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Factors influencing cryptocurrency returns during the covid-19 pandemic

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Abstract

This paper investigates the effects of volatility, trading volume, investor attention, the stock market and monetary policy measures on cryptocurrency returns during the covid-19 pandemic. Multiple OLS regressions and event studies are used to estimate the effects on the weekly returns of Bitcoin, Ethereum and XRP. Volatility and investor attention (measured by Google Trends) had a significant effect on all cryptocurrencies' returns, while the stock market had a positive significant relationship with Ethereum and XRP returns were positively affected by the Federal funds rate. Quantitative easing, measured by the size of the Federal Reserve balance sheet, and trading volume did not affect cryptocurrency returns. Event studies show no significant abnormal returns after monetary policy announcements.

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1. Introduction

While the world economy is in disarray because of the corona pandemic that started in 2020, one specific asset class has reached all-time high after all-time high: cryptocurrency. For example, the price of Bitcoin has risen astronomically during the pandemic year, from around 7,000 dollars per Bitcoin at the start of 2020 to 50,000 dollars per Bitcoin in the second month of 2021. Furthermore, the total market cap of all cryptocurrencies has increased tenfold in the period of January 2020 until May 2021, from 200 billion to a staggering 2.5 trillion.

This stunning price movement during a global crisis, as well as the increased importance of the cryptocurrency market in terms of market capitalization, naturally leads to the question: what are the factors behind these movements? Liu and Tsyvisnki (2018) found that cryptocurrency prices have little to no exposure to traditional stock market risk factors, major currencies or precious metals (with the exception of Ethereum to gold). Instead, they found factors such as investor attention and volatility to play a more significant role in determining the returns of cryptocurrency.

The importance of volatility for cryptocurrency returns is also documented by Akyildirim et al (2019), who found a positive relationship between the implied volatility of EU and US financial markets and the volatility of cryptocurrencies, which became more pronounced during times of increased financial market stress. Additionally, Zhang and Wang (2020) used Google Trends as a proxy for investor attention and found a consistent positive association between high investor attention and cryptocurrency returns. Furthermore, they found that Google Trends can significantly predict both cryptocurrency returns as well as return volatility.

Furthermore, Bouri et al. (2019) found that trading volume Granger-causes both extreme positive and negative cryptocurrency returns. Since both volume and returns have grown significantly during the pandemic (Corbet et al., 2020), this factor could be part of a possible explanation of cryptocurrency prices' spectacular increase.

To add to that, the Federal Reserve has responded to the economic turmoil caused by the pandemic in a very active way. The federal funds rate was lowered to almost zero, and large amounts of securities were bought, a policy called quantitative easing. These policies could fuel inflation, and this expectation could stimulate cryptocurrency demand since that asset class could be seen as a hedge against inflation (Isah and Raheem, 2019). Apart from the Federal funds rate and the balance sheet of the Federal Reserve, I will use a measure combing both of them, the Wu-Xia Shadow Federal funds rate (Wu and Xia, 2015), to estimate the effect of monetary policy on the returns of cryptocurrency.

Furthermore, to extend our insights about cryptocurrency as a hedge, this paper looks at the relationship between the returns of cryptocurrency and the S&P500. Earlier research has found that cryptocurrency can be used as a hedge against economic downturns (Dhyrberg, 2016). This paper builds on those findings by estimating the relationship between cryptocurrency and the S&P500 during the pandemic.

To see if these factors are still of influence during the crisis caused by the pandemic, and in what magnitude, this paper aims to answer the following research question: what factors have influenced cryptocurrency returns during the pandemic? In order to answer this question, I use the methods of linear regression and event studies. I perform a regression estimating the effect of all the factors mentioned above on the cryptocurrencies Bitcoin, Ethereum and XRP, along with four event studies estimating the specific effect of the monetary policy announcements on the cryptocurrencies mentioned. The analysed data ranges from September 2019 until May 2021, to include both a reference period and the latest data available.

This research contributes to existing literature by estimating the effects of the factors mentioned previously during an unprecedented economic event: the covid-19 pandemic. Insights in the factors influencing cryptocurrency returns in this period will shed light on how this asset class respond to a crisis, and whether it can be used as a hedge in such a situation. These insights will be of practical use to both investors and policy makers at the Federal Reserve. Investors can use the results of this paper to adapt and improve their investment strategy during crises, while policymakers at the Federal Reserve will gain a better understanding of how their actions influence this market of growing importance.

In the remainder of this paper, I start with the theoretical framework, explaining the most important theories and concepts necessary for answering the main question. Then, I discuss the data and methodology, followed by the results of the analysis. Finally, I provide a discussion of the results and end with a conclusion and identify further research opportunities.

2. Theoretical Framework

2.1 Cryptocurrency as an asset class

Since the inception of the first cryptocurrency, Bitcoin, in 2009, a growing body of literature has been devoted to defining cryptocurrency as an asset class. While some see Bitcoin and other cryptocurrencies as a purely speculative bubble (Kristoufek, 2013) which they expect to burst (Pichet, 2017), many researchers see cryptocurrency as a store of value, a hedging instrument or both. For example, Dyhrberg (2016) states that Bitcoin can be used as a hedging instrument by risk averse investors expecting a negative economic shock. As an asset class, she defines Bitcoin as somewhere between a currency, such as the dollar, and a commodity, such as gold. This is because like the dollar, Bitcoin can be used as a medium of exchange, but at the same time it can also be used as a hedging tool in a similar way to gold. Bouri (2019) also compared Bitcoin to gold and other commodities and found a low dependency of Bitcoin, gold and other commodities and the stock market, with Bitcoin being the least dependent asset. Furthermore, diversification benefits cause Bitcoin to rank higher than gold as a safe-haven asset. However, Bitcoin exhibits a strong time-variability, which makes it a riskier asset to invest in compared to gold or other commodities.

Liu and Tsyvinski (2018) extended the investigation into cryptocurrency as an asset class by extending their focus to multiple cryptocurrencies, namely Bitcoin, Ethereum and Ripple. In contrast to Dyhrberg (2016), they found that cryptocurrency has very little exposure to the traditional asset classes, including currencies and commodities. Instead, cryptocurrencies' returns were strongly driven by a momentum effect and investor attention, measured by the amount of Google searches and Tweets. The scope of cryptocurrencies was expanded by Krückeberg and Scholz (2019), who researched ten cryptocurrencies and concluded that cryptocurrency can be defined as a separate asset class, based on the high correlation between different cryptocurrencies and the absence of correlation with other asset classes. In addition, they found significant risk-adjusted upside to be captured from adding cryptocurrency to a traditional portfolio.

From the sources above, it can be concluded that cryptocurrency can be defined as an asset class on its own. This paper extends the literature by examining the factors influencing the returns of cryptocurrency during an unprecedented crisis situation, the covid-19 pandemic. Colon et al. (2020) found uncertainty to be an important factor affecting cryptocurrency returns. Furthermore, their results indicate that cryptocurrency as an asset class can be a strong hedge against uncertainty caused by geopolitical actions, but only a weak hedge against economic policy developments. Goodell and Goutte (2021) focused specifically on cryptocurrencies during the covid-pandemic and found small positive correlations between cryptocurrency and market indices, indicating that, in contrast to earlier research, the asset class is not a strong hedge against economic downturns.

2.2 Cryptocurrency specifics

2.2.1 Bitcoin (BTC)

The birth of cryptocurrency as an asset class started with the launch of Bitcoin in 2009. Its main goal was to create a decentralized alternative to fiat currency, with which users can complete transactions without the involvement of any intermediaries such as banks. Instead, transactions are verified by miners solving complex cryptography puzzles for which they are rewarded with Bitcoin. The technology used in this process is called the blockchain, a decentralized ledger of transactions distributed across a peer-to-peer network of computers.

A distinctive feature of Bitcoin is its limited supply. Bitcoins are created every time a user finds a new block in the blockchain. However, the amount of Bitcoin that can be earned per block is set to halve around every 4 years. Because of this mechanism, the total supply of Bitcoin is limited to 21 million coins. At the time of writing, the total market cap of Bitcoin is around 630 billion dollars, or around 45 percent of the total cryptocurrency market cap. Between the start of the pandemic on March 15 and 1st of May 2021, the price of Bitcoin has risen by 835 percent.

2.2.2 Ethereum (ETH)

In 2015, the blockchain platform Ethereum was launched, along with its native cryptocurrency, ether. In contrast to Bitcoin, the main focus of Ethereum is not its cryptocurrency, Ether, but the uses of its platform for decentralized finance applications using smart contracts. With Ethereum, users can build applications to provide financial services without the intervention of traditional financial intermediaries. Currently, the name Ethereum is frequently used to refer to the cryptocurrency, which I shall do as well throughout the remainder of this paper.

Unlike Bitcoin, Ethereum does not have a fixed supply. However, its yearly supply is capped at 18 million coins. Currently, Ethereum has a market cap of around 230 billion dollars, and is the second largest cryptocurrency, spanning around 18 percent of the total cryptocurrency market cap. Since the start of the pandemic, its price has risen by 2120 percent.

2.2.3. Ripple (XRP)

The payment solution Ripple, with its corresponding cryptocurrency XRP, was launched in 2012 by the company Ripple Labs Inc. Ripple’s technology enables worldwide transactions at high speed and low cost. Currently, a money transfer made with XRP takes only a few seconds to complete, making it the fastest of all cryptocurrencies. This makes it very interesting for banks and other large institutions. Like Bitcoin, XRP has a supply cap, which is set at 100 billion coins. XRP are not mined, but held and periodically released by the parent company Ripple Labs. Currently, XRP has a market cap of 30 billion dollars, translating into a 3 percent share of the total cryptocurrency market cap. Since the start of the pandemic, XRP has seen a price increase of around 945 percent.

Ripple Labs is not without controversy, however. In 2018, a class action was filed against the company, followed by a lawsuit on the 21st of December from the Securities and Exchange Commission (SEC) for selling unregistered securities. The lawsuit is still ongoing at the time of writing, forming a major cause of uncertainty for XRP.

2.3 Factors influencing cryptocurrency returns

2.3.1 Volatility

Since one of the cryptocurrency market's distinguishing features is its high volatility, estimating the effect of this volatility on the returns of cryptocurrency is important to better understand cryptocurrency as an asset class . Liu and Tsyvinski (2018) found a weak relationship between volatility and returns for Bitcoin and Ethereum, but for Ripple volatility carried more predictive power. Furthermore, Liu and Serletis (2019) investigated spill-over effects of volatility among the three main cryptocurrencies Bitcoin (BTC), Ethereum (ETH) and Litecoin (LTC). They found that past volatility of a cryptocurrency does not only serve as a strong predictor of its own future volatility, but also predicts the future volatility of the other coins.

Traditional asset pricing theory states that higher risk should be rewarded with higher returns (Jensen et al, 1972), so one would expected that an increase in risk, measured by volatility, leads to higher returns. As volatility of cryptocurrencies has increased significantly during the pandemic (Mariana et al., 2021) and cryptocurrency prices have reached all-time highs, one would expect this relationship to hold. Thus, the following hypothesis is formulated: increased volatility leads to higher cryptocurrency returns.

2.3.2 Volume

Another possible factor influencing cryptocurrency returns is trading volume. Corbet et al. (2020) found evidence of significant growth of both trading volumes and returns for a wide range of cryptocurrencies during the outbreak of the pandemic. Furthermore, Bouri et al. (2019) found that increased trading volume Granger causes both extreme positive and negative returns for Bitcoin, Litecoin and Ethereum.

Further research has shown the relationship between volume and returns to be bi-directional for cryptocurrencies (Fouzekis and Tzaferi, 2021). They found evidence of trend-following behaviour from rational uninformed investors. Since all cryptocurrencies in this paper have shown a downward trend in the period from September 1st until March 15 and an upward trend thereafter, the second hypothesis is a negative relationship between volume and cryptocurrency returns during the period before the pandemic and a positive one afterwards.

2.3.3 Google Trends

The exponential price increase of cryptocurrencies during the pandemic happened together with an increase in investor attention, similarly to the events in 2017. Since cryptocurrency investors are more active compared to investors in traditional assets (Lammer et al., 2019), investor attention is a factor that deserves academic interest. Google Trends serves as a proxy for investor attention because it is the main starting point for investors looking to obtain more information about a certain cryptocurrency. An increase in Google Trends could indicate an increase in demand, since interested investors use Google to seek ways to purchase cryptocurrency. These purchases would in turn lead to a higher price and thus increased returns.

Nasir et al. (2019) found that high Google search interest lead to positive returns for Bitcoin. Liu and Tsyvinski (2018) also documented a positive relationship between the number of Google searches and the return on Bitcoin, Ethereum and XRP. This is also confirmed by Zhang and Wang (2020), who found evidence of Granger causality for Google Trends and cryptocurrency returns. The relationship they observed was positive for Ethereum and XRP. Like Nasir et al. (2019), they found a strong positive effect of high search interest on returns. Lower search volumes yielded a more inconsistent result. For Bitcoin, the coefficient was slightly negative but insignificant.

Following the reasoning and the research mentioned above, the third hypothesis states that there is a positive relationship between Google Trends and cryptocurrency returns.

2.3.4 S&P 500

On the one hand, the S&P 500 and cryptocurrencies would be expected to have a positive relation because they are partly influenced by the same factors. For example, the current low interest rate causes low returns on savings and bonds, which drives investors to the financial market for higher returns. This would lead to higher returns for both the S&P 500 and cryptocurrency. Furthermore, at least a portion of the increased money supply through quantitative easing flows to the financial markets looking for returns, positively influencing both (groups of) assets. This positive relation was documented by Goodell and Goutte (2021) for Bitcoin and Ethereum.

However, while stocks are influenced by economic tides and perform less during an economic downturn because of reduced earnings, cryptocurrency can be viewed as a hedge against these downturns (Dhyrberg, 2016) or a store of value (Bouri, 2020). This would lead to the fourth hypothesis: that there is a positive relationship between the returns of cryptocurrency and the returns on the S&P 500 before the pandemic, and that that relation turns negative after the pandemic starts. Since stocks have recovered relatively quickly, it would be expected that the positive relationship returns in the long term.

2.3.5 Monetary Policy

The Federal Reserve has resorted to unprecedented measures to limit the economic damage caused by the corona pandemic. In a broad package of instruments, two actions at the beginning of the pandemic stand out. First, the Federal Reserve lowered the target for the Federal Funds rate overnight by 0.5 percent on March 3rd, following early reports about the coronavirus. 12 days later, the target was lowered by another 1 percent, to almost zero.

On the same date, March 15, the Federal Reserve announced the purchase of 700 billion dollars in Treasuries and government guaranteed mortgage-backed securities and on March 23 it expanded on that, promising to buy as much securities as needed in order to ensure a smooth functioning of financial markets. During the following months, market functions were improving and the Fed started tapering its purchases. However, on June 10th the Federal Reserve stopped tapering and announced the purchase of a minimum of 80 billion dollars in securities per month.

As mentioned above, the low interest rate provides an incentive for investors to seek higher returns in the financial markets. Since the fear caused by the corona pandemic drove many investors away from the stock market into so called “safe haven” assets, it is likely that cryptocurrencies profited from this movement as well. While they are not particularly “safe” because of their high volatility, they are not directly influenced by corona measures such as forced closures or capacity limits, and they could provide protection against another effect of the Federal Reserve’s actions: inflation (Isah and Raheem, 2019). The increased money supply caused by quantitative easing in combination with the near-zero interest rate erodes purchasing power, which drives investors towards assets that can serve as a store of value. Bitcoin is especially suitable for this purpose, since its supply is limited to 21 million coins. Ethereum has no such hard supply cap, however, its supply is limited to 18 million ether per year. XRP has a supply cap of 100 billion, of which around 40 percent is currently in circulation.

Taking this into account, the fifth hypothesis is formed: that there is a positive relationship between the expansion of the Federal Reserve balance sheet through the purchasing of securities, and cryptocurrency, especially for Bitcoin. Relating to this, the sixth hypothesis is a negative relationship between the Federal Funds rate target and the returns on cryptocurrency.

To avoid the multicollinearity resulting from including both the Federal Reserve balance sheet and the Federal Funds rate in a model, a I include a regression using the Shadow rate, a measure devised by Wu and Xia (2015). The shadow rate reflects the Federal Funds rate as well as the Fed's unconventional monetary policy actions in one variable, which can be negative. Following the reasoning above, the seventh hypothesis states that this coefficient is expected to be negative.

3. Data and methodology

3.1. Data

In order to estimate the relationship between cryptocurrencies and the factors mentioned above during the corona pandemic, I obtained data from multiple resources. First, I collected the daily and weekly prices, returns and trading volumes for Bitcoin, Ethereum, XRP and the S&P 500 during the period from September 1st, 2019 until May 1st, 2021 from investing.com, a financial market platform providing both real-time and historical data from large financial data providers as well as from real-time market maker CFDs. I use the data on returns to calculate the volatility, as described in the methodology section.

Secondly, I obtained weekly data on relative interest as expressed by Google searches through Google Trends, for the same period. Google Trends uses a sample of Google searches for a term during a specific period and normalizes it to scale of 0-100. Each datapoint is divided by the highest point (100), which makes it a measure of relative interest. The name of each cryptocurrency is used as input.

Thirdly, I collected weekly data on the total amount of assets on the Federal Reserve balance sheet during the analysed period from the official website of the Federal Reserve. The historical federal funds rate targets come from Macrotrends, a financial data platform. Finally, I obtained the monthly levels of the Wu-Xia shadow federal funds rate from the personal website of Jing Cynthia Wu, which I interpolated linearly to arrive at weekly levels.

Sample selection

At the time of writing, there are more than 5000 different cryptocurrencies, with a combined market capitalization of 2.5 trillion dollars. Since it is virtually impossible to analyse all these different coins, I decided to use a representative subsection of the market, based on the following criteria: market capitalization, maturity and popularity. Bitcoin, Ethereum and XRP together make up around 65% of the cryptocurrency market, which makes the selection representative for the cryptocurrency market as a whole. While Bitcoin and Ethereum are clearly the largest coins in terms of market capitalization, forming 45 percent and 18 percent of the market respectively, XRP has more competition with its market cap of around 3 percent. Coins with a similar market cap are for example Tether, Cardano or Binance Coin. However, both Cardano and Binance Coin were launched in 2017, which makes them less mature and more developing than XRP and Tether, which launched in 2013 and 2014 respectively. The final decision between XRP and Tether is based on popularity measured by Google Trends, where XRP clearly outperforms Tether.

Timeframe selection

Because this paper focuses specifically on the period of the covid-19 pandemic, I use a timeframe starting a few months before the pandemic (September 1st, 2019) until the most recent date on which all data was available (May 1st, 2021). I decided to include 6 months before the start of the pandemic as a reference period, in order to estimate whether there were any significant changes in the effects of the different variables before and during the pandemic. I chose the 15th of March as the start date for the pandemic, since two unprecedented monetary policy announcements regarding the pandemic were made. Also, the first lockdowns in the U.S. were implemented on that date. Furthermore, weekly data was chosen because the Google Trends variable and the variable representing the Federal Reserve Balance sheet were only available at the weekly level.

Generalization

Since the global circumstances during the period analysed in this paper is are very unusual, only limited generalization of the results to other periods is possible. For example, the insights gained from this analysis can be extrapolated to estimate the effect of a future pandemic or a significantly dangerous new strain of covid-19 on the cryptocurrency market. To a lesser extent, it can also be used for other crises with similar characteristics. However, since there are many factors to consider one should be careful in generalizing these results to other situations.

With regards to the cryptocurrency market as a whole, the selected sample is representative because it includes a significantly large part of the overall market capitalization. Furthermore, since many alternative cryptocurrencies are influenced by the price movements of Bitcoin (Ciaian et al., 2017; Demir et al., 2021), the results can be generalized to a certain extent. However, caution is needed because each cryptocurrency can react differently to the analysed factors, as the results of this paper show.

3.2. Methodology

To assess the effect of different factors on the returns of cryptocurrencies during the pandemic, I employed two statistical methods: an OLS-regression analysis and an event study. First, the OLS-regression will be discussed.

Mathematical model specification

To create a robust estimation of the effect of the monetary policy measures on the returns of cryptocurrencies, multiple models are employed. Since the Federal funds rate and the Fed Balance sheet exhibit a high degree of correlation and thus multicollinearity, I performed two separate regressions for each variable. Furthermore, in order to estimate the combined effect of both variables without multicollinearity, I created another model including the Wu-Xia shadow federal funds rate. This represents a broad measure of monetary policy, including the federal funds rate but also more unconventional policies such as quantitative easing.

The first model, including only the Federal funds rate, is defined as:

$$\begin{aligned} Return_{i,t} = {} & \alpha_i + \beta_{1,i} Volatility_{i,t} + \beta_{2,i,t} logVolume_{i,t} + \beta_{3,i,t}\, Google\ Trends_{i,t} \\ & + \beta_{4,,t} Federal\ funds\ rate_t + \beta_{5,t} S\&P500_t + \varepsilon_{i,t} \end{aligned}$$

For cryptocurrency i at time t.

The second model, including only the Federal Reserve balance sheet, is defined as:

$$\begin{aligned} Return_{i,t} = {} & \alpha_i + \beta_{1,i} Volatility_{i,t} + \beta_{2,i,t} logVolume_{i,t} + \beta_{3,i,t}\, Google\ Trends_{i,t} \\ & + \beta_{4,t} logFed\ Balance\ sheet_t + \beta_{5,t} S\&P500_t + \varepsilon_{i,t} \end{aligned}$$

For cryptocurrency i at time t.

The third model, including the Wu-Xia shadow federal funds rate, is defined as:

$$\begin{aligned} Return_{i,t} = {} & \alpha_i + \beta_{1,i} Volatility_{i,t} + \beta_{2,i,t} logVolume_{i,t} + \beta_{3,i,t}\, Google\ Trends_{i,t} \\ & + \beta_{4,t} Shadow\ rate_t + \beta_{5,t} S\&P500_t + \varepsilon_{i,t} \end{aligned}$$

For cryptocurrency i at time t.

In these models, $Return_{i,t}$ is the weekly return percentage for cryptocurrency i at time t, $Volatility_{i,t}$ is the weekly volatility for cryptocurrency i at time t, $logVolume_{i,t}$ is the logarithm of weekly trading volume for cryptocurrency i at time t and $Google\ Trends_{i,t}$ is the Google Trends score for each cryptocurrency i at time t. $Federal\ funds\ rate_t$ is the Federal funds rate target at time t, $logFed\ Balance\ sheet_t$ is the logarithm of the total amount of assets on the Federal Reserve Balance sheet at time t, $Shadow\ rate_t$ is the monthly Wu-Xia Shadow federal funds rate interpolated to a weekly level and $S\&P500_t$ is the weekly return percentage of the S&P500 at time t. $\varepsilon_{i,t}$ is the error term, α_i is the constant and the β's are the regression coefficients.

Specification of the variables

$Return$ is the weekly return percentage of each cryptocurrency. It is calculated using the simple return method, which consists of dividing the current price by the previous price, then subtracting one.

$Volatility$ is the weekly volatility of each cryptocurrency. It is calculated by summing the daily squared standard deviations of the daily returns for each week and then dividing this number by the number of observations.

$logVolume$ is the logarithm of the weekly trading volume of each cryptocurrency, measured in units.

$Google\ Trends$ is the Google Trends score for each cryptocurrency on a scale of 0-100, where a score of 100 indicates the highest search rate in a given period.

$Federal\ funds\ rate$ is the Federal funds rate target set by the Federal Reserve, measured in percentages.

$logFed\ Balance\ sheet$ is the logarithm of the total amount of assets on the balance sheet of the Federal Reserve, measured in millions of dollars.

$S\&P500$ are the returns of the S&P500, calculated using the simple return method, which consists of dividing the current price by the previous price, then subtracting one.

$Shadow\ rate$ is the Wu-Xia shadow federal funds rate. The shadow rate reflects the Federal Funds rate as well as the Fed's unconventional monetary policy actions in one variable, which, unlike the federal funds rate, can be negative. Like the federal funds rate, it is measured in percentages.

Descriptive statistics

Summary statistics of the variables mentioned above can be found in Table 1. Furthermore, Table 2 until Table 4 contain the correlation between the returns of the three cryptocurrencies and the independent variables.

Table 1 Summary statistics of weekly cryptocurrency returns, volatility, volume (log), Google Trends, S&P 500 returns, Federal funds rate, Federal Reserve balance sheet (log) and the Shadow Federal funds rate.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Returns BTC	87	0.0268	0.1072	-0.4169	0.2677
Volatility BTC	87	0.0017	0.0041	0.0002	0.0379
Volume BTC (log)	87	6.4239	0.4671	5.6186	7.7525
Google Trends BTC	87	29.0345	22.3931	12	100
Returns ETH	87	0.0426	0.1385	-0.4830	0.6470
Volatility ETH	87	0.0028	0.0062	0.0001	0.0567
Volume ETH (log)	87	7.7623	0.3835	6.9832	8.4276
Google Trends ETH	87	22.5632	26.0517	4	100
Returns XRP	87	0.0427	0.2339	-0.4890	1.3742
Volatility XRP	87	0.0046	0.0096	0.0001	0.0519
Volume XRP (log)	87	10.0977	0.2107	9.7551	10.7057
Google Trends XRP	87	14.1839	17.0120	4	100
S&P 500 Returns	87	0.0047	0.0352	-0.1498	0.1210
Federal Funds Rate	87	0.6030	0.7540	0.0400	2.1400
Fed Balance sheet (log)	87	6.7718	0.1176	6.5754	6.8933
Fed Shadow Rate	87	0.4986	0.9817	-1.7998	2.0100

Table 2 Correlation between Bitcoin returns, volatility, volume (log), Google Trends, S&P 500 returns, Federal funds rate, Federal Reserve balance sheet (log) and the Shadow Federal funds rate.

Variable	1	2	3	4	5	6	7	8
1 Return	1.0000							
2 Volatility	0.1984	1.0000						
3 Volume (log)	-0.2359	0.1726	1.0000					
4 Google Trends	0.1655	0.0987	-0.4708	1.0000				
5 ReturnS&P500	0.1937	-0.4385	-0.1553	-0.0246	1.0000			
6 Fed funds rate	-0.2065	0.0066	0.3912	-0.4297	-0.1720	1.0000		
7 Fed Balance sheet (log)	0.2299	-0.0402	-0.5192	0.5207	0.1496	-0.9749	1.0000	
8 Fed Shadow rate	-0.1893	0.0086	0.6293	-0.6896	-0.0988	0.8429	-0.9067	1.0000

Table 3 Correlation between Ethereum returns, volatility, volume (log), Google Trends, S&P 500 returns, Federal funds rate, Federal Reserve balance sheet (log) and the Shadow Federal funds rate.

Variable	1	2	3	4	5	6	7	8
1 Return	1.0000							
2 Volatility	0.0735	1.0000						
3 Volume (log)	-0.2109	0.1379	1.0000					
4 Google Trends	0.2790	0.0391	-0.7694	1.0000				
5 ReturnS&P500	0.3134	-0.4591	-0.1157	0.0303	1.0000			
6 Fed funds rate	-0.1732	-0.0044	0.3623	-0.4468	-0.1720	1.0000		
7 Fed Balance sheet (log)	0.2070	-0.0311	-0.5043	0.5519	0.1496	-0.9749	1.0000	
8 Fed Shadow rate	-0.2128	-0.0026	0.6626	-0.7504	-0.0988	0.8429	-0.9067	1.0000

Table 4 Correlation between XRP returns, volatility, volume (log), Google Trends, S&P 500 returns, Federal funds rate, Federal Reserve balance sheet (log) and the Shadow Federal funds rate.

Variable	1	2	3	4	5	6	7	8
1 Return	1.0000							
2 Volatility	-0.0373	1.0000						
3 Volume (log)	0.0031	0.4191	1.0000					
4 Google Trends	0.2833	0.6658	0.3895	1.0000				
5 ReturnS&P500	0.1631	-0.0711	-0.1180	0.0799	1.0000			
6 Fed funds rate	-0.1408	-0.1799	0.0862	-0.3273	-0.1720	1.0000		
7 Fed Balance sheet (log)	0.1755	0.2133	-0.1550	0.4248	0.1496	-0.9749	1.0000	
8 Fed Shadow rate	-0.2680	-0.3241	0.0283	-0.6548	-0.0988	0.8429	-0.9067	1.0000

Analytical method specification

In this study, I use linear regression analysis to estimate the relationship between cryptocurrency returns and trading volume, volatility, Google Trends, S&P500 returns and various monetary policy measures, namely the Federal funds rate, the Federal Reserve balance sheet and the Wu-Xia shadow Federal funds rate. Using each model mentioned above, I perform five regressions: a regression over the whole period, a regression before the pandemic, a regression on the first 7 months after the start of the pandemic, a regression on the whole period after the start of the pandemic and finally a regression over the months after the pandemic, excluding the first two months of the pandemic.

Assumptions

To comply with the first assumption of OLS, linearity, some variables had to be transformed to their logarithmic version. This was the case for volume and Fed Balance sheet. The second assumption, which is that the mean of the error term must be zero, has been met by including a constant in the model, which forces the average value of the residuals to equal zero.

Furthermore, I try to achieve the third assumption, that the conditional mean should be zero, by including relevant factors influencing the returns, based on previous research. Since earlier research by Fouzekis and Tzaferi (2021) indicated that the relationship between volume and returns is bi-directional, I created a model without volume to see if the coefficients changed. The coefficients turned out to change only very slightly and not significantly so (See Table A2). Therefore, I decided to keep the volume coefficient included. The fourth assumption, which is the absence of multicollinearity, has been validated by creating different models for the multicollinear variables (Fed funds rate and Fed Balance sheet), as well as adding a model which includes a variable combining them both. The fifth assumption has been dealt with by transforming some variables into log-variables to avoid heteroskedasticity. Also, I performed a Ljung-Box Q-test to confirm the absence of autocorrelation.

Event study

In addition to the OLS-regressions, I also performed multiple event studies to test whether the announcements of the Federal Reserve's monetary policy actions, rather than the actual changes in the federal funds rate and balance sheet, had an effect on the returns of cryptocurrency during the pandemic. For this purpose I selected four main announcements of the Federal Reserve in response to the pandemic. First, I analyse the large decreases in the Federal funds rate target at the 3rd of March and the 15th of March. Then, I examine the announcements of increased quantitative easing on the 23rd of March and the 10th of June. In order to arrive at a precise estimate, the daily returns of each cryptocurrency are used.

Specification of the variables

$Return$ is the daily return percentage of each cryptocurrency. It is calculated using the simple return method, which consists of dividing the current price by the previous price, then subtracting one.

Descriptive statistics

Table 5 provides summary statistics of the daily cryptocurrency currency returns used in the event studies.

Table 5 Summary statistics of daily returns of Bitcoin, Ethereum and XRP.

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Return BTC	640	0.0035	0.0390	-0.3918	0.1941
Return ETH	640	0.0054	0.0498	-0.4455	0.2588
Return XRP	640	0.0048	0.0679	-0.4178	0.5667

Analytical method specification

In this event study, I compare the returns of a cryptocurrency in the event window to the average returns of that cryptocurrency over the estimation period. The estimation period is in each case around two months, or 63 days.

Assumptions

The first assumption, that the asset returns in the event window of the event study application accurately reflect the economic impact of the event, is difficult to confirm. This is because the Federal Reserve actions are triggered by a pandemic which impacted markets in a way never seen before since the launch of cryptocurrency.

The second assumption, which is that the event is unexpected, and has not yet been factored into the asset price, can be partly confirmed. The event that urged the Federal Reserve to take action, the pandemic, was indeed unexpected. Furthermore, since the first lockdowns in the U.S. started on March 15th, the economic impact could not be fully assessed before. However, considering the Federal Reserve's action during earlier crises, there could be a chance that investors anticipated stabilizing measures from the Fed as soon as the pandemic started.

The final assumption is that there are no other events during the event window which could cause the change in returns. This cannot be confirmed for the first three announcements, since they were all relatively close to each other, in a month where a lot of developments took place. For example, news about rising infections and the implementation of lockdowns caused panic amongst investors. For the event study investigating the 10th of June, however, this assumption can be confirmed since the month of June was relatively calm, both in terms of new developments concerning the pandemic and in the crypto markets in general.

4. Results

In this section, the models containing the Federal Reserve balance sheet as monetary policy variable are selected to estimate the coefficients of the other variables, since those models overall had the highest R-squared. The other models can be found in the Appendix.

Volatility

First, the hypothesis that an increase of volatility leads to an increase in returns will be assessed. As shown in Table 6, the results of the regression over the whole period confirm this hypothesis for Bitcoin and Ethereum, since the returns of these currencies are positively and significantly correlated with volatility. The returns of XRP, however, show a negative and significant correlation with volatility. Furthermore, when the dataset is split before (see Table 7) and after the start of the pandemic (see Table 9) the positive correlation between Bitcoin and Ethereum and becomes insignificant while the negative coefficient of volatility for XRP remains significant. This could be explained by the ongoing lawsuit against Ripple Labs filed in 2018. The uncertainty caused by developments in this case could be a strong driver of volatility, as well as of fear which causes investors to sell XRP.

Table 6 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the size of the Federal Reserve balance sheet (log) (01-09-2019/01-05-2021)

Variable	**Returns_BTC**	**Returns_ETH**	**Returns_XRP**
Volatility	9.8103***	5.7633**	-9.1415***
	(2.9476)	(2.5350)	(3.4131)
Volume (log)	-0.0477*	0.0006	-0.0413
	(0.0284)	(.0579)	(0.1348)
Google Trends	-0.0001	0.0013	0.0074***
	(0.0005)	(0.0009)	(0.0021)
S&P500 Returns	0.9495***	1.6622***	0.5850
	(0.3410)	(0.4394)	(0.6879)
Fed Balance sheet (log)	0.0882	0.01803	0.0170

	(0.1147)	(0.14129)	(0.2398)
Constant	-0.2832	-0.1381	0.2788
	(0.8514)	(1.1106)	(2.4536)
Observations	87	87	87
R-squared	0.2041	0.2235	0.1817

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Volume

The second hypothesis was that there would be negative relationship between volume and returns before the start of the pandemic and a positive one afterwards. The results in Table 7 show indeed a significant negative relationship between volume and returns before March 15 for Ethereum and XRP. Bitcoin's coefficient is negative as well, but not significant. After March 15, Ethereum's coefficient becomes positive but insignificant. For XRP and Bitcoin the coefficient remains negative, with weak significance for Bitcoin only in the short term (see Table 8)

Google Trends

Thirdly, I formed the hypothesis of a positive relationship between Google Trends and cryptocurrency returns. The results show that this is indeed the case for XRP, which consistently exhibits a positive and significant relationship between Google Trends and returns. To a lesser extent it also holds for Ethereum, with a weakly significant positive relationship both before (see Table 7) and in the long run after the pandemic started (see Table 9). In the short run, the coefficient was positive but insignificant (see Table 8). Bitcoin, however, has a slightly negative coefficient before the pandemic started and a slightly positive one afterwards, but it is only weakly significant in the short run (see Table 8).

Table 7 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the size of the Federal Reserve balance sheet (log) (01-09-2019/14-03-2020)

Variable	**Returns_BTC**	**Returns_ETH**	**Returns_XRP**
Volatility	5.6189	-2.5501	18.6076
	(22.4791)	(15.0664)	12.3980
Volume (log)	-0.1597	-1.0474***	-0.5958***
	(0.2469)	(0.3600)	(0.1747)
Google Trends	-0.0065	0.0443***	0.0562***
	(0.0080)	(0.0143)	(0.0144)
S&P500 Returns	1.7936**	1.8011**	1.3742**
	(0.6640)	(0.8679)	(0.5788)
Fed Balance sheet (log)	1.6094	4.2423*	2.1934
	(1.8528)	(2.0815)	(1.3608)
Constant	-9.4841	-19.9525	-8.8502
	(11.0867)	(11.9121)	(8.0047)
Observations	28	28	28
R-squared	0.4876	0.6253	0.6722

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

S&P500

The fourth hypothesis states that there will be a positive relationship between the returns of the S&P500 and cryptocurrency returns before the pandemic, which will reverse in the short term after the pandemic starts and return again in the long term. The results in Table 7 show that there is indeed a positive relation between the returns of the three cryptocurrencies and the returns on the S&P 500 before the pandemic. As shown in Table 8 his relationship becomes insignificant during the first half year of the pandemic, and only reverses for Bitcoin. Thereafter, the relationship becomes weakly positive again, but only significantly for Ethereum. Over the whole period, only Bitcoin and Ethereum exhibit a positive significant relationship. This could indicate that XRP is influenced by factors significantly different from those affecting the other cryptocurrencies and the stock market.

Table 8 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the size of the Federal Reserve Balance sheet (log) (15-03-2020/01-10-2020)

Variable	**Returns_BTC**	**Returns_ETH**	**Returns_XRP**
Volatility	-2.2238	1.1232	-0.3520
	(4.2790)	(4.6606)	(6.5831)
Volume (log)	-0.0557*	0.0032	-0.0779
	(0.0305)	(0.1118)	(0.1459)
Google Trends	0.0069*	0.0041	0.0170*
	(0.0034)	(0.0048)	(0.0097)
S&P500 Returns	-0.3784	0.3424	0.3414
	(0.3873)	(0.6609)	(0.5169)
Fed Balance sheet (log)	-0.8190	-0.3333	-0.9938
	(0.5673)	(1.0655)	(1.0931)
Constant	5.8699	2.2372	7.4833
	(3.9449)	(7.7671)	(8.5610)
Observations	30	30	30
R-squared	0.3489	0.0589	0.2153

Note: standard errors are in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Monetary Policy

Federal Reserve balance sheet

The fifth hypothesis says that there will be a positive relationship between the Fed balance sheet and the returns on cryptocurrency. Over the whole period and before the pandemic, as shown in Table 6 and 7 respectively, the Federal Reserve balance sheet coefficient was indeed slightly positive for each cryptocurrency. When splitting the dataset at the March 15 announcement, the relationship reversed in the short term. None of these coefficients was significant, however. In the long term, the coefficient became negative and significant for XRP (see Table 9). This relationship does not have a relevant economic explanation, so it could be a case of spurious correlation.

Table 9 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the size of the Federal Reserve balance sheet (log) (15-03-2020/01-05-2021)

Variable	Returns_BTC	Returns_ETH	Returns_XRP
Volatility	4.1199	4.6248	-14.4856***
	(5.2436)	(4.5081)	(4.3477)
Volume (log)	-0.0467	0.0475	-0.3243
	(0.0343)	(0.0718)	(0.2468)
Google Trends	0.0004	0.0017*	0.0138***
	(0.0007)	(0.0010)	(0.0038)
S&P500 Returns	0.2372	1.0445*	0.0482
	(0.4651)	(0.6076)	(0.8927)
Fed Balance sheet (log)	-0.4705	0.2369	-3.5049**
	(0.7409)	(0.9712)	(1.5668)
Constant	3.5386	-1.9981	27.1848**
	(5.1874)	(6.9150)	(12.5892)
Observations	59	59	59
R-squared	0.0977	0.1407	0.2425

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Federal funds rate

Furthermore, the sixth hypothesis stated that there will be a negative relationship between the Federal funds rate and cryptocurrency return. For Bitcoin and Ethereum, this holds during the period following the start of the pandemic, while before the pandemic it is slightly positive. However, the coefficients are not significant. For XRP, the coefficient is negative but insignificant before the pandemic, however it turns positive and significant afterwards (see Table 10). This positive coefficient could be explained by the fact that the price of the currency is influenced by the issuing company, Ripple Labs. The main clients of this company are banks, which benefit from higher interest rates since it increases their profitability. This increased profitability can enhance their willingness to invest in new technologies such as those provided by Ripple Labs, and thus increase the value of the company and its cryptocurrency. However, this relationship is still speculative and deserves further research.

Table 10 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the Federal funds rate (15-03-2020/01-05-2021)

Variable	**Returns_BTC**	**Returns_ETH**	**Returns_XRP**
Volatility	11.6271	9.4096	-14.4800***
	(10.0083)	(7.3339)	(4.3911)
Volume (log)	-0.0390	0.0309	-0.0820
	(0.0302)	(0.0651)	(0.1870)
Google Trends	0.0001	0.0015	0.0097***
	(0.0006)	(0.0010)	(0.0026)
S&P500 Returns	0.3474	0.9732*	1.1239
	(0.4236)	(0.5490)	(1.0576)
Federal Funds Rate	-0.1865	-0.3280	0.7529**
	(0.3589)	(0.3935)	(0.3515)
Constant	0.28390	-0.2269	0.7249
	(0.2054)	(0.5225)	(1.8515)
Observations	59	59	59
R-squared	0.0955	0.1509	0.2370

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Wu-Xia shadow rate

The final hypothesis is that the relationship between the Wu-Xia shadow rate and cryptocurrency returns is negative. This is the case in the months before the pandemic, however thereafter it turns positive. In the long run the coefficient becomes negative again for XRP. In all cases, however, the coefficient is insignificant. The tables containing the coefficients for the Wu-Xia shadow rate can be found in the appendix.

Event studies

Event studies investigating abnormal returns around the monetary policy announcement dates yielded no significant results. Table 11 shows the results of the event study conducted around the quantitative easing announcement in June, the results of the other event studies can be found in the Appendix. The lack of significant abnormal returns could be either because cryptocurrency investors already expected the Federal Reserve to step in, meaning the effect was already priced in the market, or because the actions of the central bank have no significant influence on their investment decisions.

Table 11 Event study results concerning abnormal returns of Bitcoin, Ethereum and Ripple around the Quantitative Easing announcement (10-06-2020) – Estimation window of 63 days.

	BTC		**ETH**		**XRP**	
Event window	**Diff**	**t value**	**Diff**	**t value**	**Diff**	**t value**
-7,+7	0.0036	0.5509	0.0072	0.8792	0.0049	0.7237
-5,+5	0.0067	0.8765	0.0108	1.1471	0.0070	0.8328
-3,+3	0.0060	0.5562	0.0080	0.6145	0.0095	0.7829
-2,+2	0.0087	0.5886	0.0115	0.6420	0.0115	0.6828
-1,+1	0.0200	0.8913	0.0270	1.0518	0.0275	1.1692

Note: standard errors are in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

5. Discussion and conclusion

This paper started with the question: what factors have influenced cryptocurrency returns during the pandemic? By using OLS regression and event studies, I found volatility to be one of the important drivers of cryptocurrency returns. For Bitcoin an Ethereum, the results were in line with the hypothesis based on Jensen et al. (1972): high risk is rewarded by high returns. For the whole period, the volatility coefficient was large, positive and significant. For XRP, however, it was the other way around: the volatility coefficient was large, significant and negative. A possible explanation for this finding could be the uncertainty surrounding the lawsuit filed against Ripple Labs, its parent company.

Furthermore, I estimated the effect of volume and found the effect to be negative before the start of the pandemic, in line with the hypothesis based on Fouzekis and Tzaferi (2021), among others. After the start of the pandemic, the trend turned positive for all three cryptocurrencies, but the volume coefficient remained negative for Bitcoin and XRP, contrary to expectations. The volume coefficient became positive for Ethereum, however this and the volume coefficients of the other cryptocurrencies were insignificant after the pandemic.

Another effect I investigated was that of investor attention, measured by Google Trends. The results show that in accord with the hypothesis building on earlier research by Liu & Tsyvinski (2018), the coefficients were positive, and for XRP consistently significant. Only before the pandemic, it was slightly negative but insignificant for Bitcoin, similar to the findings of Zhang and Wang (2020).

Additionally, I looked at the relationship between cryptocurrency returns and S&P500 returns. The first part of the hypothesis, which was a positive relationship between the variables before the pandemic, could be significantly confirmed for all cryptocurrencies before the pandemic. The second part of the hypothesis stated that the relationship would reverse after the start of the pandemic. This was only the case for Bitcoin, however, with an insignificant coefficient. Finally, I expected the relationship to become positive in again in the long run after the pandemic, which was confirmed by the results. The only significant coefficient in this case however was Ethereum. Contrary to Dhyrberg (2016), but in line with Goodell and Goutte (2021), these results indicate that the investigated cryptocurrencies are not a strong hedge against downturns in the stock market.

Lastly, I estimated the effect of monetary policy on the returns of cryptocurrency returns. The first hypothesis was that an increase in the size of the Federal Reserve balance sheet would have a positive effect on cryptocurrency returns. Over the whole period and before the pandemic, this was indeed the case. However, after the pandemic started this relationship turned negative. Nevertheless, these coefficients were insignificant (except for XRP) so the hypothesis cannot be rejected. In the case of XRP, no apparent economic explanation appeared, so its negative coefficient might be spurious. Furthermore, the event studies showed no significant abnormal returns following announcements of increased quantitative easing.

The second hypothesis was a negative relationship between the Federal funds rate and the returns on cryptocurrencies. This holds for Bitcoin and Ethereum after the start of the pandemic, before the pandemic the coefficient was slightly positive. These coefficients were insignificant. For XRP on the other hand, the coefficient was positive and significant after the pandemic, which could be explained by the fact that the main clients of its parent company Ripple Labs are banks, which profit from higher interest rates. The event studies showed no significant abnormal returns following the announcements of decreases in the federal funds rate. Finally, the effect of the Wu-Xia shadow federal funds rate was also hypothesized to be negative, which holds before the pandemic. After the pandemic, the coefficient became positive. However, all coefficients were insignificant so this hypothesis cannot be rejected.

Returning to the main question, it can be stated that cryptocurrency returns were influenced significantly by the amount of volatility during the pandemic. Volatility had a positive effect on Bitcoin and Ethereum and a negative effect on XRP. Additionally, Google Trends has had a positive effect on all three cryptocurrencies during the pandemic. Furthermore, there is a significantly positive relationship between Ethereum and the S&P500 returns. Also, the federal funds rate had a positive effect on XRP returns during the pandemic. In contrast, trading volume and the size of the Federal Reserve balance sheet did not have a significant effect on any of the studied cryptocurrencies during the investigated period.

These conclusions should be interpreted with caution however, since this research has some limitations. First of all, I used weekly data on cryptocurrencies in the regressions. This makes the results less accurate since in the cryptocurrency market sentiment can shift quite fast depending on external events. Furthermore, since weekly data was collected for the timespan of a little over one and a half year, the number of observations is limited. This poses the risk of an overfitted model. Finally, this paper uses relatively simple methods to measure the effects of various factors. To obtain more robust and specific results, future research could decrease the scope of factors under investigation.

Despite these limitations, some practical implications can be drawn from the results. First of all, there is a clear distinction between on the one hand Bitcoin and Ethereum and on the other hand XRP. XRP reacts differently to volatility and the federal funds rate compared to the other cryptocurrencies. This makes XRP a useful tool for diversification within a cryptocurrency portfolio. Furthermore, cryptocurrency investors can use the results of this paper to decide on which factors to focus when making investment decisions. For example, this research has shown that cryptocurrency is positively correlated with the stock market, and thus does not serve as a strong hedge against economic downturns. Additionally, the absence of a significant relationship between monetary policy measures and cryptocurrency returns can be useful for Federal Reserve policymakers in evaluating their policy effects.

Additionally, this research has added to the understanding of cryptocurrency behaviour during a crisis. The results open up interesting new avenues for further research, for example one could dive deeper into the relationship between XRP and banks. Furthermore, the relationship between cryptocurrency returns and monetary policy decisions could be further investigated, for example by using a longer time period to increase robustness of the results. Finally, once the corona pandemic is officially over a new study can be done to estimate the factors' effects during the period and compare it with the time before and after.

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Appendix

Overall period (01-09-2019/01-05-2021)

Table A1 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the Federal funds rate (01-09-2019/01-05-2021).

Variable	Returns BTC	Returns ETH	Returns XRP
Volatility	9.7612***	5.8131**	-9.1519***
	(2.9597)	(2.5407)	(3.4134)
Volume (log)	-0.0517*	-0.0007	-0.0409
	(0.0274)	(0.0574)	(0.1289)
Google Trends	0.0007	0.0014	0.0074***
	(0.0006)	(0.0009)	(0.0020)
S&P500 Returns	0.9490***	1.6854***	0.5772
	(0.3441)	(0.4430)	(0.6913)
Federal Funds Rate	-0.0095	0.0036	-0.0046
	(0.01637)	(0.0205)	(0.0343)
Constant	0.3437*	-0.0104	0.3927
	(0.1816)	(0.4591)	(1.2881)
Observations	87	87	87
R-squared	0,2016	0,2236	0,1818

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility and Google Trends, as well as S&P500 returns and the size of the Federal Reserve balance sheet (log), without volume (01-09-2019/01-05-2021).

Variable	**Returns_BTC**	**Returns_ETH**	**Returns_XRP**
Volatility	8.8673***	5.7691**	-9.3450***
	(2.9253)	(2.4535)	(3.3292)
Google Trends	0.0002	0.0013*	0.0072***
	(0.0006)	(0.0006)	(0.0020)
S&P500 Returns	0.9716***	1.6622***	0.6048
	(0.3445)	(0.4367)	(0.6811)
Fed Balance sheet (log)	0.1538	0.0178	0.0437
	(0.1090)	(0.1391)	(0.2222)
Constant	-1.0412	-0.1321	-0.3150
	(0.7294)	(0.9343)	(1.4951)
Observations	87	87	87
R-squared	0.1765	0.2235	0.1807

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the Wu-Xia Shadow federal funds rate (01-09-2019/01-05-2021).

Variable	**Returns_BTC**	**Returns_ETH**	**Returns_XRP**
Volatility	9.9160***	5.8291**	-8.9948**
	(2.9600)	(2.5355)	(3.4346)
Volume (log)	-0.0566*	-0.0044	-0.0261
	(0.0303)	(0.0585)	(0.1356)
Google Trends	0.0001	0.0015	0.0068**
	(0.0007)	(0.0010)	(0.0026)
S&P500 Returns	0.9888***	1.6864***	0.5937
	(0.3405)	(0.4370)	(0.6858)
Shadow Rate	0.0018	0.0075	-0.0127
	(0.0171)	(0.0214)	(0.0349)
Constant	0.3641*	0.0145	0.2542
	(0.1935)	(0.4637)	(1.3476)
Observations	87	87	87
R-squared	0.1984	0.2245	0.1829

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Before March 15

Table A4 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the Federal funds rate (01-09-2019/14-03-2020).

Variable	**Returns_BTC**	**Returns_ETH**	**Returns_XRP**
Volatility	-3.7043	-1.5277	21.4426
	(22.9793)	(16.3913)	(13.0690)
Volume (log)	0.2484	-0.4395	-0.5020**
	(0.2722)	(0.3714)	(0.2094)
Google Trends	-0.0129	0.0341**	0.0548***
	(0.0081)	(0.0161)	(0.0175)
S&P500 Returns	1.8606**	2.5722***	1.4658**
	(0.6558)	(0.8913)	(0.6123)
Federal Funds Rate	0.1534	0.0479	-0.0567
	(0.1378)	(0.1340)	(0.1034)
Constant	-1.7295	3.2229	4.7951**
	(1.9280)	(3.0330)	(2.1542)
Observations	28	28	28
R-squared	0.4983	0.5571	0.6385

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the Wu-Xia Shadow Federal funds rate (01-09-2019/14-03-2020).

Variable	**Returns_BTC**	**Returns_ETH**	**Returns_XRP**
Volatility	5.8169	0.8021	21.9319
	(23.1371)	(16.0559)	(12.9756)
Volume (log)	-0.1222	-0.8640**	-0.5304**
	(0.3019)	(0.4022)	(0.1980)
Google Trends	-0.0072	0.04143**	0.0543***
	(0.0085)	(0.0153)	(0.0156)
S&P500 Returns	1.8773**	2.2798**	1.5186**
	(0.6756)	(0.8677)	(0.5942)
Shadow Rate	-0.0932	-0.2174	-0.1016
	(0.1895)	(0.1932)	(0.1253)
Constant	1.0662	6.9983**	5.1608**
	(2.2028)	(3.3816)	(2.0805)
Observations	28	28	28
R-squared	0.4758	0.5788	0.6442

Note: standard errors are in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

After March 15 (15-03-2020/01-05-2021)

Table A6 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the Wu-Xia Shadow Federal funds rate (15-03-2020/01-05-2021)

Variable	Returns_BTC	Returns_ETH	Returns_XRP
Volatility	5.659942*	3.475491	-10.55952**
	(3.340363)	(2.942553)	(4.50312)
Volume (log)	-0.0579366*	0.0292558	0.0745217
	(0.0335702)	(0.0687401)	(0.2086161)
Google Trends	0.0007516	0.0019876*	0.0069603
	(0.0007422)	(0.0010869)	(0.0044175)
S&P500 Returns	0.3098659	0.960687*	-0.0830822
	(0.4187662)	(0.553563)	(0.939505)
Shadow Rate	0.0438456	0.0205905	-0.0028351
	(0.0330176)	(0.046062)	(0.1002222)
Constant	0.3731017*	-0.240197	-0.7425396
	(0.2124732)	(0.541109)	(2.063855)
Observations	59	59	59
R-squared	0.1202	0.1430	0.1710

Note: standard errors are in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

After March 15 (15-03-2020/01-10-2020)

Table A7 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the Federal funds rate (15-03-2020/01-10-2020)

Variable	Returns_BTC	Returns_ETH	Returns_XRP
Volatility	3.3044	11.9004	-7.0581
	(10.0580)	(9.4461)	(16.3945)
Volume (log)	-0.0434	-0.0310	0.0540
	(0.0318)	(0.1061)	(0.1152)
Google Trends	0.0068*	0.0044	0.0108
	(0.0036)	(0.0045)	(0.0095)
S&P500 Returns	-0.0641	0.5753	0.5353
	(0.3341)	(0.5761)	(0.4622)
Federal Funds Rate	-0.0160	-0.4879	0.3506
	(0.3450)	(0.4559)	(0.4912)
Constant	0.1845	0.2384	-0.6171
	(0.1984)	(0.8458)	(1.1306)
Observations	30	30	30
R-squared	0.2925	0.0981	0.2052

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the Wu-Xia Shadow Federal funds rate (15-03-2020/01-10-2020)

Variable	**Returns_BTC**	**Returns_ETH**	**Returns_XRP**
Volatility	1.0690	1.4854	4.1162
	(3.4384)	(3.4481)	(4.6678)
Volume (log)	-0.0565	-0.0053	0.0107
	(0.0349)	(0.1149)	(0.1350)
Google Trends	0.0066*	0.0047	0.0138
	(0.0035)	(0.0052)	(0.0107)
S&P500 Returns	-0.2039	0.3702	0.5515
	(0.3778)	(0.6008)	(0.4780)
Shadow Rate	0.0747	0.0696	0.0098
	(0.0983)	(0.1663)	(0.1379)
Constant	0.2490	-0.0080	-0.1914
	(0.1972)	(0.8687)	(1.2806)
Observations	30	30	30
R-squared	0.3090	0.0619	0.1885

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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Table A9 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the Federal funds rate (01-05-2020/01-05-2021)

Variable	**Returns_BTC**	**Returns_ETH**	**Returns_XRP**
Volatility	15.2553	9.5202	-14.7740***
	(12.2657)	(9.6454)	(4.6902)
Volume (log)	-0.0400	0.0416	-0.1879
	(0.0340)	(0.0717)	(0.2461)
Google Trends	0.0001	0.0017	0.0108***
	(0.0007)	(0.0010)	(0.0030)
S&P500 Returns	1.0347*	1.8031*	1.7727
	(0.5988)	(0.7642)	(1.5290)
Federal Funds Rate	0.8542	1.5319	1.2079
	(1.0620)	(1.3119)	(2.6026)
Constant	0.1869	-0.4729	1.7220
	(0.2602)	(0.5874)	(2.4422)
Observations	52	52	52
R-squared	0.1381	0.2097	0.2533

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the size of the Federal Reserve balance sheet (log) (01-05-2020/01-05-2021)

Variable	**Returns_BTC**	**Returns_ETH**	**Returns_XRP**
Volatility	13.0394	8.0285	-16.6036***
	(12.0811)	(9.8406)	(4.8701)
Volume (log)	-0.0735*	-0.0067	-0.3688
	(0.0382)	(0.0815)	(0.2822)
Google Trends	0.0009	0.0022*	0.0157***
	(0.0009)	(0.0012)	(0.0050)
S&P500 Returns	0.8532	1.5589**	1.4002
	(0.5796)	(0.7615)	(1.4964)
Fed Balance sheet (log)	-1.9837	-2.2783	-5.0681
	(1.5677)	(2.2102)	(3.9801)
Constant	14.0491	15.6363	38.3225
	(10.8606)	(15.4518)	(28.7885)
Observations	52	52	52
R-squared	0.1554	0.2046	0.2754

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A11 Linear regression results for the relationship between returns of Bitcoin, Ethereum and Ripple, and each currency's volatility, volume (log) and Google Trends, as well as S&P500 returns and the Wu-Xia Shadow Federal funds rate (01-05-2020/01-05-2021)

Variable	**Returns_BTC**	**Returns_ETH**	**Returns_XRP**
Volatility	11.3777	9.0305	-14.8451
	(12.2604)	(9.9452)	(5.0520)
Volume (log)	-0.0669*	0.0236	-0.2015
	(0.0359)	(0.0754)	(0.2709)
Google Trends	0.0007	0.0018	0.0112**
	(0.0008)	(0.0012)	(0.0050)
S&P500 Returns	0.9155	1.6505**	1.6424
	(0.5774)	(0.7628)	(1.5099)
Shadow Rate	0.0416	0.0221	0.0153
	(0.0338)	(0.0483)	(0.1025)
Constant	0.4161*	-0.2100	1.9526
	(0.2262)	(0.5916)	(2.6701)
Observations	52	52	52
R-squared	0.1539	0.1899	0.2502

Note: standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Event studies (Daily Data 01-01-2020/01-05-2021)

Table A12 Event study results concerning abnormal returns of Bitcoin, Ethereum and Ripple around the Federal funds rate announcement (03-03-2020) – Estimation window of 63 days.

	BTC		ETH		XRP	
Event window	**Diff**	**t value**	**Diff**	**t value**	**Diff**	**t value**
-7,+7	0.0187*	1.9727	0.0309*	1.8938	0.0218*	1.5028
-5,+5	0.0117	1.0045	0.0196	0.9960	0.0132	0.8044
-3,+3	-0.0036	-0.3713	-0.0012	-0.0691	-0.0008	-0.0644
-2,+2	-0.0087	-0.7340	-0.0007	-0.0400	-0.0053	0.3731
-1,+1	-0.0055	-0.3040	-0.0010	-0.0329	-0.0075	-0.3276

Note: standard errors are in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01

Table A13 Event study results concerning abnormal returns of Bitcoin, Ethereum and Ripple around the Federal funds rate announcement and the first Quantitative Easing announcement (15-03-2020) – Estimation window of 63 days.

	BTC		ETH		XRP	
Event window	**Diff**	**t value**	**Diff**	**t value**	**Diff**	**t value**
-7,+7	0.0224	0.6870	0.0402	1.0208	0.0270	0.8411
-5,+5	0.0121	0.2743	0.0284	0.5440	0.0188	-0.4876
-3,+3	0.0403	0.6133	0.0528	0.6657	0.0369	0.6014
-2,+2	-0.0244	-0.5757	-0.0212	-0.3392	-0.0229	0.4614
-1,+1	0.0317	0.9047	0.0632	1.6609	-0.0367	0.8704

Note: standard errors are in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A15 Event study results concerning abnormal returns of Bitcoin, Ethereum and Ripple around the open ended Quantitative Easing announcement (23-03-2020) – Estimation window of 63 days.

	BTC		ETH		XRP	
Event window	**Diff**	**t value**	**Diff**	**t value**	**Diff**	**t value**
-7,+7	-0.015407	-0.8618	-0.0032362	-0.1673	-0.0099538	-0.5890
-5,+5	-0.0193127	-0.9475	-0.0109519	-0.5089	-0.0187368	-1.0297
-3,+3	-0.0132772	-0.6340	-0.0004107	-0.0177	-0.0106599	-0.4736
-2,+2	-0.0161412	-0.5495	-0.0021502	-0.0676	-0.0075457	-0.3272
-1,+1	-0.0313938	-0.6304	-0.0142	-0.2587	-0.0112489	-0.2789

Note: standard errors are in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Visual comparisons (graphs)

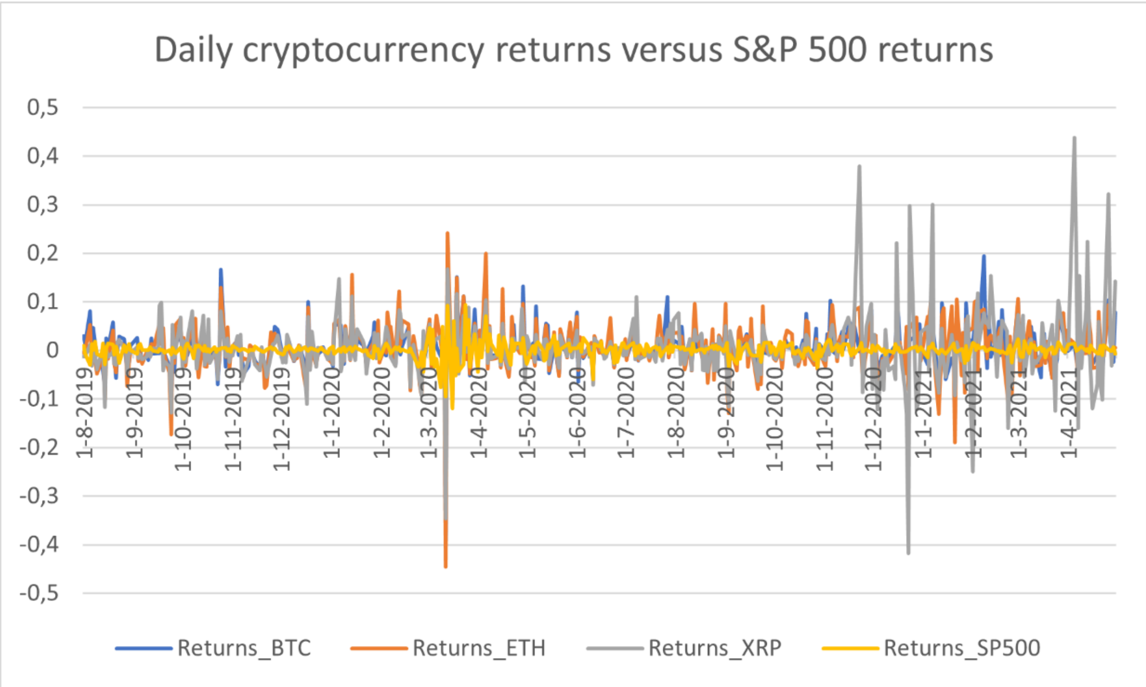

Figure A1 Visual comparison of cryptocurrency and S&P 500 daily returns between 01-09-2019 and 01-05-2021.

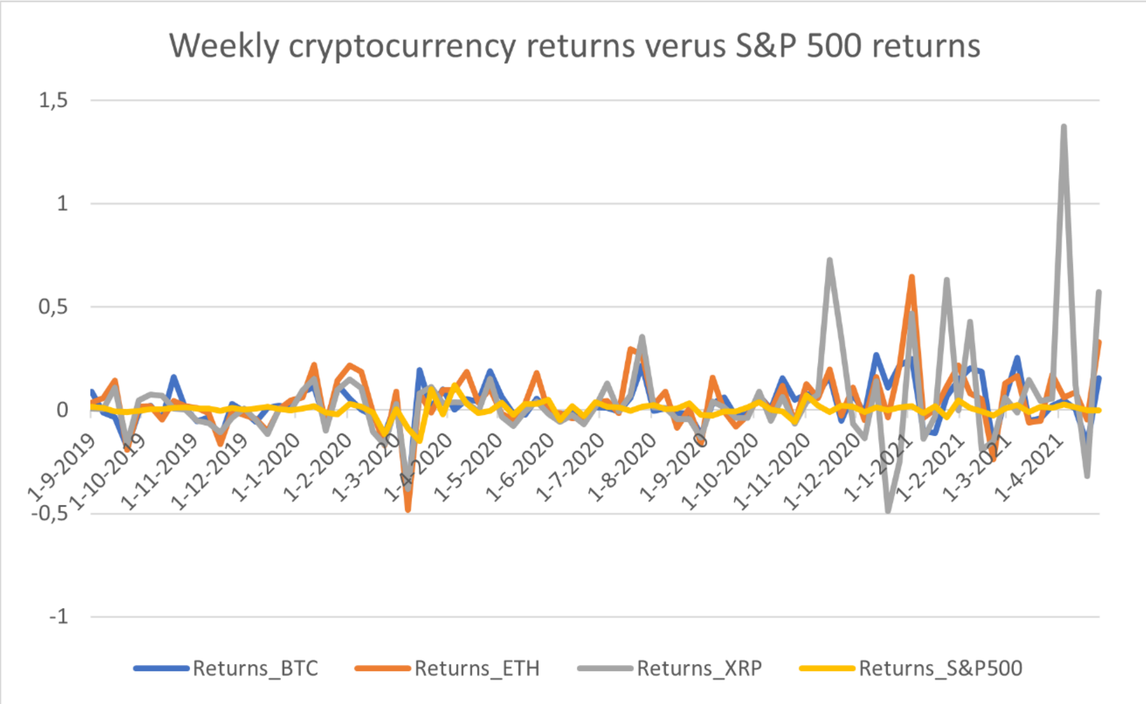

Figure A2 Visual comparison of cryptocurrency and S&P 500 weekly returns between 01-09-2019 and 01-05-2021.

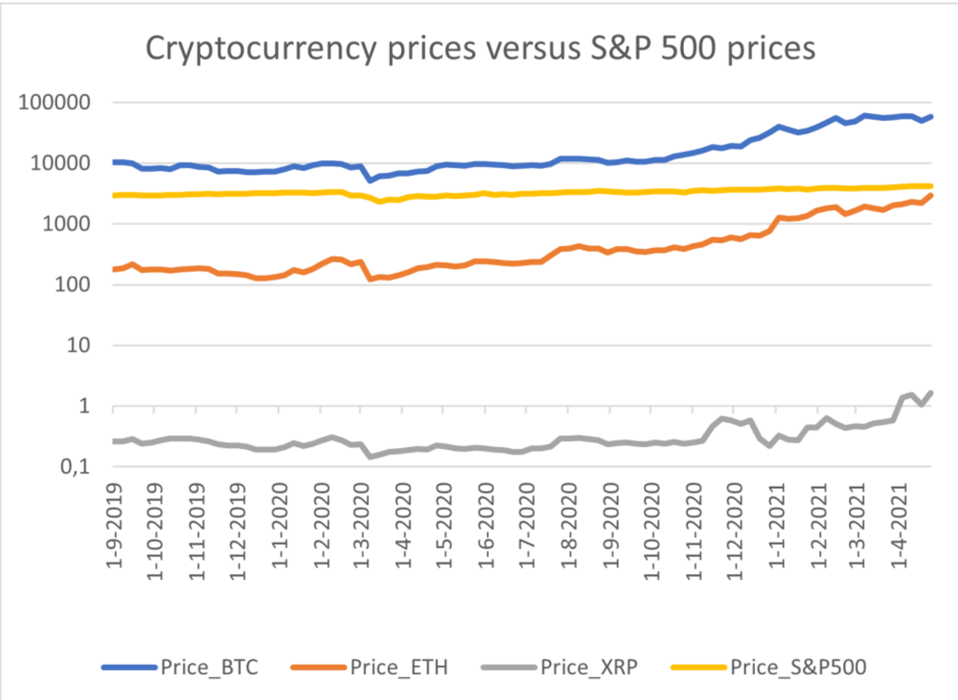

Figure A3 Visual comparison of cryptocurrency and S&P 500 weekly prices between 01-09-2019 and 01-05-2021.