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MSc Economics & Business
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Bitcoin risk and return analysis: did the pandemic shift dynamics?

Abstract

This paper examines the relationships of Bitcoin returns and risks on a daily time frame with respect to other asset classes and some additional fundamental factors for the years 2018-2020. GARCH-models are used in order to capture the dynamics of Bitcoin returns and volatility. In general, evidence in this paper indicates a change in the relationships between Bitcoin and traditional assets in the period of the COVID-19 pandemic, particularly regarding S&P 500 returns. These returns appear to significantly comove with Bitcoin returns during the sample period in 2020. Additionally, evidence shows that Bitcoin returns are significantly related to the stock market premium in the period of January 2020 up until August 2020, suggesting that Bitcoin is subject to systematic risk during a time of uncertainty. Furthermore, the evidence indicates that hash rate negatively affects Bitcoin volatility, which may suggest that Bitcoin becomes less risky as its network security improves.

Keywords: Bitcoin Returns, Volatility, Risk Factors, GARCH, cryptocurrencies, currency exposure, time series momentum

JEL classification: G15

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1. Introduction

For several years, cryptocurrencies and blockchain technology have increasingly been gaining attention among investors, academics and regulators. While academic research in the field of cryptocurrencies is still in its infancy, the number of studies related to this area is exponentially expanding. Furthermore, interest in Bitcoin is also growing among institutional entities, such as hedge funds (Hajric, 2020). These institutions search for alternative investment instruments in order to increase the diversification of their portfolios. In that perspective, Bitcoin offers a new instrument that is appealing because it may be uncorrelated to traditional assets.

A booster to the growing interest in cryptocurrencies might be the current – to some extent 'inefficient' – financial system that is subject to high transaction fees, delays in transactions and other frictions. On top of that, due to its centralized nature, banking systems show vulnerabilities to cyber-attacks. Additionally, cryptocurrencies such as Bitcoin might offer a solution to the existence of financial exclusion, implying billions of people not having access to simple banking tools (Tapscott & Tapscott, 2017). Furthermore, in countries that face hyperinflation, such as Venezuela, Bitcoin and other cryptocurrencies can serve as substitutes for local currencies. This offers inhabitants the possibility to maintain their purchasing power, especially when legislation restricts the exchange of the local currency to foreign currencies.

As a matter of course, there still remains a lot of controversy on cryptocurrencies as well. There are concerns regarding the regulatory framework that should be applied to this new asset class. In particular, it is still ambiguous to what kind of legal category cryptocurrencies belong. Furthermore, it is argued that Bitcoin is used a lot for money laundering and financing of criminal activities since it is hard to trace down transactions to a specific person.

The current establishment of Bitcoin and other cryptocurrencies as a new type of asset class generates a growing demand for academic research. Specifically, there is an ongoing debate about what asset class digital currencies and especially Bitcoin should be assigned to, i.e. is Bitcoin a security or not? Therefore, it is of interest to improve the understanding of this new asset class. Hitherto, scrutiny does not provide unambiguous conclusions regarding the dynamics of Bitcoin returns and risks. However, one study by Liu and Tsyvinski (2018) does provide an interesting empirical framework for studies that focus on determinants of returns and risks of Bitcoin.

As a follow-up of their work, this paper aims to provide some additional insights into the relationships between, on the one hand, Bitcoin returns and volatility, and on the other hand, returns on traditional assets. These assets include gold, silver, the treasury yield and stocks that are measured by the S&P 500 index. In other words, this paper attempts to answer the question whether Bitcoin returns and risks are related to traditional asset classes. In addition to financial factors, this paper also examines Bitcoin's hash rate, mining difficulty and the total number of transactions.

This study uses daily data concerning the period from March 1, 2018 up until August 26, 2020, hence it includes recent market movements induced by the COVID-19 uncertainty. In order to detect potential differences throughout the years, for each analysis 2020 is separated from the other years. By means of several GARCH-models, the relationships between the aforementioned variables and Bitcoin returns and volatility are examined.

Additionally, this paper also covers the exposure of Bitcoin returns to risk factors in the stock market, the exposure to currency returns, the time series momentum effect and the dynamics between Bitcoin returns and returns on alternative cryptocurrencies. Regarding the latter analysis, a vector autoregressive model is applied in order to detect potential Granger causal relationships between Bitcoin and respectively Ethereum, Ripple, Bitcoin Cash, Binance Coin, Chainlink, Cardano and Litecoin.

This research shows that for 2018 and 2019, S&P 500 returns negatively influence Bitcoin volatility, which is in line with the findings of Dyhrberg (2016a). It suggests that Bitcoin offers hedging opportunities against the S&P 500 index in relatively stable time periods. Furthermore, hash rate appears to consistently negatively impact Bitcoin volatility and the total number of transactions is positively related to volatility. Additionally, the results indicate that on a daily time frame past Bitcoin returns and past volatility contain information concerning the next day's volatility.

The analysis on return relationships highlights a change in the relationship between Bitcoin returns and returns on the S&P 500 index. In contrast to 2018 and 2019, Bitcoin returns are positively correlated to S&P 500 returns in 2020. This finding suggests that Bitcoin is less of a hedge against the stock market in times of uncertainty. Additionally, gold returns are perceived to have a significant and positive correlation with Bitcoin returns in 2020 as well. These findings correspond with the expectation that due to the COVID-19 uncertainty in financial markets, all markets suffer to some extent and move together. Furthermore, the results are supported by the prior finding that Bitcoin positively relates to financial markets in times of economic fear (Klein, Thu, & Walther, 2018).

Additionally, the applied risk factor models suggest that in 2018 and 2019 Bitcoin behaves as a non-systematic risk asset, whereas for 2020 the results indicate Bitcoin excess returns to be significantly related to market risk. This suggests that the change could be driven by the sudden global uncertainty.

Further, no evidence is found for the exposure of Bitcoin returns to traditional currencies, the results do not indicate there is a time series momentum effect for Bitcoin returns, the correlations between the alternative cryptocurrencies and Bitcoin returns appear to be the highest in 2020, and finally, Bitcoin returns are not Granger caused by any of the included altcoins.

The structure of this thesis is as follows. First, a brief review of related literature can be found in section 2. A description of the data and descriptive statistics is provided in section 3. In section 4 the methodology is outlined. Section 5 discusses the empirical findings and section 6 contains conclusions, limitations and suggestions for additional research.

2. Literature review

Although academic literature regarding the risks and returns of Bitcoin is still quite confined, there are some interesting studies that provide a strong base for additional research.

The seminal work in this area is the study of Liu and Tsyvinski (2018), which focuses on the trade-off between risks and returns of cryptocurrencies. Interestingly, their results indicate low exposure to stock market factors, raising questions about the common assumption that cryptocurrencies, correspondingly stocks, serve the purpose of having a stake in blockchain technology. Additionally, the paper does not find evidence for currency exposures nor for commodity risks. In short, the paper concludes that the trade-off between risks and returns for cryptocurrencies is unrelated to traditional markets.

In line with these findings, Gilbert and Loi (2018), argue that Bitcoin is not subject to systematic risk, and therefore can offer interesting hedging opportunities for traditional assets. In contrast, systematic risk is found to affect gold excess returns, indicating gold and Bitcoin differ in behavior. In accordance with these findings Klein, Thu and Walther (2018) observe significant aberrant behavior regarding Bitcoin correlations compared to gold, especially in periods of economic distress.

On the other side, Bianchi (2020) finds a significant and positive relationship between returns on gold and cryptocurrency returns. Correspondingly, Panagiotidis, Stengos and Vravosinos (2018) identify a positive influence of gold returns on Bitcoin returns as well. Further factors that have substantial impact according to this study are policy uncertainty and Google search intensity.

Additionally, Dyhrberg (2016a) highlights some analogies between Bitcoin and both gold and the U.S. dollar. More specific, Bitcoin appears to respond similarly to particular variables as gold does. Furthermore, Bitcoin and gold both have symmetric responses to good and bad news. However, according to this study Bitcoin is affected by the federal funds rate as well, indicating similar behavior as traditional currencies. The paper concludes that Bitcoin's characteristics contain properties of both gold and the U.S. dollar. Another study by Dyhrberg (2016b) conveys hedging opportunities against the Financial Times Stock Exchange (FTSE). In line with her other work, the paper concludes that Bitcoin has similarities with respect to the hedging capabilities of gold.

Besides financial factors, research also scrutinizes technological factors that influence Bitcoin's value. Li and Wang (2017) focus on both economic and technological determinants of Bitcoin's exchange rate. First of all, the study finds that in Bitcoin's early years the exchange rate was mostly driven by speculative grounds, whereas once Bitcoin became more mature its exchange rate movements became more reactive to economic fundamentals. Furthermore, mining difficulty is argued to be a technological factor of interest in explaining Bitcoin’s value. The authors conclude that the exchange rate is positively affected by an increase in mining difficulty in the short run, however, the effect declines in the long run due to a constantly improving technological efficiency.

Polasik, Piotrowska, Wisniewski and Lightfoot (2015) argue that Bitcoin returns are sentiment driven. On top of that, the paper states that the number of transactions is positively associated with Bitcoin’s price. On the other hand, Koutmos (2018) proves there is a bidirectional relationship between transaction activity and returns. In fact, a shock in Bitcoin returns explains a larger part of the variation in transaction activity than the other way around.

Finally, in addition to the previously mentioned relationships, Ciaian, Rajcaniova and Kancs (2018) focus on interdependencies between Bitcoin and alternative cryptocurrencies, i.e. altcoins. With respect to prices, Bitcoin and altcoins appear to be related in the short run, specifically altcoin prices tend to be driven by price movements in Bitcoin. However, in the long run the relationship between Bitcoin price movements and altcoins seems generally weaker.

3. Data

3.1 Data gathering and variable descriptions

The sample period used in this paper covers the period from March 1, 2018 up until August 26, 2020. Data is retrieved from several resources.

First of all, a large part of the data is retrieved from Coin Metrics[1]. Coin Metrics is an open-source project that provides blockchain data in order to help foster the research field of digital assets. Furthermore, by providing community network data the website aims to improve financial decision-making for cryptocurrency investors. For this research, the community dataset regarding Bitcoin is used. This dataset contains aggregated network data as well as financial data for Bitcoin. Variables of interest are the Bitcoin price index, hash rate, mining difficulty and the number of transactions.

Coin Metrics makes use of their self-developed Coin Metrics Bletchley indices (CMBI). The CMBI single asset index for Bitcoin provides an index of Bitcoin's closing price per 11.59 p.m. UTC based on several established cryptocurrency exchange platforms, including Coinbase, Binance, Kraken, Gemini, Bitstamp, Bittrex and itBit. CMBI aggregates these platforms' closing prices and weights these prices by the exchange volume and by time. Hash rate represents the speed by which mathematical calculations are solved by the network's miners. It is expressed in terahashes per second and the value it takes in the dataset represents the average hash rate for a time interval of 24 hours, measured at 11:59 p.m. UTC. The formula used to calculate the terahashes per second is the following:

$$Hash\,rate = \left(\frac{Blockcount}{144}\right) * Miningdifficulty * \left(\frac{\frac{2^{32}}{10^{12}}}{600}\right) \qquad (1)$$

Here Blockcount is the realized amount of blocks mined in one single day. The number 144 represents the expected number of blocks mined in 24 hours at a rate of 10 minutes per block. Mining difficulty times 2^{32} is the amount of hashes that is expected to find a block. Finally, this is scaled in order to measure the hash rate in terahashes per second. For more technical details see the paper of O'Dwyer and Malone (2014). Mining difficulty is the average difficulty of finding a new block. This variable is expressed as a dimensionless number. At the time Bitcoin was created the difficulty started at one. Each time 2016 blocks are mined the difficulty is adjusted based on the realized time it took to mine these blocks, scaled by a target time for

[1] https://coinmetrics.io/

mining these 2016 blocks. This target time is based on the desired rate of mining one block every ten minutes. The number of transactions is simply the total number of transactions that took place within 24 hours, where a transaction is defined as each action by a participant in the network that adjusts the ledger.

Additionally, indices of several asset classes are retrieved from Investing.com[2], a financial markets platform that provides real-time financial data. In particular, the S&P 500 index, gold and silver spot rates in U.S. dollars, and the 10 year treasury rates are obtained through this website.

For the analysis on the exposure of Bitcoin returns to stock factor loadings, data regarding these factors are retrieved from Kenneth French's Website[3], which provides datasets on factor models based on CRSP data. These factors are based on U.S. stock portfolios and include the following factors: market premium, size premium (SMB), value premium (HML), momentum (MOM), profitability premium (RMW), and investment premium (CMA). Definitions can be found in Appendix A and further clarifications are given in the methodology section.

To measure currency exposures, spot exchange rates in U.S. dollars per foreign currency (e.g. EUR/USD) are obtained through the Federal Reserve Bank of St. Louis (FRED)[4]. Concretely, the Australian dollar, Canadian dollar, Euro, British pound and Singapore dollar are the variables of interest.

The historical price data for cryptocurrencies are retrieved from Yahoo Finance. Cryptocurrency data on this website are provided by CoinMarketCap[5]. The specific coins used in this paper are Ethereum, Ripple, Chainlink, Litecoin, Bitcoin Cash, Cardano and Binance Coin. This selection is based on the top 10 cryptocurrencies ranked by market capitalization according to CoinMarketCap. Tether (USDT), a stable coin pegged to the U.S. dollar, is left out due to its different dynamics compared to the other altcoins. Additionally, due to a lack of data for the time period of interest, Polkadot, a competitor to Ethereum, is also left out of the sample.

Finally, there exists an inconsistency in the data regarding weekend days. In contrast to Bitcoin, traditional asset classes do not have price data during the weekend. Therefore, two different samples are used. In the first sample prices are linearly interpolated over the weekend, representing more sophisticated investors. In the second sample prices are held constant over the weekend, hence Friday's closing price is used, representing less sophisticated investors in the market.

[2] https://www.investing.com/

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

[4] https://fred.stlouisfed.org/

[5] https://coinmarketcap.com/

3.2 Data characteristics

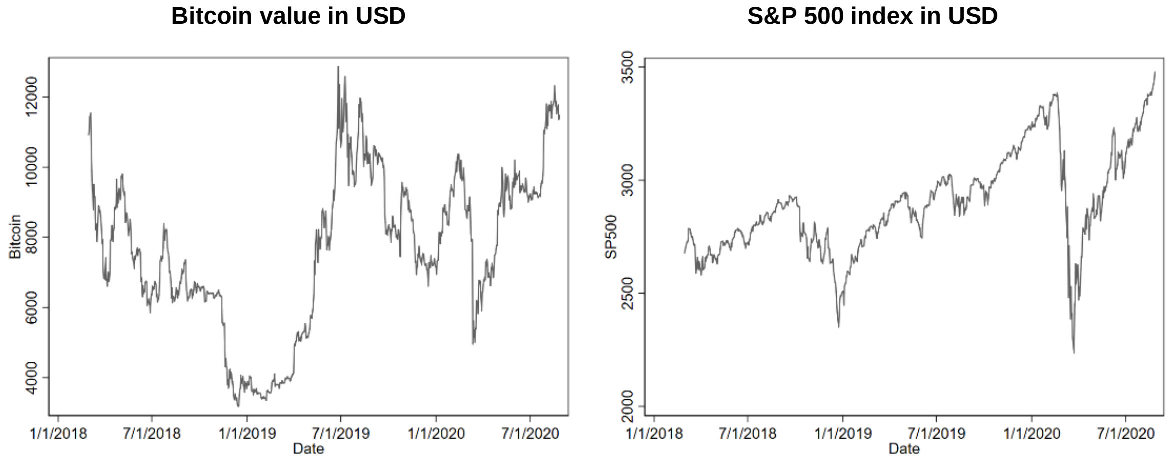
Table 1: Descriptive statistics
This table tabulates the summary statistics regarding the main data set. Prices are given in U.S. dollars, returns are expressed in percentages and the fundamentals are absolute values.

Variable	N	Mean	St. dev	Min	Max
Prices					
Bitcoin	910	7595.36	2251.34	3185.07	12863.46
S&P 500	910	2895.42	220.61	2237.40	3478.73
Gold	910	1430.35	200.09	1174.16	2063.19
Silver	910	16.50	2.36	12.01	29.15
Treasury yield (10yrs)	910	2.09	0.85	0.51	3.24
Log-returns					
Bitcoin	909	0.01	3.95	-47.06	16.97
S&P 500	909	0.03	1.13	-9.99	8.97
Gold	909	0.04	0.69	-5.89	4.30
Silver	909	0.06	1.39	-16.20	7.66
Treasury yield (10yrs)	909	-0.15	3.41	-26.89	36.78
Fundamentals					
Hash rate	910	6.94×10^{7}	3.24×10^{7}	2.19×10^{7}	1.41×10^{8}
Mining difficulty	910	9.53×10^{12}	4.43×10^{12}	3.01×10^{12}	1.76×10^{13}
Transactions	910	285905	60001.52	133901	453346

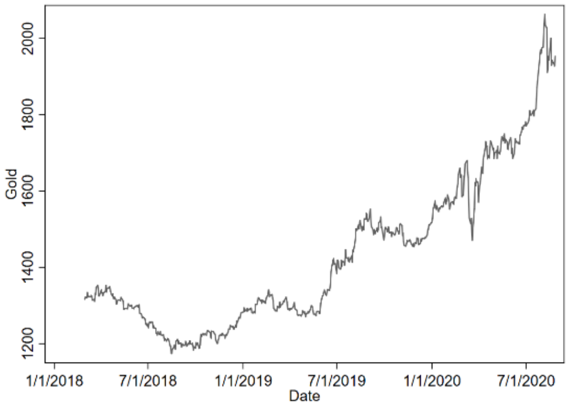
Table 1 lists the descriptive statistics of the main variables. The average daily Bitcoin return is lower than the returns on gold, silver and the S&P 500 index. This is in line with the expectations since Bitcoin was in a bear cycle during 2018, resulting in an average negative return on Bitcoin for this period. However, due to a positive market sentiment in 2019 prices and returns started to increase. Furthermore, after COVID-19 fear in financial markets cooled down mid-2020, prices started to rise again.

Figure 1 depicts the movements in asset values over time. For all assets a significant drop in value occurs around the end of March 2020, when market uncertainty reached its peak. In Figure 2 the corresponding log-returns are plotted.

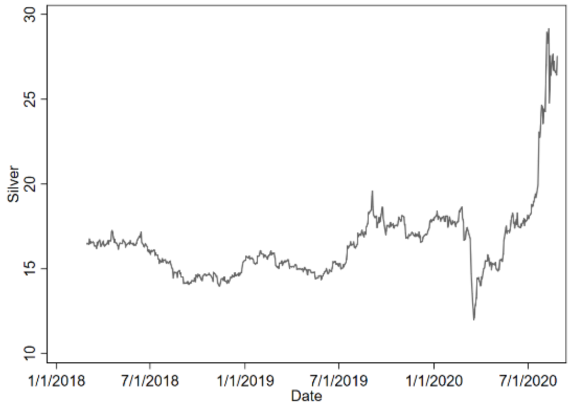
Figure 1: Asset values over time



Gold index in USD



Silver index in USD



10 year treasury rate

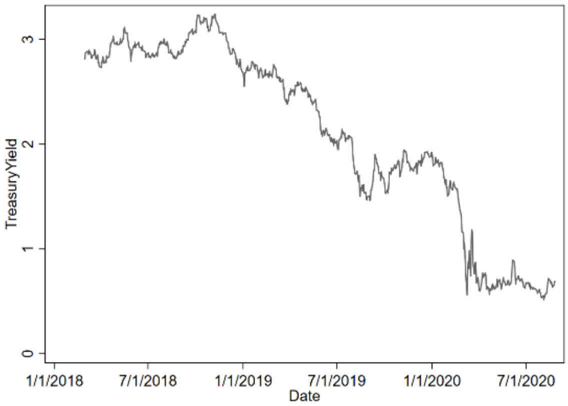


Figure 2: Log-returns

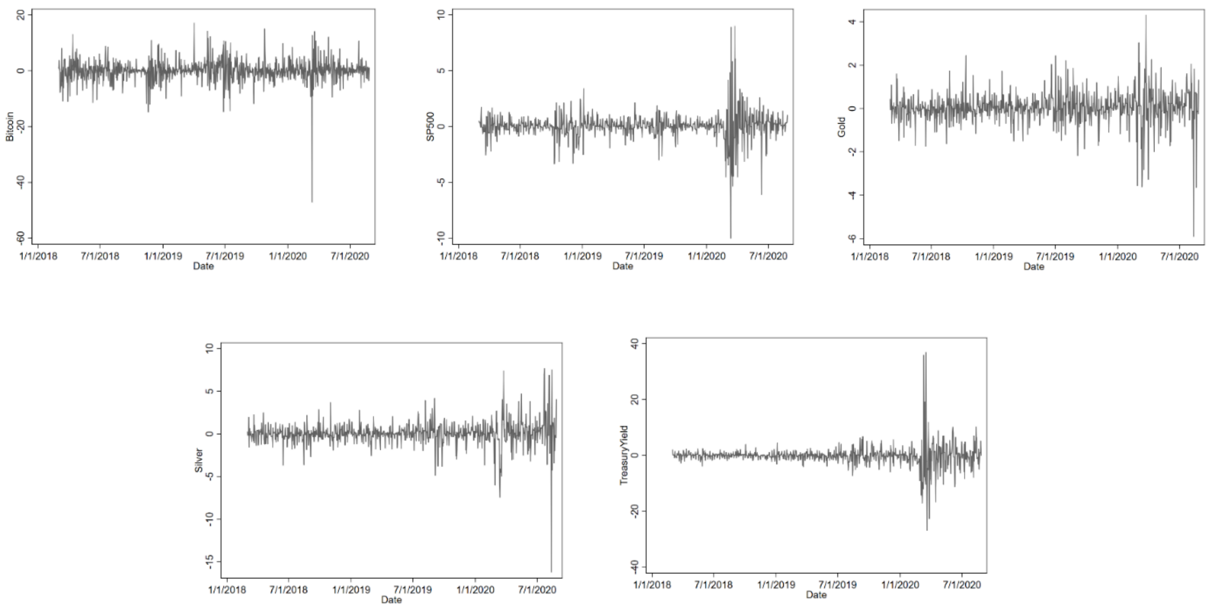


Table 2 reports the Pearson correlation coefficients for the main variables over the period 2018-2019. These coefficients indicate to what extent the variables are statistically linearly related to each other (Brooks, 2014) and are computed as follows:

$$\rho_{x,y} = \frac{\sum(x_i - \bar{x}_i)(y_i - \bar{y}_i)}{\sqrt{\sum(x_i - \bar{x}_i)^2 \, (y_i - \bar{y}_i)^2}} \qquad (2)$$

Where ρ represents the correlation coefficient, the numerator defines the covariance and the denominator is the product of the two standard deviations.

It appears that there is substantial correlation with respect to the Bitcoin price and the asset values of interest; gold, silver and the S&P 500 index indicate roughly the same positive coefficients, whereas the treasury rate is negatively correlated to the value of Bitcoin. Conversely, with respect to returns it is observed that none of the assets is highly correlated to Bitcoin returns. Based on the correlations during each year individually (see Appendix B, Table 14) it is perceived that during 2018 and 2019 there is almost no correlation at all between the asset returns and Bitcoin returns. Strikingly, regarding 2020 the correlations are perceived to be substantially higher, for example S&P 500 returns increase from roughly zero correlation with Bitcoin returns to a correlation of 44%. Increased correlations are observed for the other asset returns in 2020 as well.

Table 2: Correlation matrix
This table reports the Pearson correlation coefficients.

Values	Bitcoin	S&P 500	Gold	Silver	Treasury yield
Bitcoin	1.00				
S&P 500	0.58	1.00			
Gold	0.60	0.62	1.00		
Silver	0.57	0.66	0.74	1.00	
Treasury yield (10yrs)	-0.53	-0.53	-0.95	-0.53	1.00
Log-returns	Bitcoin	S&P 500	Gold	Silver	Treasury yield
Bitcoin	1.00				
S&P 500	0.23	1.00			
Gold	0.16	0.03	1.00		
Silver	0.16	0.16	0.78	1.00	
Treasury yield (10yrs)	0.11	0.56	-0.28	-0.14	1.00
Technical variables	Bitcoin return	Δ Hash rate	Δ Difficulty	Δ Transactions	
Bitcoin return	1.00				
Δ Hash rate	-0.06	1.00			
Δ Difficulty	0.02	-0.08	1.00		
Δ Transactions	0.04	0.38	-0.06	1.00	

4. Methodology

4.1 Stationarity

In time series analyses it is of great importance to check for stationarity among variables. This implies a data series to have a constant mean, constant variance and constant autocovariances. One of the reasons for the importance of stationarity is the impact non-stationarity can have on a variable's characteristics and behavior. For instance, the effect of an unanticipated shock to a stationary variable would fade away over time, whereas for a non-stationary series a shock could persist over time. A second problem that could arise when using a non-stationary process is the concept of spurious regressions. A spurious regression is a regression that seems to be meaningful, whereas in fact it is not. In other words, the regression could indicate evidence for a relationship between two variables that in fact does not exist (Brooks, 2014).

In order to overcome these issues the variables are tested for stationarity first. A widely used method to check for stationarity is the augmented Dickey-Fuller (ADF) test. The ADF test checks whether there is a so-called unit root in the series. A unit root indicates the presence of a stochastic process, hence non-stationarity (Brooks, 2014). Mathematically, the basic form of the Dickey-Fuller test implies the following for a first-order autoregressive model:

$$y_t = \emptyset y_{t-1} + \varepsilon_t \qquad (3)$$

$$H_0: \emptyset = 1 \; and \; H_a: \emptyset < 1$$

If $\emptyset$ is significantly equal to 1 the series has a unit root, hence the null hypothesis of having a unit root cannot be rejected in this case and the series will be non-stationary. The regression is commonly rewritten as follows:

$$\Delta y_t = y_t - y_{t-1} = \varphi y_{t-1} + \varepsilon_t \qquad (4)$$

Here φ equals $(\emptyset - 1)$, and therefore, to test the previous null hypothesis, one has to test whether $\varphi = 0$. For the augmented Dickey-Fuller test the model above is expanded by including additional terms for differencing, although the model still examines the same hypothesis as the standard Dickey-Fuller test. It takes the following form:

$$\Delta y_t = \varphi y_{t-1} + \sum_{i=1}^{p} a_i \Delta y_{t-1} + \varepsilon_t \qquad (5)$$

As a robustness check, the Phillips-Perron (Phillips & Perron, 1988) test is executed as well. The main difference between the ADF test and the PP test is that the latter is a non-parametric test that accounts for autocorrelation and heteroscedasticity (Phillips & Perron, 1988). After both tests are applied, the non-stationary variables are made stationary by log-differencing the specific variables (Appendix B, Table 15).

4.2 Generalized autoregressive heteroscedasticity models

In order to comprehend the dynamics of Bitcoin returns and its volatility, generalized autoregressive conditional heteroscedasticity (GARCH) models are applied. GARCH models are widely used in modeling volatility and are considered to be a successful method (Bollerslev, Chou, & Kroner, 1992). An important feature of these models is that they enable the variance to be dependent on its own lags.

The use of a GARCH model requires that some conditions have to be met. First of all, the returns must exhibit volatility clustering, implying that periods of high volatility are followed by periods of high volatility, and conversely, periods of low volatility are followed by periods of low volatility. This condition can be observed by visualizing a variable's variance over time (Figure 2).

Secondly, there should be autoregressive conditional heteroscedasticity (ARCH) effects in the data. To check for ARCH effects, Engle's (1982) ARCH Lagrange multiplier test is performed. The null hypothesis of this test states that there are no ARCH effects. Given a 5% significance level, a test with a p-value lower than 0.05 is rejected and hence the data contains ARCH effects. The results of these tests for ARCH effects are presented in Appendix B, Table 16 and indicate that here are ARCH effects to perceive in the period 2018-2020. However, no ARCH effects are found in the data regarding 2020 only. As a result, instead of using a GARCH model for the latter period, an autoregressive moving-average (ARMA (1,1)) model is applied.

Based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) the appropriate lag-orders are chosen. In case these information criteria show contradicting results, the leading criterion of interest in this paper is the BIC. The reason for choosing this criterion as leading, is that the BIC is preferred in explanatory models, which is the aim of this paper (Shmueli, 2010). Tables containing information criteria are presented in Appendix B, Tables 17a, 17b, 17c and 17d. Based on these criteria, the specifications of the GARCH models are chosen. Since it is interesting to focus on both returns as well as on volatility, the GARCH approach used here utilizes two equations: the conditional mean equation and the variance equation. The mean equation (6) yields Bitcoin returns as a function of its lagged values including explanatory variables, their lagged values and an error term. The variance equation (7) is expressed as the conditional variance as a function of its own lags and the lagged squared residual that is derived from the mean equation. The mean equation takes the following form in this paper:

$$BTC_t = \beta_0 + \beta_1 BTC_{t-1} + X_t + Y_{t-1} + \varepsilon_t \qquad (6)$$

Here BTC_t stands for Bitcoin log returns and X_t represents all explanatory variables, including the S&P 500 returns, gold returns, silver returns, returns on the treasury rate, hash rate, number of transactions and mining difficulty. Y_{t-1} represents the lagged values of these explanatory variables and ε_t is the error term.

In order to check whether an autoregressive term should be included in the mean equation the three sample periods, 2018-2020, 2018-2019 and 2020, are tested for autocorrelation. The corresponding autocorrelation plots and partial autocorrelation plots are presented in Appendix B, Figures 3a, 3b and 3c. Based on these plots and information criteria the appropriate lag-order for the mean equation is chosen. For 2018-2019 no autocorrelation is observed and therefore this model's mean equation does not include an autoregressive process for Bitcoin returns. For the period 2018-2020 autocorrelation is observed and an autoregressive term is included in the mean model.

$$\sigma^2_{BTC,t} = \alpha_0 + X_t + Y_{t-1} + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-1} + \sum_{j=1}^{p} \delta_j \sigma^2_{t-j} \qquad (7)$$

Formula 7 expresses the variance equation examined in this paper, where $\sigma^2_{BTC,t}$ represents the conditional variance of Bitcoin returns, ε^2_{t-1} is the ARCH term and σ^2_{t-j} is the GARCH term. X_t and Y_{t-1} are similar to the definitions in formula 6. The ARCH term measures the effect that information at time t-1 has on the conditional variance. The GARCH term is defined as the lagged variance of Bitcoin returns and indicates whether past variance has an impact on today's variance.

A major disadvantage of a basic GARCH model is that it does not consider asymmetric return volatility, also known as the leverage effect. The basic GARCH model imposes a symmetric reaction to both positive and negative shocks, whereas academic papers have pointed out that a positive shock to financial time series data has less impact on volatility than a negative shock of equal size (Bekaert & Wu, 2000; Campbell & Hentschel, 1992). The issue of symmetric volatility in the basic GARCH model can be solved by adding an extra term to the model that accounts for these potential asymmetries. One such model is the GJR-GARCH model (Glosten, Jagannathan, & Runkle, 1993). The variance equation in the GJR-GARCH model takes the following form:

$$\sigma^2_{BTC,t} = \alpha_0 + X_t + Y_{t-1} + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-1} + \sum_{j=1}^{p} \delta_j \sigma^2_{t-j} + \sum_{k=1}^{r} \gamma_i \varepsilon^2_{t-1} I_{t-k} \qquad (8)$$

The additional term I_{t-k} takes a value of 1 if ε_{t-1} is smaller than 0, if not, the value equals 0. In case there is a leverage effect present the coefficient γ_i would be higher than 0 (Brooks, 2014).

4.3 Risk factor models

The second part of the analysis covers the stock factor exposures, currency exposures, the time series momentum effect and the exposure to other major cryptocurrencies.

In an effort to measure stock market exposures several factor models are exploited, in accordance with the paper of Liu & Tsyvinski (2018). The first model that is measured is the basic capital asset pricing model (CAPM), which is mathematically expressed as:

$$R_{i,t} = R_{f,t} + \beta(R_{m,t} - R_{f,t}) \qquad (9)$$

The CAPM model in this empirical analysis is adjusted to the following form:

$$BTC_{Excess\ return} = R_{BTC,t} - R_{f,t} = \alpha + \beta\left(R_{m,t} - R_{f,t}\right) + \varepsilon_t \qquad (10)$$

By subtracting the Risk free rate ($R_{f,t}$) from the daily return, the excess return on Bitcoin is computed. Subsequently, excess return is regressed on excess market return ($R_{m,t} - R_{f,t}$) in order to find the alpha and beta. In the CAPM model alpha is a measure of performance compared to the overall market. Beta indicates the systematic risk present in the market. A beta smaller than 1 would indicate excess returns on Bitcoin are less volatile than the excess returns on the overall market, whereas a beta larger than 1 means Bitcoin excess returns are more volatile than the market.

After applying the basic CAPM model, the regression is extended by the Fama and French 3-factor model, the Carhart 4-factor model, the Fama and French 5-factor model and a 6-factor model. In this consecutive order the models are expressed as:

$$BTC_{Excess\ return} = \alpha + \beta\left(R_{m,t} - R_{f,t}\right) + \beta_1 SMB_t + \beta_2 HML_t + \varepsilon_t \qquad (11)$$

$$BTC_{Excess\ return} = \alpha + \beta(R_{m,t} - R_{f,t}) + \beta_1 SMB_t + \beta_2 HML_t + \beta_3 MOM_t + \varepsilon_t \quad (12)$$

$$BTC_{Excess\ return} = \alpha + \beta(R_{m,t} - R_{f,t}) + \beta_1 SMB_t + \beta_2 HML_t + \beta_3 RMW_t + \beta_4 CMA_t \varepsilon_t \quad (13)$$

$$BTC_{Excess\ return} = \alpha + \beta(R_{m,t} - R_{f,t}) + \beta_1 SMB_t + \beta_2 HML_t + \beta_3 MOM_t + \beta_4 RMW_t + \beta_5 CMA_t + \varepsilon_t \quad (14)$$

All mentioned models are based on the CAPM and they are extended by adding additional risk factors. In the Fama and French 3-factor model a size premium (SMB) and a value premium (HML) are added in order to explain the cross-sectional variation in returns (Fama & French, 1992). The size premium accounts for the phenomenon that small market cap companies outperform large market cap companies with respect to stock returns. The value premium considers a deviation in returns between growth stocks and value stocks, specifically value stocks outperform growth stocks.

The Carhart 4-factor model takes account for the presence of momentum in stock returns. Carhart (1997) argues that recent well-performing stock portfolios outperform recent worst performing stock portfolios, and therefore, gain a premium. The Fama and French 5-factor model is an extended version of the 3-factor model, as it includes factors for investments and for profitability. The robust-minus-weak (RMW) factor accounts for the difference in profitability between firms. Furthermore, the CMA factor is included to account for the deviation in returns between firms with conservative investment programs and firms with more aggressive investments (Fama & French, 2015). Finally, the 6-factor model adds a momentum factor to the 5-factor model.

4.4 Measuring the time series momentum effect

With respect to the time series momentum analysis on Bitcoin returns it is important to note that there is a difference between time series momentum and the conventional term momentum. Momentum mostly refers to the phenomenon of cross-sectional differences in returns between past outperforming stocks and past underperforming stocks, more specific, stocks that recently performed well tend to continue to perform well and stocks that recently performed badly tend to continue in its decline (Moskowitz, Ooi, & Pedersen, 2012). On the other hand, time series momentum typically focuses on an individual asset by examining for an effect of past returns on future returns.

For the analysis regarding time series momentum, 1-day-forward up until 7-day-forward returns are regressed on today's Bitcoin return. In order to generate more easily interpretable effects, the returns are standardized by subtracting the mean return from the return, and subsequently, these are scaled by the standard deviation.

4.5 Vector autoregressive model

The final analysis of this research covers the relationships between Bitcoin and some other cryptocurrencies. Besides examining the Pearson correlation coefficients concerning these cryptocurrencies, the multivariate vector autoregressive (VAR) model is applied. VAR models are particularly useful in measuring relationships in multivariate time series. Basically, it is just an extended version of a univariate autoregressive model. As the name already reveals, instead of using a single dependent variable, the VAR model enables that a vector of dependent variables can be regressed on a lagged vector of the same group of variables.

A major advantage of VAR models is that the exogenous and endogenous variables do not have to be specified beforehand, which is particularly convenient in cases where a relationship is unknown or uncertain. Additionally, VAR models do not restrict a variable to only depend on its own lagged values but also on lagged values of other explanatory variables.

As is the case for GARCH models, the VAR model requires a lag-order specification as well. Justified by information criteria (Appendix B, Table 18) a first-order vector autoregressive model is applied. For clarification of the model, the mathematical expressions are shown below:

$$Y_t = B_n Y_{t-1} + \varepsilon_t \qquad (15)$$

$$\begin{bmatrix} BTC_t \\ ETH_t \\ XRP_t \\ \cdots \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \cdots \\ \beta_{21} & \beta_{22} & \beta_{23} & \cdots \\ \beta_{31} & \beta_{32} & \beta_{33} & \cdots \\ \cdots & \cdots & \cdots & \cdots \end{bmatrix} \begin{bmatrix} BTC_{t-1} \\ ETH_{t-1} \\ XRP_{t-1} \\ \cdots \end{bmatrix} + \begin{bmatrix} \varepsilon_{BTC,t} \\ \varepsilon_{ETH,t} \\ \varepsilon_{XRP,t} \\ \cdots \end{bmatrix} \qquad (16)$$

In formula 15, Y_t is a vector of the exogenous variables, i.e. the returns of Bitcoin, Ethereum, Ripple, Chainlink, Bitcoin Cash, Binance Coin, Cardano and Litecoin. B_n is a vector containing all coefficients of Y_{t-1}; and the latter is a vector of all lagged explanatory variables including a first-order autoregressive expression of the dependent variable itself. Basically, the specific VAR(1) model tests the following linear relationships for all cryptocurrencies in the sample:

$$\begin{aligned} BTC_t &= \beta_{11_t} BTC_{t-1} + \beta_{12_t} ETH_{t-1} + \beta_{13_t} XRP_{t-1} + \ldots + \beta_{18_t} y_{t-1} + \varepsilon_t \\ ETH_t &= \beta_{21_t} BTC_{t-1} + \beta_{22_t} ETH_{t-1} + \beta_{23_t} XRP_{t-1} + \ldots + \beta_{28_t} y_{t-1} + \varepsilon_t \quad (17) \\ XRP_t &= \beta_{31_t} BTC_{t-1} + \beta_{32_t} ETH_{t-1} + \beta_{33_t} XRP_{t-1} + \ldots + \beta_{38_t} y_{t-1} + \varepsilon_t \\ &\ldots \end{aligned}$$

Based on the obtained results of the VAR analysis, the final focus lies on Granger causality between cryptocurrencies. Granger causality is a term used to describe the potential causal relationship between two time series. The Granger causality test measures whether past values of one variable could be valuable in predicting today's value of another variable.

5. Empirical results

5.1 Bitcoin volatility and returns - GARCH modeling

By means of several GARCH models, the relationships between Bitcoin returns and variables of interest are examined. Tables 3 and 4 include GARCH models for two time periods, 2018-2020 and 2018-2019. In these GARCH models the mean equation is examined in order to identify potential return predictors and relationships. Additionally, for 2020 two ARMA (1,1) models (Table 5) help to explain the relationships and potential COVID-19 induced changes in Bitcoin returns.

Firstly, Table 3 indicates a significant negative association between S&P 500 returns and Bitcoin volatility for both samples in the period 2018-2020. Hence, an increase in S&P 500 returns is associated with lower Bitcoin volatility and vice versa. Additionally, for the samples excluding 2020 (Table 4) the same association is observed. With regard to linearly interpolated returns the coefficients of S&P 500 returns are substantially lower for the period 2018-2020 compared to 2018-2019. This might suggest Bitcoin volatility being less or not at all negatively correlated to S&P 500 returns in 2020. Higher stock returns might go accompanied by greater risk in the stock market, therefore a negative correlation between stock returns and Bitcoin volatility can suggest Bitcoin offers hedging opportunities against the stock market due to its lower volatility. Furthermore, the 2018-2019 results indicate that yesterday's stock return has a negative impact on Bitcoin volatility, supporting the belief of hedging capabilities of Bitcoin against the stock market. Dyhrberg (2016a) identifies an identical relationship. However, the relationship is not confirmed in the sample including 2020, which raises doubt on the hedging capabilities during 2020.

No consistently significant relationship is observed between gold returns and Bitcoin variance. However, gold returns for 2018-2019 are significantly negatively related to Bitcoin volatility. This only holds for the sample with linearly interpolated returns, indicating the results can be driven by a difference in returns of gold during the weekend.

In the case of silver returns and the treasury rate, no consistent statistically significant relationship with Bitcoin volatility is observed. Although, for 2018-2020 the coefficients indicate a positive association of the treasury yield with Bitcoin volatility. A possible explanation might be the rise of the treasury yield indicating a decline in demand for treasury bonds. This suggests that investors search for more risky investments. The subsequent demand for Bitcoin can increase its volatility.

In the 2018-2020 models, hash rate is significantly and negatively correlated to Bitcoin volatility. Interestingly, for both sample periods evidence suggests that a change in previous day's hash rate is significantly negatively affecting Bitcoin volatility on the current day. This suggests that an increase in hash rate, hence an improvement of Bitcoin's network security, contributes to a more mature Bitcoin environment and subsequently lowers the risk of Bitcoin. Contradictory with this finding, is the significantly positive influence on the variance that is found for mining difficulty. Intuitively the results are difficult to rhyme, since mining difficulty and hash rate are positively associated with each other. A possible explanation can be that mining difficulty only adjusts after 2016 blocks are mined, which equates to approximately once every two weeks, whereas the hash rate continuously increases or decreases over the same time period. Hence, when the hash rate increases over a two week time period, mining difficulty will be adjusted upwards. Therefore, a daily impact of mining difficulty might differ from the daily impact hash rate has on Bitcoin volatility.

Regarding the number of transactions, a positive association is found with Bitcoin volatility in both sample periods. This suggests an increase in the number of transactions is accompanied by an increase in volatility. The same positive correlation is observed by Dyhrberg, Foley and Svec (2018), who argue this can be triggered by a lack of knowledge regarding Bitcoin's fundamental value among relatively inexperienced investors. As a result, the spread in beliefs with respect to the fundamental value of Bitcoin, makes that investors trade Bitcoin against substantially different prices. The large spread in prices against which traders or investors are willing to initiate transactions can potentially increase volatility.

The statistically significant ARCH coefficients in Table 3 and 4 imply that past shocks in Bitcoin returns help predicting its volatility. Furthermore, the coefficients of the GARCH parameters indicate that Bitcoin's past volatility affects its current volatility. Regarding the asymmetric GARCH model, results are mixed: only one out of four TARCH coefficients is significant at a 5% significance level. Interestingly, the coefficient that is significant is negative, hinting at an inverse leverage effect. In other words, a positive shock for Bitcoin increases volatility more than a negative shock. This suggests similarities between Bitcoin and gold, since an inverse leverage effect is observed in the gold market (Baur, 2012). A plausible explanation for this phenomenon is that when the gold price rises it gives incentives to investors to believe there is increased uncertainty in financial markets since gold is generally considered to be a safe haven, and consequently, this belief induces uncertainty in the gold market as well. As a result volatility increases. Nevertheless, given that only one coefficient indicates an inverse asymmetric volatility effect, and the other coefficients are insignificant, it cannot just be concluded that the inverse effect is present for Bitcoin. Even more, the insignificance of the remaining coefficients indicate that Bitcoin volatility reacts symmetrically to financial shocks. To conclude, a clear conclusion on asymmetric return volatility in Bitcoin cannot be drawn since the results are mixed.

With regard to Bitcoin returns the mean equations in Tables 3 and 4 yield some interesting findings. Table 5 serves as a robustness check to inferences that can be drawn based on the mean equations. First of all, Table 3 indicates a significantly positive relationship between daily gold returns and Bitcoin returns. All four models present significant coefficients for gold returns at a 5% significance level, except for the AR(1)-GARCH(1,2) model of the linearly interpolated returns sample, which is only significant at a 10% level. The findings are supported by the significant coefficients for gold returns that are listed in Table 5. In contrast, Table 4 does not report any significant correlations with respect to Bitcoin returns, which suggests that the correlations are potentially induced by COVID-19 uncertainty commencing at the beginning of 2020, creating uncertainty among all financial markets. However, considering the GARCH(1,2) model concerning linearly interpolated returns (Table 4), the results suggest previous day's gold return has a positive and significant influence on today's Bitcoin return, i.e. at a 5% significance level. An increase in gold returns might suggest investors are starting to hedge against market uncertainty, leading other investors to hedge and allocate capital to Bitcoin since they believe Bitcoin serves the same purpose as gold.

With respect to S&P 500 returns, Tables 3 and 4 show that they do not yield a significant coherence with Bitcoin returns. However, the corresponding coefficients are consistently positive for all models including the year 2020, suggesting a positive correlation with Bitcoin returns. Table 5 shows a highly significant correlation between Bitcoin and S&P 500 returns, supporting the belief that Bitcoin returns and stock returns comove during 2020. Therefore, this casts doubt on the view that Bitcoin is digital gold and can serve as a hedge against the stock market, specifically during times of uncertainty.

Additionally, the results suggest a negative relationship between a change in hash rate and Bitcoin returns. The same negative correlation is observed in Table 5. This finding suggests that when Bitcoin returns rise, the hash rate drops simultaneously. However, the short-term relationship should be considered with caution since it is difficult to measure the hash rate accurately. The hash rate in this paper represents an average over 24 hours and therefore potentially induces a somewhat biased relationship. Nevertheless, a possible explanation for the negative relationship can be that due to the market crash in March 2020 the hash rate did not respond directly to the uncertainty while at the same time highly negative returns were produced for Bitcoin.

Finally, based on Tables 3 and 4, previous day's number of transactions consistently negatively impacts the following day's Bitcoin returns. Coefficients are significant at a 10% level for linearly interpolated returns in the period 2018-2020 and at a 5% level for 2018-2019. Overall, in each model a negative coefficient is reported. Intuitively, an increase in today's number of transactions implies an increase in demand for Bitcoin, prompting the price to augment as well. Generally, an increase in today's price yields a decrease in tomorrow's return.

Table 3: GARCH-Models 2018-2020

In this table the results of the generalized autoregressive heteroscedasticity models for the period 2018-2020 are visualized. The left half of the table shows the results of the sample containing linearly interpolated returns. The right side of the table shows the sample with constant returns over the weekend. The independent variable of the mean equation is the return on Bitcoin. For the variance equation Bitcoin's variance represents the independent variable. Z-statistics are given in parentheses. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

	Linear interpolation over the weekend								*Constant prices over the weekend*							
	AR(1)-GARCH(1,2)				AR(1)—GJR-GARCH(1,1)				AR(1)-GARCH(1,2)				AR(1)—GJR-GARCH(1,1)			
	Mean		Variance		Mean		Variance		Mean		Variance		Mean		Variance	
Variable	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat
S&P 500 return	0.264	(1.51)	-0.464***	(-2.99)	0.224	(1.39)	-0.221**	(-2.11)	0.242	(1.60)	-0.553***	(-5.20)	0.230	(1.46)	-0.620***	(-6.20)
S&P 500 return $_{t-1}$	-0.057	(-0.35)	-0.223	(-1.13)	-0.027	(-0.17)	-0.282**	(-2.12)	0.017	(0.11)	-0.066	(-0.49)	0.027	(0.17)	-0.019	(-0.14)
Gold return	0.624*	(1.69)	-0.192	(-0.71)	0.800**	(2.14)	-0.361*	(-1.82)	0.693**	(2.22)	-0.293	(-1.19)	0.637**	(1.97)	-0.299	(-1.05)
Gold return $_{t-1}$	-0.067	(-0.20)	1.081***	(5.01)	-0.006	(-0.02)	-0.031	(-0.14)	-0.118	(-0.40)	0.545**	(2.28)	-0.056	(-0.18)	0.528**	(2.04)
Silver return	0.077	(0.40)	0.149	(0.91)	0.055	(0.26)	0.185	(1.60)	0.044	(0.29)	0.213*	(1.84)	0.069	(0.44)	0.227*	(1.67)
Silver return $_{t-1}$	0.028	(0.16)	-0.280*	(-1.67)	-0.026	(-0.14)	0.023	(0.17)	-0.022	(-0.14)	-0.209	(-1.45)	-0.049	(-0.29)	-0.233	(-1.37)
Treasury yield	0.068	(1.15)	0.077	(1.51)	0.076	(1.23)	0.015	(0.31)	0.080	(1.48)	0.093**	(2.07)	0.089	(1.60)	0.115**	(2.55)
Treasury yield $_{t-1}$	0.027	(0.54)	0.034	(0.72)	0.042	(0.80)	-0.007	(-0.17)	-0.019	(-0.42)	-0.012	(-0.20)	-0.009	(-0.17)	-0.022	(-0.40)
Hash rate	-0.018	(-1.58)	-0.028**	(-2.26)	-0.022*	(-1.91)	-0.023***	(-2.91)	-0.018	(-1.50)	-0.029**	(-2.31)	-0.021*	(-1.76)	-0.040***	(-3.35)
Hash rate $_{t-1}$	0.008	(0.66)	-0.050***	(-4.23)	0.005	(0.40)	-0.039***	(-4.48)	0.006	(0.53)	-0.053***	(-4.19)	0.003	(0.29)	-0.060***	(-4.46)
Transactions	0.023*	(1.79)	0.088***	(13.11)	0.028**	(2.19)	0.055***	(5.80)	0.020	(1.50)	0.089***	(12.36)	0.021	(1.64)	0.089***	(12.79)
Transactions $_{t-1}$	-0.021*	(-1.77)	0.017	(1.46)	-0.022*	(-1.72)	0.007	(0.71)	-0.020*	(-1.70)	0.019*	(1.66)	-0.019	(-1.55)	0.009	(0.62)
Difficulty	0.064	(0.76)	-0.235***	(-2.83)	0.080	(0.86)	-0.045***	(-0.77)	0.081	(1.01)	-0.227**	(-2.41)	0.080	(0.97)	-0.177*	(-1.65)
Difficulty $_{t-1}$	-0.055	(-0.44)	0.300***	(10.15)	-0.056	(-0.62)	-0.003***	(-0.04)	-0.056	(-0.44)	0.325***	(10.88)	-0.041	(-0.33)	0.308***	(11.20)
Constant	-0.018	(-0.17)	0.093	(0.50)	0.008	(0.06)	1.404	(10.36)	-0.011	(-0.10)	0.034	(0.18)	-0.015	(-0.14)	-0.382*	(-1.78)
L. AR	-0.071*	(-1.77)			-0.074*	(-1.82)			-0.056	(-1.36)			-0.064	(-1.59)		
L.ARCH			0.096***	(4.41)			0.190***	(3.50)			0.119***	(4.89)			0.060***	(3.24)
L.GARCH			0.238***	(3.40)			0.441***	(7.62)			0.212***	(3.04)			0.782***	(28.55)
L2.GARCH			0.432***	(6.69)							0.452***	(7.45)				
L.TARCH							-0.132**	(-2.32)							0.016	(0.68)

Table 4: GARCH-Models 2018-2019

In this table the results of the generalized autoregressive heteroscedasticity models for the period 2018-2019 are visualized. The left half of the table shows the results of the sample containing linearly interpolated returns. The right side of the table shows the sample with constant returns over the weekend. The independent variable of the mean equation is the return on Bitcoin. For the variance equation Bitcoin's variance represents the independent variable. Z-statistics are given in parentheses. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

	Linear interpolation over the weekend								*Constant prices over the weekend*							
	GARCH(1,2)				GJR-GARCH(1,1)				GARCH(1,2)				GJR-GARCH(1,1)			
	Mean		Variance		Mean		Variance		Mean		Variance		Mean		Variance	
Variable	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat
S&P 500 return	-0.005	(-0.02)	-0.697***	(-2.86)	0.005	(0.02)	-0.736***	(-2.81)	0.070	(0.32)	-0.552***	(-3.20)	0.006	(0.02)	-0.537***	(-3.14)
S&P 500 return$_{t-1}$	0.025	(0.10)	-0.655**	(-2.16)	0.031	(0.12)	-0.611**	(-2.04)	0.219	(0.97)	0.866***	(4.14)	0.151	(0.61)	0.830***	(3.83)
Gold return	0.415	(0.75)	-1.073**	(-2.27)	0.255	(0.45)	-1.323***	(-2.97)	-0.137	(-0.32)	0.165	(0.37)	-0.023	(-0.05)	0.568	(1.32)
Gold return$_{t-1}$	1.058**	(2.09)	0.217	(0.42)	1.279**	(2.47)	0.210	(0.45)	0.367	(0.65)	1.770***	(4.36)	0.596	(1.05)	1.594***	(3.82)
Silver return	0.109	(0.34)	0.432	(1.47)	0.158	(0.48)	0.594**	(2.13)	0.070	(0.28)	-0.069	(-0.28)	0.057	(0.22)	-0.254	(-1.07)
Silver return$_{t-1}$	-0.317	(-1.11)	0.215	(0.67)	-0.453	(-1.56)	0.057	(0.18)	-0.122	(-0.46)	-0.500**	(-2.43)	-0.229	(-0.85)	-0.435**	(-2.05)
Treasury yield	0.073	(0.53)	0.080	(0.63)	0.061	(0.41)	0.141	(1.19)	-0.028	(-0.23)	-0.080	(-0.82)	0.009	(0.07)	-0.029	(-0.29)
Treasury yield$_{t-1}$	0.136	(1.07)	0.039	(0.20)	0.147	(1.08)	-0.041	(-0.21)	0.101	(0.85)	0.412***	(3.07)	0.102	(0.82)	0.307**	(2.06)
Hash rate	-0.003	(-0.18)	-0.013	(-0.90)	-0.006	(-0.42)	-0.017	(-1.17)	-0.008	(-0.57)	-0.022	(-1.50)	-0.007	(-0.48)	-0.021	(-1.41)
Hash rate$_{t-1}$	0.017	(1.28)	-0.039***	(-2.94)	0.017	(1.20)	-0.036**	(-2.55)	0.009	(0.71)	-0.089***	(-4.92)	0.010	(0.72)	-0.069***	(-4.22)
Transactions	0.006	(0.37)	0.087***	(11.00)	0.005	(0.29)	0.083***	(10.56)	0.004	(0.28)	0.074***	(4.11)	0.004	(0.24)	0.080***	(5.99)
Transactions$_{t-1}$	-0.032**	(-2.24)	0.026**	(2.15)	-0.031**	(-2.09)	0.020	(1.43)	-0.018	(-1.36)	0.026**	(2.22)	-0.023	(-1.61)	0.028**	(2.31)
Difficulty	0.113	(1.11)	-0.224**	(-1.99)	0.112	(1.05)	-0.199*	(-1.77)	0.142	(1.13)	-0.156	(-1.29)	0.130	(1.10)	-0.161	(-1.19)
Difficulty$_{t-1}$	-0.093	-(0.62)	0.336***	(7.66)	-0.082	(-0.57)	0.318***	(8.47)	-0.070	(-0.42)	0.353***	(8.82)	-0.051	(-0.30)	0.335***	(7.50)
Constant	-0.089	(-0.64)	0.238	(1.39)	-0.095	(-0.66)	-0.041	(-0.22)	-0.064	(-0.44)	-0.624	(-1.46)	-0.090	(-0.64)	-0.758**	(-2.11)
L.ARCH			0.107***	(3.88)			0.072***	(2.96)			0.105***	(4.59)			0.079***	(3.47)
L.GARCH			0.218***	(2.56)			0.760***	(20.92)			0.216**	(2.39)			0.805***	(29.03)
L2.GARCH			0.419***	(5.21)							0.493***	(6.11)				
L.TARCH							-0.035	(-1.17)							-0.041	(-1.46)

Table 5: ARMA-Models 2020

This table lists the results of the ARMA (1,1) models applied to the year 2020 for both linearly interpolated returns as well as for returns that remain constant over the weekend. Z-statistics are given in parentheses. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

	Linear interpolation		*Constant over the weekend*	
	ARMA(1,1)		ARMA(1,1)	
Variable	Coefficient	z-stat	Coefficient	z-stat
S&P 500 return	1.021***	(5.27)	0.897***	(4.60)
S&P 500 return $_{t-1}$	0.065	(0.29)	0.028	(0.16)
Gold return	1.045**	(2.21)	1.257***	(2.81)
Gold return $_{t-1}$	-0.163	(-0.38)	-0.302	(-0.64)
Silver return	-0.004	(-0.02)	-0.114	(-0.54)
Silver return $_{t-1}$	-0.122	(-0.51)	-0.111	(-0.45)
Treasury yield	-0.048	(-0.67)	-0.040	(-0.53)
Treasury yield $_{t-1}$	0.036	(0.67)	0.005	(0.09)
Hash rate	-0.116***	(-3.68)	-0.095***	(-2.95)
Hash rate $_{t-1}$	-0.030	(-0.83)	-0.033	(-0.89)
Transactions	0.062**	(2.00)	0.044	(1.38)
Transactions $_{t-1}$	0.030	(0.93)	0.035	(1.09)
Difficulty	0.057	(0.28)	0.074	(0.33)
Difficulty $_{t-1}$	0.013	(0.05)	0.001	(0.01)
Constant	0.081	(0.29)	0.083	(0.29)
L.AR	-0.805***	(-6.19)	-0.749***	(-3.49)
L.MA	0.636***	(3.24)	0.581**	(2.04)

5.2 Stock Factor exposures

This section presents the results on Bitcoin's exposure to the U.S. stock market on a daily level. As mentioned earlier, Bitcoin excess returns are regressed on several risk factors. Specifically, the base of every model that is tested is the widely used capital asset pricing model. By means of extended versions of this model several additional models are examined. In Table 6 a model of the entire sample is presented, i.e. from 2018 up until 2020.

Table 6: Stock factor loadings 2018-2020
This table presents the exposure of Bitcoin excess returns to stock factors based on commonly used risk factor models. Bitcoin excess return is the dependent variable, while the risk factors are the explanatory variables. The coefficients are expressed in percentages. The values in parentheses represent the corresponding t-statistics. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

%	CAPM	3-Factor	4-Factor	5-Factor	6-Factor
$Alpha_t$	0.055	0.059	0.076	0.059	0.078
	(0.43)	(0.46)	(0.59)	(0.45)	(0.59)
$R_{m,t}-R_{f,t}$	0.505**	0.483**	0.479**	0.477**	0.467**
	(2.51)	(2.37)	(2.37)	(1.98)	(1.97)
SMB_t		0.236	0.340	0.236	0.361
		(0.74)	(0.99)	(0.75)	(1.03)
HML_t		-0.007	0.212	-0.010	0.228
		(-0.04)	(0.84)	(-0.04)	(0.84)
MOM_t			0.272		0.311
			(1.19)		(1.37)
RMW_t				0.117	0.277
				(0.34)	(0.82)
CMA_t				-0.067	-0.122
				(-0.10)	(-0.19)
R-squared	0.03	0.04	0.04	0.04	0.04
N	909	909	909	909	909

Table 6 shows that the alpha's are consistent but insignificant in all models: approximately 0.06% in the models without the momentum factor and 0.08% in the two models including a momentum factor. Interestingly, all market beta' s are consistently positive, smaller than one and significant at a 5% significance level. This indicates that Bitcoin excess returns are relatively less volatile than the U.S. stock market. Given the size of the beta's, the exposure to market risk is relatively low. Put differently, when the market premium increases (decreases) by one percent, Bitcoin excess return rises (falls) by approximately 0.50%. The estimates on the size premium are consistently positive, although, insignificant. Hence, Bitcoin possibly correlates more with small cap companies than with large cap companies. The coefficients of the value premium are inconsistent across the models. The profitability factor, RMW, is not significant and consistently positive, which might indicate Bitcoin to comove more with highly profitable firms than with less profitable firms. Finally, the consistently negative coefficient on the investment factor suggests that Bitcoin excess returns might potentially be more related to aggressive investment firms than conservative investment firms. This makes sense since an investment in Bitcoin may also be classified as aggressive. All models reveal a relatively low R-squared, indicating the risk factors cannot explain much of the variance in Bitcoin excess returns.

By analyzing each year individually some interesting inconsistencies are brought to attention. Tables 20a, 20b and 20c in Appendix C list the results of the same analysis for each year individually. For 2018 the alpha's are consistently negative, however, insignificant. In contrast, the alpha's for both 2019 and 2020 are consistently positive, and yet, still insignificant.

Whereas the market beta's for 2018 and 2019 do not show significance and vary between positive and negative values, the beta's for 2020 are relatively high and consistent compared to the two previous years and show significance at a 5% level. Considering these findings, it can be concluded that the significant market beta's for the entire sample are driven by the year 2020. The beta's of approximately 0.80 indicate that the 2020 Bitcoin excess returns are still less volatile than the U.S. stock market excess returns. However, the evidence suggests it is relatively and significantly more correlated to the market premium compared to the previous years. In fact, the results of 2018 and 2019 suggest Bitcoin is a non-systematic risk asset, which is in accordance with the paper of Gilbert and Loi (2018). The significant beta in 2020 raises doubt on this conclusion. It can be argued that Bitcoin return dynamics related to the stock market drastically changed due to the impact COVID-19 has on all financial markets and the corresponding sentiment.

Additionally, the R-squared for 2020 is clearly higher compared to the other two years, suggesting the models explain the variation in Bitcoin excess returns for about 20%. A final interesting observation is the HML factor being positive and weakly significant in 2018, whereas in the later years the factor has negative coefficients. The magnitudes of these coefficients are roughly the same for 2020. For 2019 they are less consistent. It should be noted that it is difficult to draw conclusions based on these coefficients, since they lack significance. Otherwise, it may be that Bitcoin excess returns correlate more with growth stocks than with value stocks in the latter two years. This would make sense as Bitcoin can be viewed as a relatively young technology or product, and therefore, can be compared to growth stocks that have the potential to gain in value and adoption.

5.3 Currency exposures

In addition to stock market exposures, this section examines the exposure to some of the most prominent foreign exchange rates, including the British pound, Euro, Canadian dollar, Australian dollar and the Singapore dollar. The currency exposures are examined in accordance with the paper of Liu and Tsyvinski (2018), by regressing Bitcoin returns on each exchange rate return separately. As Table 7 reports, none of the coefficients are statistically significant, suggesting there is no significant exposure to traditional currencies.

Table 7: Currency exposures 2018-2020
This table presents the exposure of Bitcoin excess returns to currency returns based on several major currencies. Bitcoin log-return is the dependent variable. The currency returns are calculated as continuously compounded returns as well. The coefficients are expressed in percentages. The values in parentheses represent the corresponding t-statistics. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

	Daily Bitcoin return				
Constant	0.014	0.008	0.009	0.013	0.010
	(0.11)	(0.06)	(0.07)	(0.10)	(0.08)
AUD	1.126				
	(1.32)				
CAD		1.013*			
		(1.87)			
EUR			1.111		
			(1.04)		
SGD				2.103	
				(1.21)	
GBP					0.928
					(1.26)
R-squared	0.02	0.01	0.01	0.01	0.01

In order to distinguish potential differences over these years, the currency exposures are examined for each year individually as well. The results are depicted in Tables 21a, 21b and 21c, Appendix C. Given that these coefficients are insignificant as well, there is no evidence for Bitcoin returns to comove with traditional currency returns, and hence, no exposure to currencies is observed.

5.4 Times series momentum effect

Table 8a indicates that there is no clear time series momentum effect for daily Bitcoin returns over the years 2018-2020. Based on this table, Bitcoin returns to some extent reverse on a daily time frame. One-day-forward returns are significantly negatively impacted by today's return, a one standard deviation increase (decrease) in today's return results in a 0.40% decrease (increase) in tomorrow's return. This number is calculated by multiplying the coefficient by the standard deviation of returns (-0.104*3.85). Subsequently, the second-day-forward return is positively affected by R_t, a one standard deviation increase in today's return increases the two-days-ahead return by 0.35%. On a weekly time frame (Table 8b) the first two weeks forward appear to be positively affected by this weeks' return, however, none of the coefficients show significance. Nor is there any evidence found for the momentum effect on the weekly time frame.

Based on additional yearly analyses (Appendix C, Table 22) no clear evidence for a momentum effect is identified either. For the years 2018 and 2019, none of the coefficients are statistically significant. On the other hand, the coefficients corresponding to 2020 indicate the same impact as the results of the overall sample in Table 8a. However, instead of up until a three-day-forward impact these coefficients show to have significant influence up until the four-day-forward return, varying from negative to positive effects. This suggests daily reversal effects for Bitcoin returns. Interestingly, this does not match the findings of Liu and Tsyvinski (2018) who find a time series momentum effect in Bitcoin returns. However, this could, at least partly, be explained by the difference in sample period, i.e. 2011-2018, since this period contains multiple and completed market cycles.

Table 8a: Daily time series momentum 2018-2020

This table shows the effect of today's return on the daily forward returns for the next seven days. Returns are standardized by subtracting the mean and subsequently scaling it by the standard deviation. T-statistics are given in parentheses. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

	R_{t+1}	R_{t+2}	R_{t+3}	R_{t+4}	R_{t+5}	R_{t+6}	R_{t+7}
R_t	-0.104***	0.090***	-0.038*	0.055	-0.001	0.034	-0.006
	(-3.14)	(2.72)	(-1.15)	(1.65)	(-0.02)	(1.01)	(-0.19)
R-squared	0.01	0.01	0.00	0.00	0.00	0.00	0.00
St.dev.	3.85						

Table 8b: Weekly time series momentum 2018-2020

This table shows the effect of the weekly return on the weekly forward returns for the next four weeks. Returns are standardized by subtracting the mean and subsequently scaling it by the standard deviation. T-statistics are given in parentheses. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

	R_{t+1}	R_{t+2}	R_{t+3}	R_{t+4}
R_t	0.069	0.081	-0.044	-0.115
	(0.79)	(0.93)	(-0.50)	(-1.34)
R-squared	0.00	0.01	0.00	0.01
St.dev.	9.84			

5.5 Bitcoin and alternative cryptocurrencies

This section aims to capture the relationships between Bitcoin returns and respectively returns on Ethereum, Ripple, Bitcoin Cash, Binance Coin, Chainlink, Cardano and Litecoin. Table 9 shows Bitcoin has a daily mean return of 0.01 percent. Only Chainlink and Binance Coin experienced higher average daily returns over the recent three years. In comparison to the remaining coins, Bitcoin and Ethereum have the highest level of negative skewness and highest level of kurtosis as well, although all of the observed cryptocurrencies in fact have leptokurtic distributions.

Table 9: Summary statistics cryptocurrency returns
In this table the descriptive statistics regarding returns of several cryptocurrencies are tabulated. The second column defines the abbreviations for each cryptocurrency.

	Abbr.	Mean %	St.Dev	Min	Max	Skewness	Kurtosis
Bitcoin Cash	BCH	-0.16	6.12	-56.13	41.35	-0.50	17.31
Binance Coin	BNB	0.08	4.94	-54.31	22.97	-1.36	20.51
Bitcoin	BTC	0.01	3.95	-47.06	16.97	-1.74	26.49
Cardano	ADA	-0.11	5.62	-50.36	24.55	-0.55	11.27
Chainlink	LINK	0.34	6.84	-61.46	48.06	-0.24	13.61
Ethereum	ETH	-0.09	4.96	-55.07	17.35	-1.66	20.91
Litecoin	LTC	-0.14	4.89	-44.91	26.87	-0.59	12.82
Ripple	XRP	-0.13	4.66	-39.90	32.20	0.02	13.67

Based on the Pearson correlations (Table 10) all cryptocurrencies in the sample are highly correlated with Bitcoin throughout the sample period. The highest correlation with Bitcoin is perceived for Ethereum, whereas Chainlink experiences the lowest correlation. In light of individual years (Table 23, Appendix C), it turns out that correlations are the highest in 2020, possibly due to global economic uncertainty causing most of the financial markets to move together. Overall, 2019 has the lowest correlations, with a compellingly low correlation between Bitcoin and Chainlink, compared to the other cryptocurrencies.

Table 10: Correlation matrix of cryptocurrencies in 2018-2020
In this table Pearson's correlation coefficients are provided for the specific cryptocurrencies.

	BTC	ETH	XRP	BCH	BNB	LINK	ADA	LTC
BTC	1.00							
ETH	0.86	1.00						
XRP	0.73	0.83	1.00					
BCH	0.80	0.82	0.73	1.00				
BNB	0.71	0.75	0.63	0.65	1.00			
LINK	0.57	0.62	0.55	0.53	0.54	1.00		
ADA	0.77	0.84	0.80	0.77	0.67	0.57	1.00	
LTC	0.83	0.88	0.78	0.83	0.72	0.55	0.82	1.00

Considering changing correlation coefficients, two VAR models are estimated: one for both 2018 and 2019, and one for 2020. Table 11 tabulates the results of the VAR (1) model for 2018-2019. Table 24 in Appendix C presents the results of the corresponding Granger causality tests. The coefficients in the VAR models indicate to what extent the previous day's return of one cryptocurrency contains information of the current day's return of another coin. The term Granger causality does not necessarily indicate a causal relationship. However, it suggests that there potentially is a causal relationship between two variables.

For the years 2018 and 2019 none of the cryptocurrency returns affect Bitcoin returns, the same applies to Ethereum and Chainlink. All other cryptocurrencies show several interdependencies. Bitcoin Granger causes Binance Coin returns, however, this only is significant at a 10% level. Ethereum has a relatively large impact on a few other altcoins, specifically Ripple, Bitcoin Cash and Litecoin. However, Granger causality at a 5% significance level cannot be confirmed for Ripple and Litecoin. On the other hand, Ethereum significantly Granger causes Bitcoin Cash at a 5% significance level, indicating previous day's Ethereum return contains specific information with respect to today's Bitcoin Cash return.

Further, Ripple, Bitcoin Cash and Litecoin significantly influence their own next day's return. Binance Coin significantly Granger causes Cardano. To conclude, several interdependencies between cryptocurrencies are observed for the years 2018 and 2019.

In order to shed light on potentially different relationships in 2020, an identical VAR (1) model is examined for this year. The results of this second model are presented in Table 12 and the results of the Granger causality tests are listed in Appendix C Table 25.

Table 11: Vector Autoregressive model 2018-2019

This table represents the relationships between cryptocurrencies. The left column lists the exogenous variables, representing previous day's return. The endogenous variables are represented horizontally in bold. T-statistics are provided in parentheses. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

	BTC	ETH	XRP	BCH	BNB	LINK	ADA	LTC
BTC $_{t-1}$	-0.072 (-0.94)	-0.150 (-1.56)	-0.022 (-0.22)	-0.080 (-0.64)	-0.190* (-1.93)	0.111 (0.80)	0.002 (0.02)	-0.143 (-1.47)
ETH $_{t-1}$	-0.105 (-1.30)	-0.045 (-0.44)	-0.195* (-1.89)	-0.288** (-2.16)	-0.045 (-0.43)	0.054 (0.37)	-0.168 (-1.41)	-0.194* (-1.87)
XRP $_{t-1}$	0.032 (0.57)	0.097 (1.39)	0.205*** (2.91)	0.075 (0.82)	-0.082 (-1.14)	-0.078 (-0.78)	0.043 (0.53)	0.048 (0.68)
BCH $_{t-1}$	0.009 (0.21)	-0.001 (-0.02)	-0.011 (-0.20)	0.173** (2.46)	-0.003 (-0.06)	-0.075 (-0.96)	-0.021 (-0.34)	-0.006 (-0.10)
BNB $_{t-1}$	-0.032 (-0.78)	-0.066 (-1.27)	-0.031 (-0.59)	-0.082 (-1.21)	0.013 (0.25)	-0.111 (-1.48)	-0.131** (-2.17)	-0.050 (-0.95)
LINK $_{t-1}$	0.029 (1,12)	0.037 (1.13)	0.030 (0.90)	0.085** (2.00)	-0.017 (-0.50)	0.014 (0.30)	0.052 (1.38)	0.051 (1.54)
ADA $_{t-1}$	-0.011 (-0.20)	-0.039 (-0.57)	-0.080 (-1.15)	-0.035 (-0.39)	0.069 (0.97)	0.091 (0.91)	0.044 (0.55)	-0.013 (-0.18)
LTC $_{t-1}$	0.101 (1.52)	0.089 (1.06)	0.058 (0.69	0.145 (1.33)	0.126 (1.47)	-0.108 (-0.89)	0.140 (1.43)	0.212** (-2.49)

Table 12 shows somewhat dissimilar results. Most interdependencies between cryptocurrencies disappeared in 2020. Bitcoin still remains independent from all selected cryptocurrencies. However, its influence on some major altcoins has augmented. Whereas in 2018 and 2019 Ethereum moves independently, in 2020 its returns are significantly Granger caused by the previous day's Bitcoin return. In other words, yesterday's Bitcoin return contains information regarding today's Ethereum return. Additionally, Ripple returns bear a similar significant relationship with Bitcoin returns. Returns on Binance Coin relate similarly to Bitcoin returns in both sample periods.

To conclude, the findings suggest that Bitcoin moves independently with respect to the selected altcoins for both sample periods. Additionally, more interdependencies between altcoins are observed for the years 2018 and 2019 compared to 2020. However, the results should be considered with caution since vector autoregressive models cannot account for nonlinear relationships. Furthermore, the model only includes altcoins, which implies that other potential risk factors are omitted. Therefore, these tests are rather indicative.

Table 12: Vector Autoregressive model 2020
This table represents the relationships between cryptocurrencies. The left column lists the exogenous variables, representing previous day's return. The endogenous variables are represented horizontally in bold. T-statistics are provided in parentheses. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

	BTC	ETH	XRP	BCH	BNB	LINK	ADA	LTC
BTC_{t-1}	-0.251	-0.425**	-0.379**	-0.088	-0.339*	-0.239	-0.364	-0.269
	(-1.48)	(-2.01)	(-2.28)	(-0.38)	(-1.71)	(-0.91)	(-1.61)	(-1.39)
ETH_{t-1}	0.020	0.117	0.082	-0.005	0.049	0.127	0.128	0.008
	(0.11)	(0.53)	(0.47)	(-0.02)	(0.23)	(0.46)	(0.54)	(0.04)
XRP_{t-1}	-0.014	0.029	0.054	0.019	-0.032	0.075	-0.229	-0.036
	(-0.09)	(0.14)	(0.33)	(0.08)	(-0.16)	(0.29)	(-1.04)	(-0.19)
BCH_{t-1}	0.099	0.044	0.007	-0.024	0.179	0.232	0.210	0.039
	(0.72)	(0.26)	(0.05)	(-0.13)	(1.12)	(1.09)	(1.15)	(0.25)
BNB_{t-1}	-0.026	-0.045	-0.013	-0.013	0.000	-0.084	-0.014	0.001
	(-0.17)	(-0.24)	(-0.09)	(-0.06)	(0.00)	(-0.36)	(-0.07)	(0.01)
$LINK_{t-1}$	-0.019	0.047	0.011	-0.030	0.039	0.149	-0.015	0.007
	(-0.30)	(0.59)	(0.18)	(-0.35)	(0.52)	(1.49)	(-0.17)	(0.10)
ADA_{t-1}	0.038	-0.023	-0.003	-0.026	-0.096	0.035	-0.023	-0.064
	(0.37)	(-0.18)	(-0.03)	(-0.19)	(-0.80)	(0.22)	(-0.17)	(-0.56)
LTC_{t-1}	-0.072	-0.014	0.021	-0.060	-0.022	-0.614**	-0.041	0.051
	(-0.39)	(-0.06)	(0.12)	(-0.24)	(-0.10)	(-2.14)	(-0.19)	(0.24)

6. Conclusion

In this research Bitcoin returns and risks are scrutinized for the period of March 1, 2018 up until August 26, 2020. In particular, the relationship between Bitcoin and traditional asset classes is examined. Additionally, by deliberately including the current COVID-19 pandemic, a period of relative stability is compared with a period of fear and uncertainty. The central findings of this research are as follows.

First of all, during 2018 and 2019 daily S&P 500 returns negatively affected Bitcoin volatility. Strikingly, this effect is not observed for 2020. It can be assumed that Bitcoin offers hedging opportunities against the stock market, but that it is less effective in uncertain times.

Secondly, no consistently significant evidence is found for the individual relationship between Bitcoin volatility and returns on respectively, gold, silver and the treasury yield. Furthermore, hash rate negatively impacts the next day's Bitcoin volatility, which suggests that an improvement of the network's security contributes to a reduction of risk. The number of transactions is positively associated with Bitcoin volatility. Moreover, this paper has shown that past Bitcoin returns and volatility contain some information that helps predicting future volatility.

Additionally, the results suggest that Bitcoin returns behave differently in times of uncertainty compared to relatively more stable years. In 2020, the returns of Bitcoin and those of gold and the S&P 500 comoved significantly.

In alignment with this finding, Bitcoin returns are significantly and substantially more correlated to the market premium in 2020 compared to the previous years. Hence, evidence is found that Bitcoin is to some extent subject to systematic risk during the sample period in 2020. Since the correlation to the market premium is observed to be relatively low, Bitcoin may serve as a great instrument for financial institutions to further diversify their portfolios.

Furthermore, Bitcoin returns appear negatively correlated to the hash rate during the sample period in 2020, weak evidence is found for a negative impact of the number of transactions on Bitcoin returns, and the results do not indicate exposure of Bitcoin returns to conventional currencies. Contradictory to a time series momentum effect, significant daily reversal effects are observed. Although, correlations between Bitcoin and other cryptocurrencies are high in the entire sample, they are the highest in 2020, whereas Bitcoin returns are not Granger caused by any of the alternative cryptocurrencies.

Lastly, a few caveats must be recognized, as this research is subject to time limitations. First of all, this study did not take any reversed effects into account, e.g. it can be that the hash rate adjusts to prices instead of the other way around. Therefore, it would be interesting to conduct more in depth research into specific technological factors, such as the hash rate. Secondly, this study is solely focused on the United States stock market. It would be interesting to perform analyses including stock market indices for multiple regions and/or multiple stock markets in the United States. Furthermore, as a matter of course, multiple other factors can influence Bitcoin returns. Future research could for example include the U.S. dollar index (DXY) as a proxy for trust in financial markets. Additionally, the impact of monetary policies can be an interesting field as well.

To conclude, since Bitcoin and other cryptocurrencies are continuously developing as a new asset class, still much has to be learned. Although it is for sure that academics are provided with a fascinating area of interest.

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Appendix A

Table 13: Variable definitions

Variable	Definition	Unit
Bitcoin	Bitcoin's daily closing price based on aggregated closing prices of main exchange platforms, including Coinbase, Binance, Kraken, Gemini, Bitstamp, Bittrex and itBit.	U.S. dollars
Gold	XAU/USD, i.e. the daily spot rate of gold.	U.S. dollars
Hash rate	The speed by which mathematical calculations are solved by the network's miners.	Terahashes per second
Investment premium (CMA)	Conservative minus aggressive; The mean return on portfolios containing conservative investment firms minus the mean return on portfolios containing aggressive investment firms.	Percentage
Log-returns	The returns on each asset in this paper are continuously compounded and computed as follows: $\ln(Price_t / Price_{t-1})*100$	Percentage
Market premium	Rm-Rf; Market return minus the risk free rate. This concerns the value-weighted return of all U.S. companies listed on the NYSE, NASDAQ or AMEX available in CRSP.	Percentage
Mining difficulty	The average difficulty of finding a new block. Each time 2016 blocks are mined the difficulty is adjusted based on the realized time it took to mine these blocks scaled by a target time for mining these 2016 blocks.	Absolute value
Momentum (MOM)	Momentum is the tendency for stocks that increased in value to continue to rise further and for stocks that decreased in value to continue declining. It is measured as the mean return on a portfolio consisting of winner stocks minus the mean return on a portfolio containing loser stocks.	Percentage
Profitability premium (RMW)	Robust minus weak; The mean return on portfolios containing stocks of high profitability firms minus the mean returns of portfolios containing low profitability firms.	Percentage
S&P 500	The S&P 500 daily closing index.	U.S. dollars
Silver	XAG/USD, i.e. the daily spot rate of silver.	U.S. dollars
Size premium (SMB)	Small minus big; The mean return on the small market cap stocks in the sample minus the mean return of the big market cap stocks.	Percentage
Transaction number	The total number of transactions within each 24 hours. A transaction is defined as each action by a participant in the Bitcoin network that adjusts the ledger.	Positive integer
Treasury yield	The 10-years treasury rate, i.e. the yield for investing in a security issued by the United States government.	Percentage
Value premium (HML)	High minus low; The mean return on value stocks minus the mean return on growth stocks.	Percentage

Appendix B

Table 14: Pearson's correlation matrix of returns per year

2018	Bitcoin	S&P 500	Gold	Silver	Treasury yield
Bitcoin	1.00				
S&P 500	0.03	1.00			
Gold	-0.06	-0.10	1.00		
Silver	0.02	0.15	0.82	1.00	
Treasury yield (10yrs)	0.12	0.38	-0.18	0.02	1.00
2019	**Bitcoin**	**S&P 500**	**Gold**	**Silver**	**Treasury yield**
Bitcoin	1.00				
S&P 500	-0.04	1.00			
Gold	0.15	-0.24	1.00		
Silver	0.10	-0.16	0.80	1.00	
Treasury yield (10yrs)	-0.03	0.49	-0.64	-0.50	1.00
2020	**Bitcoin**	**S&P 500**	**Gold**	**Silver**	**Treasury yield**
Bitcoin	1.00				
S&P 500	0.44	1.00			
Gold	0.28	0.14	1.00		
Silver	0.25	0.23	0.78	1.00	
Treasury yield (10yrs)	0.20	0.61	-0.23	-0.09	1.00

Figure 3a: Autocorrelation 2018-2020

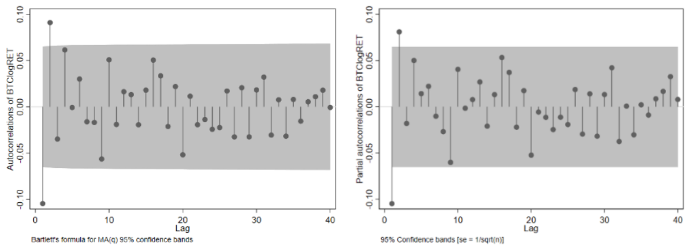

Figure 3b: Autocorrelation 2018-2019

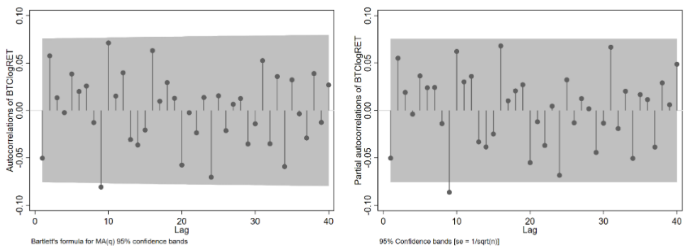

Figure 3c: Autocorrelation 2020

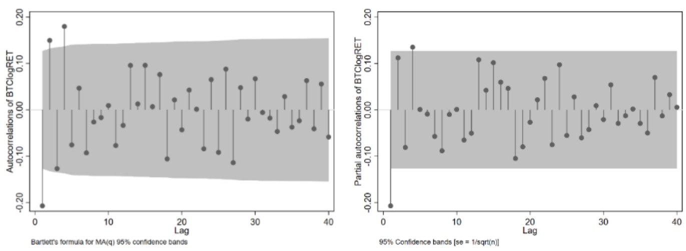

Table 15: Stationarity tests 2018-2020
The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

Variables	Dickey-Fuller t-statistic	Phillips-Perron t-statistic
Bitcoin log-return	-17.30***	-33.34***
S&P 500 log-return	-6.95***	-33.44***
Gold log-return	-5.87***	-29.11***
Silver log-return	-6.79***	-27.47***
Treasury rate 10yr (log-% change)	-10.73***	-28.34***
Treasury rate 10yr (ln)	-1.90	-2.19
Hash rate (ln)	-2.40	-11.51***
Nr. Of transactions (ln)	1.03	0.31
Network size (ln)	-3.16*	-20.38***
Mining difficulty (ln)	-2.16	-2.09
Hash rate (log-Δ)	-13.91***	-79.59***
Nr. Of transactions (log-Δ)	-8.80***	-79.45***
Network size (log-Δ)	-8.48***	-73.33***
Mining difficulty (log-Δ)	-16.61***	-23.86***

Table 16: ARCH-LM tests
The last column shows the P-values. A P-value lower than 0.05 indicates significance at a 5% level.

2018-2020			
lags(p)	chi2	df	Prob > chi2
1	3.894	1	0.0485
2018-2019			
lags(p)	chi2	df	Prob > chi2
1	7.517	1	0.0061
2020			
lags(p)	chi2	df	Prob > chi2
1	0.75	1	0.3864

Table 17a: Information criteria 2018-2020
This table contains the information criteria for the period 2018-2020, regarding the mean equation in the GARCH models.

	Linear interpolation over the weekend		*Constant over the weekend*	
Model	AIC	BIC	AIC	BIC
AR(1)	5012.723	5094.514	5013.334	5095.125
AR(2)	5014.500	5096.291	5014.920	5096.712
MA(1)	5013.912	5095.703	5014.646	5096.437
MA(2)	5015.067	5096.858	5015.374	5097.165
ARMA(1,1)	5008.068	5094.670	5009.669	5096.271
ARMA(2,2)	5015.494	5102.096	5016.390	5102.993
ARMA(2,1)	5009.619	5096.221	5009.571	5096.174
ARMA(1,2)	5010.087	5096.690	5009.962	5096.564

Table 17b: Information criteria 2018-2020
This table contains the information criteria for the period 2018-2020, for the complete GARCH models.

	Linear interpolation over the weekend		*Constant over the weekend*	
Model	AIC	BIC	AIC	BIC
AR(1)-GARCH(1,1)	4810.347	4969.118	4807.905	4966.676
AR(1)-GARCH(2,2)	4799.530	4967.924	4797.991	4966.385
AR(1)-GARCH(1,2)	4799.062	4962.644	4797.279	4960.861
AR(1)-GARCH(2,1)	4823.746	4987.328	4808.380	4971.963
ARMA(1,1)-GARCH(1,1)	4810.722	4974.304	4808.523	4972.105
ARMA(1,1)-GARCH(2,2)	4799.364	4972.569	4798.000	4971.205
ARMA(1,1)-GARCH(1,2)	4798.610	4967.004	4796.958	4965.352
ARMA(1,1)-GARCH(2,1)	4824.023	4992.416	4809.231	4977.625
AR(1)-GJR-GARCH(1,1)	4826.631	4990.214	4809.673	4973.255
ARMA(1,1)-GJR-GARCH(1,1)	4826.594	4994.988	4810.311	4978.705

Table 17c: Information criteria 2018-2019
This table contains the information criteria for the period 2018-2019, for the complete GARCH models. N.u.d. means: no uphill direction can be found, i.e. Stata cannot estimate the model.

	Linear interpolation over weekend		*Constant returns over the weekend*	
Model	AIC	BIC	AIC	BIC
AR(1)-GARCH(1,1)	3591.649	3740.339	3589.084	3737.775
AR(1)-GARCH(2,2)	N.u.d.	N.u.d.	3575.258	3732.961
AR(1)-GARCH(1,2)	3584.638	3737.835	3579.222	3732.419
AR(1)-GARCH(2,1)	3589.694	3742.890	3589.178	3742.375
GARCH(1,1)	3590.923	3735.108	3588.102	3732.287
GARCH(2,2)	3580.165	3733.362	3574.448	3727.644
GARCH(1,2)	3584.078	3732.769	3577.504	3726.195
GARCH(2,1)	3588.067	3736.758	3590.193	3738.884
AR(1)-GJR-GARCH(1,1)	3592.975	3746.171	3590.068	3743.265
GJR-GARCH(1,1)	3592.308	3740.999	3588.902	3737.592

Table 17d: Information criteria 2020
This table contains information criteria for 2020, regarding the ARMA models.

	Linear interpolation over weekend		*Constant returns over weekend*	
Model	AIC	BIC	AIC	BIC
AR(1)	1333.573	1392.602	1333.466	1392.494
AR(2)	1331.460	1393.961	1330.266	1392.767
AR(3)	1330.755	1396.728	1331.458	1397.432
MA(1)	1335.371	1394.400	1335.372	1394.401
MA(2)	1334.538	1397.039	1332.722	1395.223
MA(3)	1332.678	1398.651	1332.816	1398.790
ARMA(1,1)	1328.197	1390.698	1329.742	1392.243
ARMA(2,2)	1330.115	1399.560	1331.378	1400.823
ARMA(2,1)	1330.033	1396.006	1331.207	1397.180
ARMA(1,2)	1329.991	1395.964	1331.142	1397.115
ARMA(3,3)	1324.537	1397.455	1321.244	1390.689
ARMA(1,3)	1330.481	1399.926	1332.794	1402.240
ARMA(2,3)	1323.220	1392.665	1326.875	1396.320
ARMA(3,2)	1323.386	1392.832	1326.370	1395.815
ARMA(3,1)	1331.505	1400.950	1332.312	1408.702

Table 18: Information criteria VAR model
The sign * indicates the lowest value of the information criteria, hence the preferred model.

Lag	AIC	HQIC	SBIC
1	40.663*	40.793*	41.004*
2	40.750	41.010	41.431
3	40.805	41.195	41.826
4	40.837	41.358	42.200
5	40.903	41.553	42.606
6	40.953	41.734	42.997

Table 19: Stationarity tests cryptocurrencies
The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

Variables	Dickey-Fuller t-statistic	Phillips-Perron t-statistic
Bitcoin Cash	-12.04***	-30.01***
Binance Coin	-20.80***	-32.09***
Bitcoin	-17.30***	-33.34***
Cardano	-11.14***	-31.68***
Chainlink	-11.69***	-31.29***
Ethereum	-10.54***	-32.56***
Litecoin	-12.59***	-32.33***
Ripple	-12.39***	-31.21***

Appendix C

Table 20a: Stock factor loadings 2018

This table presents the exposure of Bitcoin excess returns to stock factors based on commonly used risk factor models. Bitcoin excess return is the dependent variable, while the risk factors are the explanatory variables. The coefficients are expressed in percentages. The values in parentheses represent the corresponding t-statistics. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

%	CAPM	3-Factor	4-Factor	5-Factor	6-Factor
$Alpha_t$	-0.293	-0.272	-0.280	-0.225	-0.237
	(-1.37)	(-1.26)	(-1.31)	(-1.02)	(-1.07)
$R_{m,t}$-$R_{f,t}$	0.014	0.139	0.059	-0.049	-0.068
	(0.951)	(0.59)	(0.26)	(-0.17)	(-0.25)
SMB_t		0.349	0.495	0.339	0.512
		(0.79)	(1.08)	(0.76)	(1.08)
HML_t		0.504	0.920	1.111*	1.431**
		(1.05)	(1.57)	(1.87)	(2.12)
MOM_t			0.833*		0.775
			(1.70)		(1.48)
RMW_t				0.067	0.358
				(0.11)	(0.59)
CMA_t				-1.570*	-1.335
				(-1.72)	(-1.45)
R-squared	0.00	0.01	0.02	0.02	0.03
N	305	305	305	305	305

Table 20b: Stock factor loadings 2019

This table presents the exposure of Bitcoin excess returns to stock factors based on commonly used risk factor models. Bitcoin excess return is the dependent variable, while the risk factors are the explanatory variables. The coefficients are expressed in percentages. The values in parentheses represent the corresponding t-statistics. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

%	CAPM	3-Factor	4-Factor	5-Factor	6-Factor
$Alpha_t$	0.272	0.273	0.265	0.278	0.269
	(1.36)	(1.35)	(1.30)	(1.37)	(1.32)
$R_{m,t}$-$R_{f,t}$	-0.319	-0.345	-0.482	-0.378	-0.495
	(-1.10)	(-1.15)	(-1.43)	(-1.13)	(-1.35)
SMB_t		0.029	-0.209	-0.021	-0.259
		(0.05)	(-0.32)	(-0.04)	(-0.39)
HML_t		-0.246	-0.556	-0.107	-0.438
		(-0.76)	(-1.04)	(-0.27)	(-0.77)
MOM_t			-0.388		-0.387
			(-0.79)		(-0.80)
RMW_t				-0.262	-0.318
				(-0.36)	(-0.45)
CMA_t				-0.326	-0.186
				(-0.28)	(-0.16)
R-squared	0.00	0.01	0.01	0.01	0.01
N	365	365	365	365	365

Table 20c: Stock factor loadings 2020

This table presents the exposure of Bitcoin excess returns to stock factors based on commonly used risk factor models. Bitcoin excess return is the dependent variable, while the risk factors are the explanatory variables. The coefficients are expressed in percentages. The values in parentheses represent the corresponding t-statistics. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

%	CAPM	3-Factor	4-Factor	5-Factor	6-Factor
$Alpha_t$	0.220	0.154	0.117	0.125	0.110
	(0.84)	(0.57)	(0.43)	(0.46)	(0.40)
$R_{m,t}-R_{f,t}$	0.754***	0.813***	0.836***	0.812**	0.823***
	(2.90)	(2.84)	(2.91)	(2.56)	(2.60)
SMB_t		0.680	0.645	0.763	0.741
		(1.38)	(1.27)	(1.45)	(1.37)
HML_t		-0.464	-0.654*	-0.609	-0.692
		(-1.58)	(-1.70)	(-1.47)	(-1.48)
MOM_t			-0.191		-0.093
			(-0.74)		(-0.38)
RMW_t				0.756	0.698
				(1.44)	(1.42)
CMA_t				-0.116	-0.186
				(-0.12)	(-0.16)
R-squared	0.17	0.19	0.19	0.20	0.20
N	239	239	239	239	239

Table 21a: Currency exposures 2018

This table presents the exposure of Bitcoin excess returns to currency returns based on several major currencies. Bitcoin log-return is the dependent variable. The currency returns are calculated as continuously compounded returns as well. The coefficients are expressed in percentages. The values in parentheses represent the corresponding t-statistics. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

	Daily Bitcoin return				
Constant	-0.349	-0.350*	-0.348	-0.346	-0.339
	(-1.63)	(-1.65)	(-1.63)	(-1.61)	(-1.58)
AUD	0.231				
	(0.41)				
CAD		0.285			
		(0.47)			
EUR			0.390		
			(0.52)		
SGD				1.141	
				(1.09)	
GBP					0.713
					(1.27)
R-squared	0.00	0.00	0.00	0.00	0.00

Table 21b: Currency exposures 2019
This table presents the exposure of Bitcoin excess returns to currency returns based on several major currencies. Bitcoin log-return is the dependent variable. The currency returns are calculated as continuously compounded returns as well. The coefficients are expressed in percentages. The values in parentheses represent the corresponding t-statistics. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

	Daily Bitcoin return				
Constant	0.182	0.169	0.188	0.181	0.178
	(0.95)	(0.88)	(0.99)	(0.94)	(0.92)
AUD	0.395				
	(0.65)				
CAD		0.918			
		(1.32)			
EUR			1.001		
			(1.33)		
SGD				0.174	
				(0.13)	
GBP					0.378
					(0.77)
R-squared	0.00	0.00	0.00	0.00	0.00

Table 21c: Currency exposures 2020
This table presents the exposure of Bitcoin excess returns to currency returns based on several major currencies. Bitcoin log-return is the dependent variable. The currency returns are calculated as continuously compounded returns as well. The coefficients are expressed in percentages. The values in parentheses represent the corresponding t-statistics. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

	Daily Bitcoin return				
Constant	0.177	0.206	0.161	0.220	0.200
	(0.60)	(0.71)	(0.49)	(0.80)	(0.69)
AUD	1.717				
	(1.20)				
CAD		1.554			
		(1.45)			
EUR			1.702		
			(0.70)		
SGD				3.502	
				(1.02)	
GBP					1.403
					(0.90)
R-squared	0.07	0.02	0.02	0.04	0.03

Table 22: Daily time series momentum per year
This table shows the effect of today's return on the daily forward returns for the next seven days. Returns are standardized by subtracting the mean and subsequently scaling it by the standard deviation. T-statistics are given in parentheses. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

	R_{t+1}	R_{t+2}	R_{t+3}	R_{t+4}	R_{t+5}	R_{t+6}	R_{t+7}
2018							
R_t	-0.050	0.108*	-0.013	-0.003	0.018	0.092	-0.030
	(-0.87)	(1.89)	(-0.22)	(-0.05)	(0.32)	(1.60)	(-0.52)
R-squared	0.00	0.01	0.00	0.00	0.00	0.01	0.00
St. dev.	3.71						
2019							
R_t	-0.058	0.011	0.020	-0.013	0.037	-0.035	0.061
	(-1.11)	(0.20)	(0.38)	(-0.25)	(0.70)	(-0.66)	(1.17)
R-squared	0.00	0.00	0.00	0.00	0.00	0.00	0.00
St.dev.	3.70						
2020							
R_t	-0.224***	0.155**	-0.149**	0.177***	-0.083	0.061	-0.075
	(-3.53)	(2.42)	(-2.31)	(2.75)	(-1.28)	(0.94)	(-1.15)
R-squared	0.05	0.02	0.02	0.03	0.01	0.00	0.01
St.dev.	4.24						

Table 23: Correlation matrix of cryptocurrencies per year
In this table Pearson's correlation coefficients are provided for the specific cryptocurrencies.

2018	BTC	ETH	XRP	BCH	BNB	LINK	ADA	LTC
BTC	1.00							
ETH	0.85	1.00						
XRP	0.70	0.81	1.00					
BCH	0.76	0.79	0.67	1.00				
BNB	0.68	0.69	0.57	0.58	1.00			
LINK	0.67	0.67	0.56	0.59	0.58	1.00		
ADA	0.80	0.84	0.79	0.73	0.61	0.63	1.00	
LTC	0.88	0.90	0.78	0.79	0.66	0.63	0.81	1.00
2019	**BTC**	**ETH**	**XRP**	**BCH**	**BNB**	**LINK**	**ADA**	**LTC**
BTC	1.00							
ETH	0.83	1.00						
XRP	0.71	0.81	1.00					
BCH	0.79	0.81	0.72	1.00				
BNB	0.58	0.64	0.54	0.56	1.00			
LINK	0.35	0.44	0.43	0.35	0.31	1.00		
ADA	0.71	0.83	0.82	0.78	0.59	0.37	1.00	
LTC	0.74	0.83	0.74	0.81	0.65	0.36	0.81	1.00
2020	**BTC**	**ETH**	**XRP**	**BCH**	**BNB**	**LINK**	**ADA**	**LTC**
BTC	1.00							
ETH	0.91	1.00						
XRP	0.85	0.90	1.00					
BCH	0.88	0.89	0.87	1.00				
BNB	0.89	0.91	0.86	0.87	1.00			
LINK	0.71	0.75	0.68	0.68	0.74	1.00		
ADA	0.82	0.86	0.82	0.82	0.84	0.72	1.00	
LTC	0.89	0.92	0.89	0.93	0.87	0.70	0.85	1.00

Table 24: The Granger causality Wald test for 2018-2019
This table shows the Chi square values of the Granger causality tests. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

Lagged variables	Dependent variables							
	BTC	ETH	XRP	BCH	BNB	LINK	ADA	LTC
BTC		2.43	0.05	0.41	3.71*	0.64	0.00	2.16
ETH	1.69		3.59*	4.68**	0.18	0.14	2.00	3.50*
XRP	0.32	1.92		0.68	1.30	0.60	0.28	0.46
BCH	0.04	0.00	0.04		0.00	0.93	0.11	0.01
BNB	0.60	1.61	0.35	1.47		2.19	4.70**	0.90
LINK	1.25	1.28	0.81	4.00**	0.25		1.91	2.39
ADA	0.04	0.32	1.33	0.15	0.95	0.83		0.03
LTC	2.32	1.13	0.47	1.76	2.16	0.80	2.05	

Table 25: The Granger causality Wald test for 2020
This table shows the Chi square values of the Granger causality tests. The signs *, **, and *** indicate significance, respectively at the levels 0.10, 0,05, and 0.01.

Lagged variables	Dependent variables							
	BTC	ETH	XRP	BCH	BNB	LINK	ADA	LTC
BTC		4.05**	5.21**	0.15	2.91*	0.82	2.60	1.94
ETH	0.01		0.22	0.00	0.05	0.21	0.29	0.00
XRP	0.01	0.02		0.01	0.03	0.09	1.08	0.04
BCH	0.52	0.07	0.00		1.25	1.19	1.32	0.06
BNB	0.03	0.06	0.01	0.00		0.13	0.00	0.00
LINK	0.09	0.35	0.03	0.12	0.27		0.03	0.01
ADA	0.14	0.03	0.00	0.04	0.65	0.05		0.31
LTC	0.15	0.00	0.01	0.06	0.01	4.57**	0.03	