelated stock return as dependent and sentiment as independent variable, the S&P500 and Bitcoin returns are added as control variables. *Standard errors are presented in parenthesis, Inference: *** p<0.01; ** p<0.05; * p<0.1*

6 Conclusion

Bitcoin has been a rising phenomenon and internet sensation ever since its invention in 2008. With Bitcoin's price rising from as low as $0.09 till over $50.000 has it been an influential asset in many investor's portfolio. Bitcoin is known to be one of the most volatile securities, mainly due to attention it has been getting from the media. Investors get influenced by the news around Bitcoin; the good stuff and the bad stuff. This sentiment has been influencing the price of Bitcoin, with low sentiment resulting in fear on the Bitcoin market making the price of Bitcoin fall and positive sentient resulting in greed making the price of Bitcoin rise. Research has shown that sentiment of a certain sector can cause excess return in another sector, this is called sentiment spillover. This sentiment spillover has proven to exist in different markets: from Chinese stock market to stock index futures (Yang & Gao, 2014), between different types of institutional investors (Tsai, 2017), from the US market to G7 countries equities (Bathia, Bredin, & Nitzsche, 2016) and between cryptocurrencies (Bouri, Gabauer, Gupta, & Tiwaride 2021; Chen & Hafner, 2019). It has been found that Bitcoin is the most connected cryptocurrency contributing heavily to the spillover risk in the cryptocurrency market, meaning that Bitcoin sends market shocks to other cryptocurrencies (Moratis, 2021). This research aims to identify the effect of negative sentiment towards the Bitcoin market on the stock market. Based on a quantitative analysis on the effect, it can be concluded that stocks that are already correlated to the returns of Bitcoin are significantly affected by the negative sentiment of Bitcoin. The results imply that when sentiment of Bitcoin declines, the stock price also declines. However, causality is not proven in this research. When looked at the effect of negative Bitcoin sentiment on the effect of the forecasts of an analyst who tracks correlated stocks on their forecasts on uncorrelated stocks, no significant effect can be found. This means that possible sentiment spillover through analysts is not proven. These results might imply one of the following: the analysts are experienced investors and do not take the negative sentiment with them when making a forecast on an uncorrelated stock, the analysts are all equally affected by the negative sentiment or an effect has not yet been proven. This might be due to the sample which is rather small or the possibility that some analysts track another correlated stock. It has also been found that stocks that are uncorrelated to the returns of Bitcoin are significantly affected by the negative sentiment of Bitcoin. However, when specifically looked at the stocks in the sample, no effect can be found on a day-to-day basis, but only on a monthly basis. The research question was formulated as follows: '*What is the effect of negative sentiment of Bitcoin on the stock market?'.* An effect can be found of negative sentiment on the stock market for both correlated and uncorrelated stocks, but causation has not been proven. An explanation of this effect could be that investors are influenced by the exposure Bitcoin has in media outlets where the fluctuations of Bitcoin are closely followed and given lots of attention, leading to spillover to all sort of stocks, leading to investors picking this sentiment up and taking it with them when making investment decisions on the stock market. Analysts are seemingly unaffected by the negative sentiment of Bitcoin, with them showing no significant spillover to uncorrelated stocks. However, this research only focusses on a limited dataset with stocks. An improvement would be to create a dataset with more stocks, making the models more reliable. A dataset that includes all stocks and can match all analysts requires a lot of computational power, but will improve the quality of the research. Another limitation is missing sentiment data in the year 2017, the index used starts in 2018. This makes it hard to model the effect of sentiment before the bear market. However, it has been found that stocks became more correlated to Bitcoin when Bitcoin entered the bear market. This might be caused by the stronger effect negative sentiment has on investor's behavior, but this research does not go in depth on this causation. The research increased the understanding of sentiment in the Bitcoin market, with respect to the stock market as other asset class and can lead to an adoption of an investment strategy based on sentiment of Bitcoin. Periods of low Bitcoin sentiment show a significant relationship with lower stock returns over that period, making it a feasible investment strategy to short the stock market during times of low sentiment. The effect of high sentiment has not been researched and might show different results, making it an avenue for future research.

Appendix A: Dataset

This section gives an overview of the main variables used in this research and its descriptive statistics.

Table 8. Stocks selected

S&P 500	Dow Jones	Nasdaq	Nikkei225	Gold	Real Estate
Apple (aapl)	Goldman Sachs (gs)	Tesla (tsla)	Toyota (toyoy)	Newmont Goldcorp (ne)	Simon Properties (spg)
Microsoft (msft)	Disney (dis)	NVIDIA (nvda)	Sony (sne)	Hecla mining (hl)	Brookfield AM (bam)
Amazon (amzn)	UnitedHealth Group (utx)	Paypal (pypl)	NIPPON TEL (nipny)	Sibanye Gold (sbsw)	American Tower (amt)
Facebook (fb)	Boeing (ba)	Adobe (adbe)	Recruit holdings (rcrrf)	Newmont Mining (nem)	Crown Castle (cci)
Alphabet Inc. (goog)	United Technologies (unh)	Comcast (cmcsa)			

Table 8 provides an overview of all selected stocks based on the literature review under section 3.1 The ticker of the stock is provided between brackets.

Table 9. Descriptive Statistics

Ticker	Mean	Standard Deviation	Min	Max
Msft	101.034	7.917807	85.01	115.61
fb	171.5109	19.97745	124.06	217.5
goog	1113.225	67.31555	976.22	1268.33
aapl	189.0534	20.59386	146.83	232.07
pypl	82.60359	4.816848	71.73	93.07
Utx	128.4057	6.825534	102.06	142.08
Ba	344.6941	17.36845	294.16	392.3
Jnj	133.0255	7.726383	119.4	148.14
Dis	108.3752	5.547858	98.54	118.9
adbe	235.0374	23.15336	177.7	275.49
amzn	1641.726	197.2751	1189.01	2039.51
nvda	232.3841	36.5	127.08	289.36

Gs	233.0922	24.79008	156.35	273.38
cmcsa	35.78163	2.894783	30.59	42.99
Unh	248.322	17.0148	212.55	286.33
Tsla	317.3099	28.7602	250.56	379.57
Sne	51.46566	3.488369	45.5	60.65
toyoy	127.6552	7.066652	111.81	140.72
sbsw	3.16741	0.884926	2.05	5.48
Hl	3.32243	0.598596	2.22	4.49
Nem	36.04151	3.501378	29.6	41.94
Spg	168.4991	11.22354	146.74	190.59
Bam	41.25004	1.771012	36.66	44.9
Amt	145.7133	8.282871	133	167.63
cci	108.3938	3.711598	100.82	117.47
Observations	251			

Table 9 provides the descriptive statistics of stock prices and Bitcoin prices over the year 2018.

Appendix B: Correlation

This section contains all correlation coefficients of the stocks used in the dataset.

Table 10. Descriptive Statistics

Ticker	2017	2018	2018-2017
aapl	0.0866	0.1081*	0.0215
adbe	0.0073	0.0562	0.0489
amt	0.1405**	0.1198*	-0.0207
amzn	0.0021	0.0409	0.0388
ba	0.0421	0.1588**	0.1167
bam	0.098	0.0592	-0.0388
cci	0.028	-0.064	-0.092
cmcsa	-0.0652	0.0189	0.0841
dis	-0.0588	0.0102	0.069
fb	0.04	0.0178	-0.0222
goog	0.0866	0.0554	-0.0312
gs	0.0351	0.1194**	0.0843
hl	-0.0005	0.0029	0.0034
msft	-0.0148	0.0811	0.0959
nem	0.0408	0.101**	0.0602
nvda	0.107*	0.1214*	0.0144
pypl	0.0257	0.0874	0.0617
sbsw	-0.0113	0.0609	0.0722
sne	0.0549	0.0289	-0.026
spg	0.0205	0.0515	0.031
toyoy	0.021	0.1226*	0.1016
tsla	-0.011	0.1274**	0.1384
unh	0.0185	0.1082*	0.0897
utx	0.1074**	0.0305	-0.0769
Observations	251		

*Table 10 provides the descriptive statistics of stock prices and Bitcoin prices over the year 2018. Inference: *** p<0.01; ** p<0.05; * p<0.1*

Appendix C: Robustness

This section contains the robustness checks performed on the data used for the research.

Table 11. Robustness Dickey-Fuller test for stationarity for positively correlated stocks

Ticker	Stationarity Daily Data (1)	Stationarity Monthly Data (2)	Normality Daily Data (3)	Normality Monthly Data (4)
aapl	Yes	Yes	No	Yes
adbe	Yes	Yes	No	Yes
amt	Yes	Yes	No	Yes
amzn	Yes	Yes	No	Yes
ba	Yes	Yes	No	Yes
bam	Yes	Yes	No	Yes
cci	Yes	Yes	No	Yes
cmcsa	Yes	Yes	No	Yes
dis	Yes	Yes	No	Yes
fb	Yes	Yes	No	Yes
goog	Yes	Yes	No	Yes
gs	Yes	Yes	No	Yes
hl	Yes	Yes	No	Yes
msft	Yes	Yes	No	Yes
nem	Yes	Yes	No	Yes
nvda	Yes	Yes	No	Yes
pypl	Yes	Yes	No	Yes
sbsw	Yes	Yes	No	Yes
sne	Yes	Yes	No	Yes
spg	Yes	Yes	No	Yes
toyoy	Yes	Yes	No	Yes
tsla	Yes	Yes	No	Yes
unh	Yes	Yes	No	Yes
utx	Yes	Yes	No	Yes
Observations	251			

Table 11 provides the robustness checks performed on the data. Column (1) and (2) are the results of the Dickey-Fuller test for stationarity. Column (3) and (4) are the results of the Skewness Kurtosis test for Normality.

Table 12. Newey-Wezt regression with monthly data

Stock	Coefficient	Standard Error	F-Value
Apple	0.922***	0.117	41.36
American Towers	0.896***	0.127	33.99
Boeing	0.894***	0.009	49.39
Goldman Sachs	0.911***	0.123	36.96
Newmont Mining	0.867***	0.108	33.48
NVIDIA Corporation	0.915***	0.108	49.70
Toyota	0.886***	0.114	41.18
Tesla	0.911***	0.113	41.45
UnitedHealth Group	0.914***	0.115	43.53
Observations	12		
Maximum Lags	2		

Table 12 provides the combined results of linear regressions with a certain correlated monthly stock return as dependent and sentiment as independent variable, the S&P500 and Bitcoin returns are added as control variables. *Standard errors are presented in parenthesis, Inference: *** p<0.01; ** p<0.05; * p<0.1*

Table 13. Newey-West regression with monthly data

Stock	Coefficient	Standard Error	F-Value
Adobe	0.901***	0.111	45.60
Amazon	0.912***	0.112	45.10
Brookfield Asset Management	0.901***	0.111	47.83
Crown Castle	0.896***	0.125	34.87
Comcast	0.921***	0.122	38.94
Disney	0.893***	0.117	39.52
Facebook	0.902***	0.123	33.67
Google Inc.	0.893***	0.117	38.74
Hecla Mining	0.874***	0.116	39.02
Microsoft	0.900***	0.113	43.29
Paypal	0.907***	0.129	32.42
Sibanye Gold	0.844***	0.138	26.19
Sony	0.899***	0.109	47.93
Simon Property Group	0.912***	0.120	38.71
UnitedTechnology	0.900***	0.107	50.34
Observations	12		
Maximum Lags	2		

Table 13 provides the combined results of linear regressions with a certain uncorrelated monthly stock return as dependent and sentiment as independent variable, the S&P500 and Bitcoin returns are added as control variables. *Standard errors are presented in parenthesis, Inference: *** p<0.01; ** p<0.05; * p<0.1*

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