Nijmegen School of Management
Department of Economics and Business Economics
Master's Thesis Economics (MAN-MTHEC)

Inflation Hedging: Is Bitcoin used as a hedge against increasing inflation?

By Molesini (S1061498)

Nijmegen, 14 December 2022

Program: Master's Program in Economics
Specialization: Financial Economics
Supervisor: Frank Bohn

Radboud Universiteit

Table of Contents

ABSTRACT:

This study investigates the usage of Bitcoin as a hedge against unexpected inflation. The research is done using event studies and google trends, it analyzes the changes in Bitcoin during inflation rate announcements. While employing the event studies method, the results show no relationship between Bitcoin returns and high unexpected inflation in the days surrounding the announcements. However, evidence of a positive relationship between both variables is observed when examining changes in the popularity of keywords associated with cryptocurrencies for the same events. Search results numbers are obtained using Google Trends.

Keywords: Inflation, Hedging, Bitcoin, Cryptocurrencies

1 Introduction:

Cryptocurrencies have been around for more than a decade. They are decentralized digital "currencies", with a peer-to-peer electronic cash system. Although cryptocurrencies can´t be considered, as of today, to be currencies, since they don´t fulfill the basic requisites of money. "[They] can be understood as a system intended for the issuance of tokens which are intended to be used as a general or limited-purpose medium-of-exchange, and which are accounted for using an often collectively-maintained digital ledger making use of cryptography to replace trust in institutions to varying extents." Pernice, I. G. A. & Scott, B. (2021). Cryptocurrencies were first introduced with the creation of Bitcoin in October 2008 by an anonymous person or group of persons, with the pseudonym Satoshi Nakamoto. It´s popularity exploded around 2013, when its price reached 100 US dollars. Around this time other cryptocurrencies appear in the crypto market. First being Litecoin in 2011, Ripple in 2013 and later Ethereum in 2015.

Research in the usage of cryptocurrencies as more than a speculative asset flourished in the second part of the previous decade. Plenty of research has been produced on the usage of cryptocurrencies in countries with high inflation, such as Venezuela, Argentina, and Turkey. The people in these countries have been using cryptocurrencies as a workaround of the extremely high loss of value and high uncertainty levels caused by the decreasing value of their currencies. (Chohan (2021); Cifuentes (2019); and Wulf (2018)). Not only have they been used as a store of value but also as a medium of exchange. Researchers have also studied the possibility for the usage of cryptocurrencies as money (Mattke, J., Maier, C., & Reis, L. (2020); Baur, D. G., Hong, K., & Lee, A. D. (2018)); analyzed the possible use of cryptocurrencies as a store of value (Ammous (2016)); and studied the properties of Bitcoin and the possibility the be used as a medium of exchange (Lee, Hong & Baur (2017)).

From all the possible functions cryptocurrency could be used for, this study focuses on their hedging capabilities. "A hedge is a position expected to offset potential losses of a companion investment" Feng, Wang & Zhang (2018). Hedging tools are assets that serve to lower exposition to investments. There is a variety of assets used for hedging depending on the idiosyncrasies of the risk wanted to be hedged. Gold, Commodities, Real estate, CPI-linked bonds are Common stocks are some of the assets used for hedging purposes. Lately, with the rise of inflation rates across the world many have questioned if cryptocurrencies could be used as a hedging tool for high inflation. Although, research hasn´t reached a consensus, some studies offer evidence of cryptocurrencies having hedging properties in specific scenarios.

Previous research on inflation hedging capabilities of cryptocurrencies focuses on their whether cryptocurrencies can be an efficient hedge against high inflation rates. In the studies, researchers searched for evidence of positive correlation between cryptocurrencies and inflation rates. In this research I depart from the normative analysis. Instead, I focused on the positive Bitcoin inflation hedging capabilities of cryptocurrencies. I analyze the actual use of cryptocurrencies as an inflation hedge, regardless of whether they are a robust hedge or not. I obtained Bitcoin´s returns to construct a daily pricing model, using the obtained Bitcoin´s abnormal returns to analyze any change in valuation during the days surrounding the inflation rate announcements done monthly by the US Bureau of Labor Statistics. A Bitcoin price increase during announcement of high inflation could serve as evidence that Bitcoin in used to hedge against high inflation rates. Thereafter, I use Google searches to examine any popularity change in the search results of cryptocurrency and hedging keywords during the period the inflation rate announcements are made public. I find no evidence of an increase demand for Bitcoin during announcements of high and unexpected inflation rates when using the event studies approach. Whereas Google Trends show higher number of searches of the keywords when inflation rates were unexpectedly high.

2 Literature:

There has been significant research on possible alternative functions of cryptocurrencies. As discussed previously, many studies investigated the usage of cryptocurrencies as money Ammous, S. (2018); Mattke, J., Maier, C., & Reis, L. (2020); Baur, D. G., Hong, K., & Lee, A. D. (2018). To do so, they must be able to serve as a medium of exchange, store of value, and unit of account. Only Mattke, J., Maier, C., & Reis, L. (2020) find evidence that Bitcoin is perceived as money. Another type of use for cryptocurrencies researchers has focused on is their hedging capabilities. Bouri, Gupta, Tiwari and Roubaud (2017) study the possibility to hedge global uncertainty using Bitcoin. They find a positive correlation between both variables, which shows Bitcoin is a possible hedge against uncertainty. Nevertheless, the positive correlation is only shown when short investment periods are analyzed. For longer investments horizons the effect can´t be observed. Dyhrberg (2015) also finds that Bitcoin can be used as a safe heaven, in this case, against the Financial Times Stock Exchange Index (FTSE) Index, as it has some of the same hedging capabilities as gold. Fenga, Wanga and Zhangb (2018) also explore the safe heaven capabilities of numerous cryptocurrencies. They evaluate the tale risks, tale diversification and tale hedging capabilities of cryptocurrencies. The results showed that cryptocurrencies and other types of assets, mainly stocks, are not highly correlated, which gives cryptocurrencies the capacity to be used as a save heaven and a diversification tool. However, they still show high tail risks, and are not a viable hedge against negative events. Thomas Conlon, Richard McGee (2020) also studied the safe haven capabilities of Bitcoin. They do so during the financial crisis of the Covid-19 pandemic. The findings show a higher downside risk compared to the S&P 500, negating Bitcoin´s safe heaven potential during a crisis.

Focusing on the usage of cryptocurrencies as an inflation hedge, in countries with high inflation rates, people adopted cryptocurrencies more rapidly than in countries with the same characteristics but lower inflation. The people in these countries use cryptocurrencies as a mechanism to save their depreciating savings and even their monthly income in extreme cases. Moreno, E. C. (2016); Wulf, C. (2018); Cifuentes, A. F. (2019). Although cryptos had been used for this purpose on several occasions, their feasibility as a hedging against inflation has not reach a consensus. There is research that places cryptocurrencies as a hedge against inflation; Smales, L. A. (2021) finds cryptocurrencies returns are positively correlated with United States inflation expectations. Although, the relationship is only significant for short-term inflation expectations.

Choi, S., & Shin, J. (2022) find that Bitcoin appreciates against positive inflation and inflation expectation shocks, showing Bitcoin´s inflation-hedging capacity. However, they reject its safe-haven property. On the other end, Bouri, et. al. (2017) and Conlon, Corbet, & McGee (2021) find no clear evidence of any inflation hedging capacity for Bitcoin, and, for Bitcoin and Ethereum respectively. Bouri, et. al. (2017) examines the hedging capabilities of Bitcoin for different types of stock indexes and oil, gold, and inflation. The results show that Bitcoin can only be used as a hedge for Chinese stocks.

It is important to notice that the results of the previous studies vary greatly depending on the time period taken, and the set of assets that are being compared against. As an example, Conlon & McGee (2020), make their analysis using data from March 21st, 2019, to March 20th, 2020. The time-period studied ends before the 2020 bull market that saw cryptocurrency prices soar rapidly. The high volatility of cryptocurrencies makes difficult to obtain consistent results throughout diverse studies.

The research shown previously focuses on the technical capacity of cryptocurrencies as an inflation hedge. However, this research does not analyze whether cryptocurrencies can be used efficiently as an inflation hedge, but if they are used as an inflation hedge. My research strives to find evidence on whether investors are using cryptocurrencies to decrease the risk posed by increasing prices or not. In this line of research, Cong Gu et. al. (2021) used cumulative abnormal returns (CAR) to evaluate the usage of Bitcoin and Ethereum as an inflation hedge tool during the US Federal Reserve Board announcement of unlimited quantitative easing, during the beginning of the covid-19 pandemic. After the announcement, both cryptocurrencies experienced statistically significant positive abnormal returns. The results indicate that after the unlimited QE announcement, investors lean towards cryptos, possibly as a hedge against future high inflation. I have used this study as a base for my research.

3 Data and Methodology

The analysis was made on the period between January of 2017 and March of 2022. For the data on inflation, I use the United States of America´s domestic inflation. The US domestic inflation was chosen as the measurement of inflation in the study because, as the United Stated of America is the world´s biggest economy and the US dollar is the world´s reserve currency, the changes in US domestic inflation have significant impact worldwide, a more significant impact than any other mayor currency. The inflation rate is measured by the Consumer Price Index (CPI)[1] obtained by the US Bureau of Labor Statistics. As stated by the BLS, the CPI measures the change in prices paid by consumers for goods. It includes urban households, leaving rural areas out of the surveys. The urban population in the United States of America represent 93% of the total

[1] Consumer Price Index News Release - 2022 M03 Results (bls.gov)

population of the country, meaning that price changes for most citizens are being included in the measurements. The index is produced monthly and includes food, energy, services, medical care, transportation costs, and shelter. The CPI is not seasonally adjusted.

I collected daily data on Bitcoin prices, NASDAQ index, and gold prices measured in troy ounces. All data is included as daily returns, measured as price inflation. This was done due to non-stationarity detected in the data. Using Bitcoin returns, the dependent variable used in the regression as an example, the variables are measured as following:

$$\boldsymbol{BTCReturns_t = \frac{BTCPrice_t - BTCPrice_{t-1}}{BTCPrice_t}} \qquad \textbf{(1)}$$

The data on Bitcoin prices was acquired using Yahoo Finance[2], same as for the data on the NASDAQ index values. For Gold price, the data was obtained in Datahub.io[3]. Lastly, to measure consumer´s monthly expected inflation I used the "United States Michigan 1-year Expected Inflation" obtained at the Federal Reserve of Economic Data (FRED)[4]. This measurement is obtained through monthly surveys conducted to US consumers. The data is not seasonally adjusted. As explained by FRED "The Index of Consumer Expectations focuses on three areas: how consumers view prospects for their own financial situation, how they view prospects for the general economy over the near term, and their view of prospects for the economy over the long term."[5] [6]

The events used in the analysis are the Consumer Price Index announcements made by the Bureau of Labor Statistics[7]. The announcements are made monthly. They provide the monthly inflation rate, the cumulative inflation rate for the year so far and the yearly inflation rate for the previous 12 month. The monthly inflation rates in the announcements correspond to the inflation

[2] Bitcoin Price: Bitcoin USD (BTC-USD) Price History & Historical Data - Yahoo Finance

NASDAQ Index: NASDAQ Composite (^IXIC) Historical Data - Yahoo Finance

[3] Gold Prices (Monthly in USD) - Dataset - DataHub - Frictionless Data

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

[5] https://tradingeconomics.com/united-states/michigan-inflation-expectations

[6] Each monthly survey contains approximately 50 core questions, each of which tracks a different aspect of consumer attitudes and expectations. The samples for the Surveys of Consumers are statistically designed to be representative of all American households, excluding those in Alaska and Hawaii. Each month, a minimum of 500 interviews are conducted by telephone.

[7] Consumer Price Index Archived News Releases: U.S. Bureau of Labor Statistics (bls.gov)

rate obtained the month before the announcement. As an example, the announcement given in January of any year presents the monthly inflation rate of December of the previous year. The news is given the second week of each month. However, the announcements are not made in the same weekday every month. They are done mostly the Wednesday of Thursday of the second week of the month.

3.1 Bitcoin:

The cryptocurrency chosen for the research is Bitcoin. I only use Bitcoin as it represents 57% of dominance[8] on average on the period analyzed, with its highest dominance of 97% during 2017, and around a 43% dominance for the first months of 2022.

Bitcoin was the first ever digital currency, presented in 2008 and introduced to the public in 2009 by an anonymous person using the pseudonym Satoshi Nakamoto. In the first years after its creation, Bitcoin was barely noticed; most people didn´t know about it or saw Bitcoin as just another niche creation that would be used just by a small group of people with deep understanding on the technology behind it. A couple of years after its birth, the currency and its blockchain technology was spread worldwide. There were two main characteristics of the cryptocurrency that gave it the means to jump into fame. First, the realization that due to the code´s specifications, the number of Bitcoins was finite, reaching its limit at twenty-one million units. At the time of the writing, Bitcoin has just surpassed nineteen million units created. This upper limit gave investors the certainty that the number of coins was going to stay stable throughout its life, contrary to most fiat currencies[9]. And second, the blockchain system enabled Bitcoin to exist without a central institution that controls it. Bitcoin miners function as the controlling body by regulating the transactions in exchange for a chance of earning Bitcoin. Moreover, no changes can be made to the cryptocurrency unless all miners agree of them. Which gives Bitcoin´s blockchain even more stability on its source code.

Bitcoin had extraordinary price hikes in three different occasions between 2011 and 2014 that cemented it as one on the most profitable high-risk investments. Bitcoin got its notoriety around 2011, when the currency experienced its first exceptional price surge, between April and May 2011. The currency went from around $1.10 US dollars at the end of April to $30 US dollar at the end of May/ beginning of June. Although it gave incredible returns of about 2900% in on month for the lucky few that sold at its peak, this event was short lived. Dropping its price steadily for the next

[8] Dominance is the percentage of market capitalization of Bitcoin, in comparison with the market capitalization of the cryptocurrency market as a whole. A 57% dominance of Bitcoin means that Bitcoin represents the 57% of the total crypto market.

[9] Money declared by a person, institution or government to be legal tender. Montgomery (1917)

for month, bottoming at $2 US dollar in the middle of November. The second surge occurred in 2013, rising for $15 US dollars in January to $230 US dollar at the beginning of April. Despite a hard crash in the days after, with Bitcoin dropping to $68 US dollar, its price stabilized at around 100 US dollars. This gave many investors the possibility of selling their Bitcoin and obtaining substantial gains. Lastly, at the end of 2013, between the middle of October and the beginning of December, Bitcoin soared from $100 USD to $1100 USD. At this point, Bitcoin had already become mainstream, and many new investors got into the crypto market searching for the crazy returns Bitcoin could provide.

In 2022, after an important crash of the cryptocurrency that saw it lose more than half of its price, Bitcoin has stabilized around $20.000 US dollars. For many, the period of Bitcoin´s impressive gains have come to an end. And many believe this is the start of cryptocurrencies to be used more as a medium of exchange than a speculative investment[10].

3.2 Methodology

I analyze the use of cryptocurrencies to hedge investments against the risk that high and increasing inflation presents. "A hedge is a position expected to offset potential losses of a companion investment" Wenjun Feng, Yiming Wang & Zhengjun Zhang (2018). "According to Branch (1974), Fama and MacBeth (1974), and Oudet (1973), a security is an inflation hedge if its returns are independent of the rate of inflation. As noted by Bodie (1976), such independence can be loosely defined as a positive correlation between the nominal rate of return on a particular asset and the rate of inflation." (Blau, Griffith, & Whitby, 2021, p. 2)

For the analysis I use the Event Studies methodology. Event studies are used to evaluate the effect of a time specific event on the variable of interest. The Event Studies methodology is done in a three-step process. First step is to generate an OLS regression with the variable of interest (Bitcoin returns) as the dependent variable, this is called a counter factual. With the counter factual, I obtained the estimated values, or "fitted values", of the dependent variable. After obtaining the "fitted values", the second step is to subtract the actual values of the dependent variables, from the fitted values (the predicted values of the dependent variable obtained by the ARCH regression). This will give the values of the "Abnormal Returns" for every day during the event. The abnormal returns are the difference between the actual returns observed during each day of the event, and the hypothetical returns on the same day had the event not happened. The hypothetical returns are

10 Bitcoin Will Eventually Stabilize – Here's Why (cryptonews.com)

Kitamura, Y. (2022). Can we stabilize the price of a cryptocurrency? Understanding the design of Bitcoin and its potential to compete with Central Bank money.

given by the fitted values of the regression. The abnormal returns will show any possible unusually large positive or negative impact the event may generate. Final step is to analyze the abnormal returns of the day surrounding each monthly event, both before and after the event. In this paper I will evaluate the Bitcoin abnormal returns the days before and after the Fed´s inflation rate announcements. The Abnormal returns are obtained for every month´s inflation rate announcements that take place during the 5-year period selected. I will analyze both daily abnormal return and Cumulative Abnormal Returns (CAR).

$$\boldsymbol{CAR_{[t_1,\ t_2]} = \sum_{t=t_1}^{t_2} AR_t} \tag{2}$$

Abnormal returns analyze each day of the event separately, conversely the CAR method groups the days of the event together and analyzes the abnormal returns as a bundle. The composition of CAR is shown in equation 1. By studying the daily abnormal return separately, I can analyze changes in Bitcoin prices for each particular day. Instead, by using CAR I can analyze if there are significant effect in the studied period as a whole, or in parts of the event period, mainly the periods before and after the event.

Lastly, after the event study analysis, I research the usage of cryptocurrencies as an inflation hedge by analyzing people´s Google searches. I obtained a number of keywords related to inflation hedging and cryptocurrencies using Google Trends. Then, applying the OLS method, regress the popularity each keywork every week, against the unexpected monthly inflation variable (difference between actual monthly inflation and expected inflation) in the days around each inflation announcement. The results allow me to test for correlations between unexpected high inflation rates and the usage of cryptocurrencies, possibly for inflation hedging purposes.

4 Results

4.1 Event studies

To set up the event studies analysis, I needed to construct a pricing model. The model is generated using an autoregressive conditional heteroskedasticity (ARCH) regression. I use the ARCH model as the diagnosis for the residuals of the OLS regression done initially vary over time. The results indicated that the regression presents time-varying variance, therefore the ARCH model is used as a treatment. The initial regression has Bitcoin Price Returns as dependent variable and the NASDAQ Index Returns and Gold Price Returns as independent variables:

$$\boldsymbol{BTCReturns_t = \alpha_t + \beta_0\, NASDAQReturns_t + \beta_1\, GoldReturns_t + \varepsilon_t} \quad \textbf{(2)}$$

α_t is the constant, and ε_t the residuals of the model. Other variables such as Crude Oil returns, Volume of Bitcoin measured in US dollars, the VIX[11] and various lagged Bitcoin returns were included in the regressions but were all not significant. See in Annex N°1.

TABLE 1 INITIAL ARCH REGRESSION, COUNTER FACTUAL

Bitcoin price USD	Coef.	St. Err.	t-value	p-value
Gold price	.493**	.222	2.21	.027
NASDAQ	.752***	.171	4.39	0.00
Constant	.002	.001	1.35	.176
Number of obs.	1308			

*Notes: *** p<.01, ** p<.05, * p<.1 Source: Author calculations.*

Table 1 shows that Both NASDAQ and Gold Returns have a positive coefficient, meaning a positive relation between Bitcoin returns and the other two variables. Both coefficients are

[11] The VIX is a Volatility Index constructed by the Chicago Board of Options Exchange (CBOE). The index is obtained by using the implied volatility of the S&P 500 Index options.

significant, with Gold having a 95% significance level and NASDAQ with a 99% significance. Due to the use of the ARCH model, the regression doesn´t provide the R^2. In the OLS regression done previously, the R^2 was around 6%, thus the value for the ARCH model regression should be around a similar level.

After the ARCH regression, I obtained the expected values of the Bitcoin returns generated by the first regression or the "fitted values" of the regression. Then, subtracted, for each day, the fitted values of the Bitcoin returns obtained previously from the actual Bitcoin return values. The resulting value from the subtraction is the "Abnormal return" for each day of the studied period. The abnormal returns show the difference between the true returns and the expected returns based on the previous OLS regression (these are the hypothetical returns had the event not happened, discussed previously). Positive abnormal returns around means that, in this case, there is an unexpected increase in Bitcoin returns before, during, or after the monthly inflation announcements, depending on the day of this abnormal return is generated. And vice versa when observing negative abnormal returns.

$$\boldsymbol{Abnormal\ returns_t = Bitcoin\ Returns_t - Fitted\,Values\ OLS_t} \qquad \textbf{(3)}$$

There is one inflation announcement each month, thus one event per month. For each inflation announcement I took the period starting from 8 days before the announcement, the day of the announcement (Day 0), and up until 4 days after each inflation announcement. Making a total of 13 days taken into consideration for each month, each event. The period taken is of 5 years and 3 months, so there are sixty-three announcements during the period selected for the study.

Normally, all research on event studies analyzes each event separately. Instead, I have grouped all sixty-three events together in one series to be able to analyze the abnormal returns as a time series. I have done this both for the abnormal returns and for the CAR analysis. First, for the analysis of each day´s abnormal return separately, I divided the abnormal returns of each month, between Day -8 and Day +4. I created 13 groups of abnormal returns from the 13 days of each event. The days of each abnormal return are identified by the relative distance to the day of the inflation announcement. This entails that for every day of the event period (Day -8 to Day +4), there is a series with its respective abnormal returns for each month. Each series including 63 data points. As an example, the series of data for Day +1 includes the data for the abnormal returns one day after the announcement, for every monthly inflation announcement, from 2017 until March of 2022. After obtaining the 13 abnormal returns series, I used again the OLS method to regress the abnormal returns against what I call "Unexpected inflation". With the abnormal returns as the dependent variable and the "Unexpected inflation" as the independent variable.

$$\boldsymbol{Abnormal\ returns\ DayX_t = \alpha_t + \beta_0\ Unexpectd\ Inflation_t + \varepsilon_t} \qquad \textbf{(4)}$$

The "Unexpected inflation" represents the difference between the actual monthly inflation in the US, represented by the Fed´s Consumer Price Index (CPI), and the monthly expected inflation. As I pointed in the previous section, to measure expected inflation I used the "United Stated Michigan 1-year Expected Inflation". Although the variable is obtained monthly, the expected inflation variable specifies what people expect the yearly inflation will be. Thus, to acquire the monthly expected inflation, I obtain the monthly equivalent to the yearly inflation rate given in the surveys. A positive value of the variable indicates a higher inflation rate than what was expected, and a negative value indicates higher expected inflation than what was actually recorded in the CPI.

4.2 Abnormal returns

TABLE 2 OLS REGRESSIONS, DAILY ABNORMAL RETURNS

Day	Coef.	St. Err.	t-value	p-value	R-squared	Number of obs.
-7	-.055**	.024	-2.27	.027	0.078	63
-2	.033*	.02	1.71	.093	0.046	63
-1	.056***	.019	2.94	.005	0.124	63
+4	-.042**	.021	-2.02	.048	0.063	63

*Notes: *** p<.01, ** p<.05, * p<.1 Source: Author calculations.*

Table 2 shows the results of the regressions for each day with statistically significant abnormal returns. The table with all thirteen regressions for each day of the event period can be found in Annex N°2. Each day´s abnormal returns are measure separately. Only four days regressions show a significant relation between Bitcoin Price abnormal returns and Unexpected Inflation. The first regression to have a significative coefficient was the regression of Day -7, a week before the announcement. It shows a negative relationship between the Bitcoin´s abnormal returns and the "unexpected inflation" variable. A 5.5% negative change on Bitcoins returns for every 1% increase in the unexpected inflation. It is a puzzle why the negative coefficient can be seen a week before the inflation announcement. One possible scenario is the use of short-term future contract against the expected high future inflation rate. Investors could prefer to use short term forward contracts, which their minimum length is 7 days, to hedge against the instability caused by the possible high future inflation rate. This is a possibility because no similar negative effect produced by high unexpected inflation can be seen of the subsequent days before the announcement (Day -6 to Day -3), and the next day with a significant abnormal return shows a positive relationship between unexpected inflation and Bitcoin´s abnormal returns.

Day -2 and Day -1, the next two days with a significative coefficient, show a positive correlation between the variables. With a 3.3% and 5.6% increase in its abnormal returns for every 1% increase in unexpected inflation, respectively. Although is pertinent to point out that for Day -2 the variable is significant only at a 90% level. This could indicate that people anticipate the jump in monthly inflation. The change in abnormal returns prior to the inflation announcement could point out that investors have rational expectation, changing their expectation within 48 hours of the announcements. One possibility is that information about the monthly inflation rate is leaked in the days before the announcements, especially in months when the inflation rate is higher than anticipated. This information could be used by investors to change their expectations, providing a possible explanation for the positive changes in abnormal return days before the announcement of higher inflation than previously expected.

Finally, four days after the announcement, there is again a significative correlation between the two variables. Nevertheless, contrary as expected, the coefficient of the unexpected inflation is negative. Showing a decrease of 4.2% in the abnormal return for each 1% increase in unexpected inflation. This could be explained by an overshooting problem. Markets are often seen overreacting to news announcements, and after the first hasty reaction, many tend to go back to a stance closer to their original position. It is plausible that after an announcement of unexpected high inflation people would want to hedge their riskier positions; not only on positions where high inflation could lead to a loss of profit, but also hedge other risky position, as high inflation levels can be used to evaluate the situation of the economy as a whole, according to Barro, R. J. (2013). After the announcement, when the high inflation rate does not produce the expected negative outcome in the markets, is it possible for investors to correct their previous overreaction days after the event and get rid of the hedging assets.

Regardless, the coefficient of the regression for Day 4 after the inflation announcement shows the average effect for every month´s "Day 4 abnormal return" during the 5 years of the studied period. This means that people would, on average, overreact to negative news continuously, without learning from their past mistakes. The repetition of the mistake in their reaction that leads to an overshooting would mean that their behavior is not rational. "Rational expectations maintains that agents will not make systematic errors when formulating expectations in an uncertain world and will, therefore, efficiently use information to enhance their forecasting accuracy." Krause, G. A. (2000). Thus, the negative coefficient of Day 4 regression that could corresponds to a correction of an overreaction in the days prior is not consistent to the "strong" rational expectations theory. The "strong" version assumes that individuals can access all the available information and shall make rational decisions, based on that information. However, the "weak" rational expectations theory is congruent with the findings. In the "weak" version, the individual is rational but does not possess all the necessary information to make the proper decision. In this theory people have a limited amount of information and even if their decisions are rational based on that information, there could be error in their behavior, even continuous errors through multiple nodes of decision. The "weak" rational expectations theory, accompanied with lacking information, could be the reason behind this odd behavior.

The behavior shown by Table N°1 can also be explained by "Active trading" or short-term trading. Where investors take a long position on Bitcoin just to sell it hours or days later. The investors could obtain information of the possible inflation rate days before the announcement and buy Bitcoin just to sell if after the price has gone up, obtaining some profits. This strategy also explains the dip in the abnormal returns seen in the days after the announcement. As many investors try to sell their Bitcoins after the price increased, supply of Bitcoin grows, pushing prices down.

When observing the coefficients of the unexpected inflation variable before and after the announcement, we can observe that the sum of all statistically significant abnormal returns coefficients is close to 0, this means that the overall change in abnormal returns at the end of the event period doesn't show an increase in Bitcoin´s returns after high unexpected inflation rates, contrary to what was hypothesized.

4.3 Cumulative Abnormal returns

TABLE 2 OLS REGRESSIONS, CUMULATIVE ABNORMAL RESULTS

Days	Coef.	St. Err.	t-value	p-value	R-squared	Number of obs.
-3; -1	.022**	.01	2.27	.027	0.078	63
1; 3	-.022*	.012	-1.84	.071	0.053	63
0; 4	-.017*	.01	-1.72	.09	0.046	63

*Notes: *** p<.01, ** p<.05, * p<.1 Source: Author calculations.*

In the previous section the regression between the daily abnormal returns and the unexpected inflation rate variable were analyzed. Analyzing each day separately. In this next section, the Cumulative Abnormal Returns (CAR) are regressed again against the unexpected inflation rate variable. As previously stated, the CAR is the sum of a number of abnormal returns from different days. Table 2 shows the results of the CAR regression. The different CARs include different groups of days; from the sum of all days of the event period (Day -8 to Day +4), to only the days before (Day-8 to Day -1) and after the event (Day +1 to Day +4), and groups of days in between. The regressions are done with the same variables and the same OLS method as the regressions showed in the previous table. Each CAR group of days was regressed against the unexpected inflation variable. The table includes only the groups of days with a significant coefficient. A table including all the CAR regression, also containing the results of the regressions that didn´t show a significant coefficient. It can be found in the annex N°3. Granting, the significance level of all coefficients is rather low, only the coefficient of the regression for the CAR from Day -3 to Day -1 before the inflation announcement is significant to a 95% level, the other two coefficients are only significant at a 90% level.

The CAR regressions with a significant coefficient match, in a way, the regressions from the previous table, as all the significative coefficients include the days with significant coefficients from the previous table. Despite that, the coefficients have smaller values; whereas the signs of the coefficients don´t change. Before the announcement there is a positive coefficient between the cumulative abnormal return and the unexpected inflation, whilst after the announcements the coefficient between the two variables is negative. From "Day-3" to "Day -1" (before the inflation announcement) the positive relationship between the variables is of 2.2% for every 1% increase in unexpected inflation, whilst from "Day 1" to "Day 3" after the announcement the negative relation between the variable is also of 2.2% for every 1% increase in unexpected inflation. Both changes combined show again the total effect to be close to 0. Same conclusion obtained from the analysis of singular abnormal returns. Displaying no overall change in Bitcoin price returns after high rates of unexpected inflation.

For the coefficient of the CAR regression for days "Day 0" to "Day +4" the results are similar to the coefficient of the regression for "Day +1" to "Day +3". Both show a negative relation between Bitcoin abnormal returns and Unexpected Inflation. However, for the regression for "Day 0" to "Day +4" the coefficient has a smaller absolute value, at 1.7%. It is noteworthy to see that no regression including "Day -7" showed a significant coefficient. Probably because all abnormal returns regressions surrounding "Day-7" had no significant effect between the variables.

4.4 Abnormal Returns:

Months with highest unexpected inflation rates

TABLE 3 ABNORMAL RETURNS, MONTHS WITH HIGHEST INCREASE IN INFLATION RATE

				Abnormal Return Day		
Date	**Inflation Rate**	**Previous Monthly Inflation**	**Expected Inflation**	**-2**	**-1**	**0**
2/2017	0.6%	0.3%	0.22%	-0.0024	0.0096	-0.0033
7/2020	0.6%	-0.1%	0.25%	0.0016	0.0074	-0.0061
4/2021	0.6%	0.4%	0.28%	-0.0012	0.0326	0.0453
5/2021	0.8%	0.6%	0.38%	-0.0103	0.0176	-0.1158
7/2021	0.9%	0.6%	0.39%	0.0186	-0.0204	-0.0154
11/2021	0.9%	0.4%	0.41%	0.0935	-0.0074	-0.0292
3/2022	0.8%	0.6%	0.45%	0.0051	0.0636	-0.0585

	Abnormal Return Day				
Date	**1**	**2**	**3**	**4**	**Sum:**
2/2017	0.0162	0.0113	0.0652	-0.0062	0.0904
7/2020	-0.0128	-0.0038	-0.0019	-0.0215	-0.0373
4/2021	-0.0007	-0.0132	-0.0375	-0.0919	-0.0668
5/2021	-0.0021	-0.0200	-0.1401	-0.0157	-0.2867
7/2021	0.0000	-0.0256	-0.0106	-0.0094	-0.0629
11/2021	-0.0202	-0.0103	-0.0638	0.0037	-0.0338
3/2022	0.0007	0.0446	-0.0232	0.0157	0.0480

Source: Author calculations.

The previous two sections analyzed the relationship between Bitcoin and inflation rate by regressing the Bitcoin´s abnormal returns (AR) obtained in each month against the unexpected inflation rate. This was done to analyze the tendencies for the days before, during, and after the inflation rate announcements. This section, instead, focuses on the actual values of the abnormal returns for the months with the highest unexpected inflation rates (difference between actual inflation rate and expected inflation rate). Each announcement is studied separately, and not as part of a regression. The months included in the table are not only the ones with the highest unexpected inflation, but they are also the months with the highest difference between the month´s current inflation rate and its previous month inflation rate. This is done to assure that the months chosen not only have a high unexpected inflation rate, but also that there is a substantial increase in the inflation rate from the previous month. 7 months were chosen from the 63 months that are included in the study. Table N°3 provides the abnormal returns of Bitcoin, including only Day -1 and Day -2, before the inflation announcement, the day of the announcement, and Day 1 to Day 4, after the announcement. I have excluded "Day -8" to "Day-3" of each month due to the coefficients for these days not being significant in the previous analyses. However, the results would not have changed have I included them.

The table can be analyzed in two ways. First, looking at each column separately, to analyze the table day by day. When doing this, it can be observed that the abnormal returns in the table display similar results to the ones observed in the previous two sections, for the days with a significant coefficient. For "Day -2" and "Day -1" most of the abnormal returns are positive. In "Day -2" 4 out of 7 months exhibit positive abnormal returns; and "Day -1" presents positive abnormal returns in 5 out of the 7 months included in the table. Conversely, starting on the day of the announcement up until "Day 4" the abnormal returns are mostly negative. Six out of seven months exhibit negative AR in "Day 0" and "Day 3". "Day 2" and "Day 4" present negative AR in 5 out of 7 months; and negative AR in 4 out of 7 months in "Day 1". For the months chosen, there are, in most of the months, positive abnormal returns before the inflation announcements are made, and negative abnormal returns during the day of the announcement and the days after.

The second approach to analyze the results of the table is to sum the AR for each month, essentially obtaining the CAR of each month. The last column of the table exhibits the final sum for each month inflation announcement. Unexpectedly, 5 out of the 7 months have an overall negative cumulative abnormal return at the end of each event. It is important to remember that the months in the table are the ones with the highest unexpected inflation rate from the whole studied period. If people were using Bitcoin to hedge against high inflation, we would observe, at least in these months, a positive CAR in most of the months chosen.

The results don´t support the hypothesis of the use of cryptocurrency as a hedging tool against inflation. First, when focusing of the different days, with each day as its own group, there is an increase of the Bitcoin returns over the expected value during Day -2 and Day -1. However, that increase in returns is cancelled the following days. Furthermore, the CAR for most months, including the days before and after the event, gives a negative outcome for the event, a decrease in Bitcoin returns. Concluding that, even in the months with the highest difference between inflation rate and expected inflation rate, no increase on Bitcoin returns in the days surrounding the inflation rate announcement can be seen. On the contrary, the findings present a lower Bitcoin price than before the inflation rate announcement.

4.5 Google trends

Finally, in this section I depart from the analysis of abnormal returns. Instead, I use Google Trends to analyze the relationship between Bitcoin´s returns and unexpected inflation. I use the keywords searched through Google as proxies of Bitcoin interest. The different search terms are measured depending on their popularity. Google does not show the actual number of searches for every term done each week, but it shows the search percentage in comparison to all other weeks of the time-period selected. Google makes this by giving a percentage from 0 to 100 to every week chosen, with the week with the highest number of searches receiving a 100% score. Another complication arises with the information provided by Google Trends. The data is divided weekly, not daily, so it is not possible to select the precise period around each announcement, just the week of the event. This restricts the analysis. However, even without being able to separate each day Google trends results, the announcements are made the second week of every month, on a Wednesday or Thursday. This means that, because the announcements are done in the middle of the week, by analyzing the week of the announcement, the days before and after the event are included in the regressions. Thus, the research was possible to be done in the week surrounding the announcements. Similarly to what was done in the previous section, with the use of Cumulative Abnormal Returns during the event studies analysis.

$$\boldsymbol{Search\ term_t = \alpha_t + \beta_0\ Unexpected\ infaltion_t + \varepsilon_t} \quad \textbf{(5)}$$

For each term, a separate regression was made using the OLS method. With the popularity of each search term as dependent variable and the unexpected inflation as independent variable. All regressions are made using the data collected on the week of the inflation rate announcement, for each month of the 5-year period chosen for the analysis. Table N°4 shows the results of the OLS regressions between the “Unexpected inflation” variable used previously and the popularity of each Google search term. All the terms used in the analysis are related to cryptocurrencies and hedging. I chose the terms that had enough information throughout the entire study period, and that displayed a coefficient significant to at least a 90% level. The search terms are Cryptohedging, Cryptocurrency and Bitcoin. The β_0 coefficient for each regression is positive and significant to at least a 95%, exhibiting a positive correlation between a period of unexpected high inflation and the percentage of searches for the search terms chosen. Although all three regressions show a significant interaction coefficient, the R squared for each regression is not particularly high; the highest value being 13,9% for the regression for the “Cryptocurrency” term.

TABLE 4 OLS REGRESSION BETWEEN KEYWORDS POPULARITY AND UNEXPECTED INFLATION

Keyword	Coef.	St. Err.	t-value	p-value	R-squared	Number of obs.
Cryptohedging	17.332**	8.478	2.04	.045	0.065	62
Cryptocurrency	26.547***	8.518	3.12	.003	0.139	62
Bitcoin	14.588**	6.825	2.14	.037	0.071	62

*Notes: *** p<.01, ** p<.05, * p<.1 Source: Author calculations.*

The regressions for the terms “Cryptocurrency” and “Bitcoin” show a positive β_0 coefficient of 26.54 and 14.58 respectively, denoting an estimated increase of 26.54 and 14.58 percentage points above average respectively in the keywords interest, for every percentage increase in the unexpected inflation variable. A high correlation between the variables. The last regression, the one for the “Cryptohedging” term is particularly interesting as it not only shows an increased interest in Cryptocurrencies during a period of unexpected high inflation, but also provides evidence for the increase appeal of cryptocurrencies for the specific use of hedging purposes. This regression presents a positive β_0 coefficeint of 17.33. An increase of 17 percentage points above the average level in the search term popularity for every 1% increase in the value of Unexpected Inflation.

When comparing the results obtained with the Google trends regressions and the results of the previous three sections, a clear contrast among them can be seen. In the results obtained from the abnormal returns and the CAR regressions, an initial positive correlation between the abnormal returns and the “Unexpected inflation” on the days prior to the announcement is followed by a negative correlation starting at the day of the announcement. The negative effect being predominantly stronger than the previous positive effect. This gives an overall negative impact for high unexpected inflation on Bitcoin price returns. Likewise, the results of the previous section, which analyses the abnormal returns of the months with the highest unexpected inflation, exhibit again a negative relationship between Bitcoin´s return and elevated levels of unexpected inflation. Despite of previous results, all google search terms have a positive correlation between their popularity and the unexpected inflation rate during the events. A possible cause for this discrepancy could be caused by the divergence between the individual´s intentions and actions. “Not all intentions are carried out; some are abandoned altogether while others are revised to fit changing circumstances.” (Ajzen, 1985, p. 263). In this case, even if individuals do actually think about using cryptocurrencies to hedge against the rising inflation and go online to research about cryptocurrencies and how to use them for hedging, they could opt for other hedging tools like Gold, Bonds, Real state or other types of assets. This scenario could result in a spike in the number of searches about cryptocurrency, and a later lackluster effect on the expected Bitcoin price returns.

5 Conclusions:

The research analyses the behavior of Bitcoin´s price returns during inflation announcements, to put to test the hypothesis of Bitcoin being used as an inflation hedge. The event study analysis on abnormal return displays three main results. First, a negative and significant coefficient on Day -7 for the correlation between Bitcoin return and Unexpected Inflation. It remains a puzzle why a week before the announcement this negative effect is observed. Later, a positive coefficient for Day -2 and Day-1, due to a possible foresight of a higher-than-expected inflation rate, or an expectation of a price increase with the goal to sell the Bitcoin for a profit in the days after. The last regression presents a negative coefficient between the two variables on Day 4. A possible cause of this behavior is an overreaction of the market in the days prior, cause by the uncertainty of possible negative news. Another possibility is an increase willingness to sell, to obtain profits from the previous price increase. The overall relationship between the Bitcoin´s return and the unexpected inflation rate is negative when adding all effects. The CAR analysis provides coinciding results. A positive correlation between the variables for the group that includes the days before the announcements, and a negative correlation in the day of the announcements and the days after. The overall effect is null when both results are added together.

In the months with the highest unexpected inflation, the data shows results consistent with the previous findings. Most of the 7 months chosen, exhibit positive abnormal returns before the day of the announcement, and negative abnormal returns on the day of the announcement and the days after. Examining each month separately, the sum of the abnormal returns for most months was again negative, suggesting no effect between abnormal returns and unexpected inflation.

The analysis of the announcements using event studies presents contradicting results. All search terms have a positive relationship with unexpected inflation. There is a spike in interest for cryptocurrencies and hedging during the weeks of unexpected high inflation announcements. Nevertheless, as seen previously, this surge doesn´t translate to higher Bitcoin returns.

Lastly, it is important to notice there are some caveats to the finding of this research. First, the initial ARCH regression has a low explanation power to Bitcoin´s returns, which may hinder the robustness of the results. And second, the data obtained for the expected inflation was obtained by surveying people on their yearly inflation expectations (although the survey were done monthly). The process of obtaining the monthly expected inflation rate from the yearly data may diminish the accuracy of the expected inflation variable.

6 Bibliography:

- Claeys, Gregory; Demertzis, Maria; Efstathiou, Konstantinos (2018): Cryptocurrencies and monetary policy, Bruegel Policy Contribution, No. 2018/10, Bruegel, Brussels.

- Vujičić, D., Jagodić, D., & Ranđić, S. (2018, March): Blockchain technology, bitcoin, and Ethereum: A brief overview. In *2018 17th international symposium infoteh-jahorina (infoteh)* (pp. 1-6). IEEE.

7 References:

- Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. Action Control, 11–39. doi:10.1007/978-3-642-69746-3_2

- Ammous, S. (2018). Can cryptocurrencies fulfil the functions of money?. The Quarterly Review of Economics and Finance, 70, 38-51.

- Barro, R. J. (2013). Inflation and economic growth. Annals of Economics & Finance, 14(1).

- Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets?. Journal of International Financial Markets, Institutions and Money, 54, 177-189.

- Blau, B., Griffith, T., & Whitby, R. Inflation and Bitcoin: A descriptive time-series analysis, 2021.

- Bouri, E., Gupta, R., Kumar, Tiwari, A. and Roubaud, D. (2017) Does Bitcoin Hedge Global Uncertainty? Evidence from Wavelet-Based Quantile-in-Quantile Regressions. Center for Energy and Sustainable Development (CESD), Montpellier Business School, Montpellier Research in Management, Montpellier, France.

- Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?. Finance Research Letters, 20, 192-198.

- Choi, S., & Shin, J. (2022). Bitcoin: An inflation hedge but not a safe haven. Finance Research Letters, 46, 102379.

- Cifuentes, Andres F. "Bitcoin in Troubled Economies: The Potential of Cryptocurrencies in Argentina and Venezuela". Latin American Law Review n.º 03 (2019): 99-116, doi: https://doi.org/10.29263/lar03.2019.05

- Cong Gu*, Benfu Lv, Ying Liu, Geng Peng (2021). The Impact of Quantitative Easing on Cryptocurrency. School of Economics and Management, University of Chinese Academy of Sciences, Beijing, China. https://doi.org/10.32479/ijefi.11532

- Conlon, T., Corbet, S., & McGee, R. J. (2021). Inflation and cryptocurrencies revisited: A time-scale analysis. Economics Letters, 206, 109996.

- Dyhrberg, Anne Haubo (2015): Hedging capabilities of bitcoin is it the virtual gold?, UCD Centre for Economic Research Working Paper Series, No. WP15/21, University College Dublin, UCD School of Economics, Dublin.

- Kitamura, Y. (2022). Can we stabilize the price of a cryptocurrency? Understanding the design of Bitcoin and its potential to compete with Central Bank money. In Quest for Good Money (pp. 103-123). Springer, Singapore.

- Krause, G. A. (2000). Testing for the Strong Form of Rational Expectations with Heterogeneously Informed Agents. Political Analysis, 8(03), 285–305. doi:10.1093/oxfordjournals.pan.a029817

- Mattke, J., Maier, C., & Reis, L. (2020). Is cryptocurrency money? Three empirical studies analyzing medium of exchange, store of value and unit of account. In Proceedings of the 2020 on Computers and People Research Conference (pp. 26-35).

- Montgomery Rollins (1917). Money and Investments. George Routledge & Sons. ISBN 9781358416323

- Moreno, E. C. (2016). Bitcoin in Argentina: inflation, currency restrictions, and the rise of cryptocurrency.

- Pernice, I. G. A. & Scott, B. (2021). Cryptocurrency. Internet Policy Review, 10(2). https://doi.org/10.14763/2021.2.1561

- Smales, L. A. (2021). Cryptocurrency as an alternative inflation hedge?. Available at SSRN 3883123.

- Thomas Conlon, Richard McGee, (2020). Safe Haven or Risky Hazard? Bitcoin during the Covid-19 Bear Market, Finance Research Letters doi: https://doi.org/10.1016/j.frl.2020.101607

- Wenjun Feng, Yiming Wang & Zhengjun Zhang (2018): Can cryptocurrencies be a safe haven: a tail risk perspective analysis, Applied Economics, DOI: 10.1080/00036846.2018.1466993

- Wulf, Connor, "Bitcoins in Venezuela: Examining the Origins, Nature, and Viability of Cryptocurrencies in the Hyperinflated Country of Venezuela" (2018). University Honors Theses. Paper 518. https://doi.org/10.15760/honors.523

8 Annexes:

8.1.1 Annex N°1: Initial Regression

OLS Regression including Crude Oil Price, Volume of Bitcoins (measured in US dollars) and the VIX (a measure of volatility in the stock market).

High multicollinearity between NASDAQ Index Price and VIX is observed when testing the variables. This may decrease the significance of both variables.

Bitcoin price USD	Coef.	St. Err.	t-value	p-value
Gold price troy ounce	.538***	.156	3.45	.001
WTI Crude Oil price	.012	.039	0.31	.753
NASDAQ	.557***	.14	3.97	0
VIX	-.04*	.023	-1.73	.084
Volume by dollars	-.002	.002	-1.07	.283
Constant	.002	.001	1.50	.135

Mean dependent var	0.003	**SD dependent var**	0.050
R-squared	0.060	**Number of obs.**	1308

**** p<.01, ** p<.05, * p<.1*

8.1.2 Annex N°2: Daily Abnormal Returns Regressions

OLS Regression with Bitcoin´s Abnormal Returns as dependent variable and Unexpected Inflation rate as independent variable. The coefficient column shows the effect of the Unexpected Inflation rate on the dependent variable for each day´s regression.

Day	Coef.	St. Err.	t-value	p-value	R-squared	Number of obs.
-8	.021	.021	0.99	0.99	0.016	63
-7	**-.055****	**.024**	**-2.27**	**.027**	**0.078**	**63**
-6	.004	.019	0.20	.843	0.001	63
-5	.017	.021	0.80	.425	0.010	63
-4	-.025	.027	-0.93	.354	0.014	63
-3	-.023	.016	-1.48	.143	0.035	63
-2	**.033***	**.02**	**1.71**	**.093**	**0.046**	**63**
-1	**.056*****	**.019**	**2.94**	**.005**	**0.124**	**63**
0	-.018	.022	-0.81	.419	0.011	63
+1	-.002	.035	-0.05	.962	0.000	63
+2	.006	.017	0.34	.733	0.002	63
+3	-.03	.022	-1.34	.184	0.029	63
+4	**-.042****	**.021**	**-2.02**	**.048**	**0.063**	**63**

**** p<.01, ** p<.05, * p<.1*

8.1.3 Annex N°3: Cumulative Abnormal Returns Regressions

OLS Regression between Bitcoin´s Cumulative Abnormal Returns as dependent variable and Unexpected Inflation rate as independent variable. The CAR´s value are the sum of a number of the days abnormal returns. The coefficient column shows the effect on each CAR for every 1% change in the Unexpected Interest Rate variable.

Days	Coef.	St. Err.	t-value	p-value	R-squared	Number of obs.
-8; -6	-.01	.012	-0.86	.391	0.012	63
-7; -5	-.012	.012	-1.00	.32	0.016	63
-6; -4	-.002	.014	-0.12	.902	0.000	63
-5; -3	-.011	.014	-0.80	.43	0.010	63
-4; -2	-.005	.013	-0.41	.685	0.003	63
-3; -1	**.022****	**.01**	**2.27**	**.027**	**0.078**	**63**
-2; 1	.070	.052	1.35	.183	0.029	63
1; 3	**-.022***	**.012**	**-1.84**	**.071**	**0.053**	**63**
0; 4	**-.017***	**.01**	**-1.72**	**.09**	**0.046**	**63**
1; 4	-.017	.012	-1.44	.154	0.033	63
-8; 4	-.059	.083	-0.71	.483	0.008	65

*** $p<.01$, ** $p<.05$, * $p<.1$