Bitcoin? Why not! But for whom? Empirical investigation of inflation hedging properties of cryptocurrencies.

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ABSTRACT,
In turbulent inflationary times, unevenly rising prices inevitably diminishes purchasing power of investors. The main objective of this research is to examine whether investing in cryptocurrencies can protect investors from rising inflation. This study uses inflation indicators from Switzerland, United States and Turkey as predictors variables for cryptocurrencies returns. We use monthly indicators for the three countries and also daily for the US. As a quick scan for hedging abilities we use Pearson's correlation coefficient. Grounded on the Fisher theory, the main model used is the extended version proposed by Fama and Schwert (1977) followed by an OLS estimation of the so called "Fisher coefficient". Using monthly frequencies, the regression coefficients reveal that hedging capabilities differ per country. However such estimates are not statistically significant to consider cryptocurrencies as a hedge against inflation in monthly frequencies. The OLS estimates in daily frequencies provides more significant results but still not statistically significant.

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Inflation hedging, Inflation, Cryptocurrencies, Bitcoin, Fisher Equation, OLS estimates

1. INTRODUCTION

Following the COVID-19 pandemic back in March 2020, inflation has been a concern hardly impossible to avoid. Inflation is defined as "a process a process of continuously rising prices, or equivalently, of a continuously falling value of money" (Laidler and Parkin 1977). Central banks and authorities try to manage inflation targets by assessing levels of key interest rates and money supply. In developed countries the target is around 2%. Taking as an example the United States, the inflation rate from 1960 to 2021 averaged 3.28% according to world data info. However, in the current days and since the pandemic started, inflation has increased considerably reaching the frightening percentage of 8.5% at the time of writing this paper in March 2022 (Statistics 2022). Having thousands of people locked for such a long time, with the economy blocked, authorities such as the Federal Reserve or the European Central Bank decided to pump trillions of dollars into markets to stimulate the economies. For example, the US government decided to pass an economic stimulus of 2.2 trillion dollars as a response to the pandemic (Parkinson 2020). With inflation rates going up, investors are afraid that high inflation environments won't be transitory but permanent. As a result, it has become very relevant which returns can provide a stable real return over time.

The best hedges against inflation are those that have a limited supply, those that cannot easily be devalued by increasing the amount of supply in circulation. Traditionally, these have been hard assets like gold whose supply is limited and it is independent of government, therefore not possible to be depreciated by them. Launched in 2008, a decentralized technology became a reality, starting a new era in finance, with a maximum of 21 Million, Bitcoin shares one same characteristic as gold: its limited supply.

Introduced by an anonymous online user whose nickname was Satoshi Nakamoto, bitcoin was defined to be a peer-to-peer electronic cash system allowing online transitions between two individual parties without financial institution serving as a trusted third party to process and evaluate the electronic payment (Nakamoto 2008). Due to its exponential rising market capitalization in recent times, Bitcoin has attracted the attention of big investors. Indeed, in 2020 PayPal announced that they would allow their users to use bitcoin among others cryptocurrencies. Moreover, in January 2021, Tesla announced its acquirement of 1.5 billion dollars in bitcoin and even contemplated the possibility to accept cryptocurrencies as a payment for their products in the future (journal 2021). More recently, between February and April 2022, MicroStrategy Inc., a bitcoin-accumulating business-intelligence software company announced the purchase of approximately 4,167 bitcoins (commission 2022). With this last purchase the company owns a total of 129,218 at the time of writing this thesis.

The main reason among bitcoin investors as an inflation hedge is the supply restrictions of such asset, a total of 21 million coins. Another important factor to consider is the deflationary nature of bitcoin. With a decreasing emission schedule, bitcoin's inflation rate keeps falling and approaches zero over time. This phenomenon is called the halving, and more specifically means that once every 210,00 blocks, which is approximately 4 years, the rewards for miners is cut in half (Schär 2020). Reducing the rewards leads to an increase in demand and therefore an increase in the market value of bitcoin (Meynkhard 2019). Last but not least, the bitcoin network is decentralized, meaning that it can't be controlled by any centralized authorities but rather by the market (Ammous 2018). This last characteristic can be very relevant, especially for countries in which there is no trust in the local financial system.

Over the past decades, with its rise in popularity bitcoin became a trendsetter for a wave of cryptocurrencies built on this decentralized, immutable, and shared ledger called the blockchain. With the creation of new "altcoins", which stands for alternatives coins, the dominance of bitcoin has been in decline. According to Statista its relative market share based on market capitalization declined from 49.92% in January 2019 to 40.03% in January 2022. This decrease in dominance gives us a good reason to also consider other altcoins for this research. Instead of choosing another altcoin, we choose the Royalton CRIX crypto Index since it includes the most important cryptocurrencies based on both market capitalization and trading volume. As stated by the authors, this index has already been used in researches about the cryptocurrency market returns (Trimborn and Härdle 2018).

Given its characteristics together with its rising popularity among investors, cryptocurrencies could be an alternative asset to fight the rising inflation. The purpose of this research is to deepen into it by providing empirical results.

2. THEORY

2.1 Inflation hedging theories

Informally, an asset can be classified as an inflation hedge if it can protect investor's return from the general increase of good prices. In the existing literature, theories about inflation hedging have been established in several ways.

The fisher effect is the most commonly used theory in economics. Created by Irving Fisher, this measure describes the relationship between inflation and both real and nominal interest rates. The fisher effect states that the nominal interest rate equals the expected real return plus the expected inflation rate (Fisher 1930). Therefore, this definition suggests that nominal interest rates should move one to one with expected inflation. Fisher's main hypothesis has been applied in several ways, depending on inflation proxy, variables used and investments horizons.

This paper is based on the approach proposed by Fama and Schwert who converted the fisher hypothesis into an empirical test. Their extend approach also accounts for unexpected inflation in addition to expected inflation. Similar to the original fisher hypothesis, an asset is considered to have hedging capabilities if asset's returns move one to one with inflation. The difference is that their model also accounts for unexpected inflation, which coefficient should also move one to one in order for an asset to be considered a complete hedge against inflation (Fama and Schwert 1977).

Apart from the fisher hypothesis, this study also uses the Pearson correlation coefficient as a measure to express the linear dependence between returns and inflation. The higher the correlation is, the better the hedging capabilities of an asset are. (Bodie 1976). Other measures have been evaluated in the literature such as cointegration approach used by Ely and Robinson (Ely and Robinson 1997), hedge ratio plus cost of hedging used by Bodie (Bodie 1976) and hedging demand and inflation tracking portfolio from Schotman & Scweitzer (Schotman and Schweitzer 2000).

Most of the studies assessed the models mentioned above mostly include assets such as gold, stocks, bonds, T-Bills, real state and their hedging abilities against rising inflation. Although quite small, some studies have also tried to determine the properties of Bitcoin and its potential role as an inflation hedge. In this section, we summarize the findings regarding the inflation hedging abilities of different types of assets.

2.2 Inflation hedging assets

2.2.1 Literature on Gold

People have believed that metals such as gold and silver offer a natural hedge against inflation because they have historically maintained their purchasing power. Even if gold is used in the electronic industry it is also known that governments hold gold because it represents protection against inflation and other uncertainties. In his article Peter Macmillan develops a model with several conditions that need to be satisfied to consider gold as an inflation hedge. He studies the relationship between the nominal price of gold and the USA retail price index. He differentiates short versus long term hedge effectiveness by using cointegration regression techniques. His results finally confirm that gold can be a good hedge against inflation only in the long term (Ghosh, Levin et al. 2004).

Lucey et al. also study the relationship between gold and inflation and how stable this relationship is over time for three different economies: USA, UK, and Japan. By contrasting multiple inflation indicators they obtained significant evidence for the importance of money supply in the relation between gold and inflation (Lucey, Sharma et al. 2017).

2.2.2 Stocks, bonds, T-Bills and real state

Apart from gold, previous literature also analyzed the inflation-hedging properties of other assets such as stocks, bonds, and T-Bills. A study made by Laura Spierdijk and Umar provides several methods to study the behavior of such assets against inflation from the years 1983 to 2012. In their study, the authors use common methods such as the VAR (Vector autoregression model) followed by an estimation using OLS (Ordinary least square regression). Then they also use Pearson correlation to quickly scan the hedging capabilities of an asset. Their findings differ for each asset, indeed only T-Bills evidence hedging properties in the long term (Spierdijk and Umar 2015).

In addition to the literature mentioned above, we found a research paper in which the authors make a comparative analysis of inflation hedging properties of stocks, real states and gold for the US. Following the Fisher's hypothesis for asset-inflation hedging, a bivariate and multivariate framework is modelled. The authors use typical features from predictive models such as time-variation, structural breaks and asymmetry. Their results imply that unlike gold, real states and stocks prove to be efficient against inflation (Salisu, Raheem et al. 2020).

2.3 Inflation hedging bitcoin

Although small, few studies have been done on Bitcoin's properties of inflation hedging, Benjamin M.Blau et al stated that "a security is an inflation hedge if its returns are independent of the rate of inflation" (Blau, Griffith et al. 2021). To analyze whether this statement holds, a VAR model was used. Vector Autoregression is a multivariate forecasting algorithm that is used when two or more time-series influence each other. This model can be used as a quick scan to see whether bitcoin changes in price causes changes in the forward inflation rate. Their results indicate that Bitcoin price movements have causation in the forward inflation rate but not vice-versa. Such findings provide evidence of a positive correlation between the return of Bitcoin and the rate of inflation and therefore imply that bitcoin can hedge expected inflation.

In line with the previous paper mentioned above, Sangup Choi and Junkhyeok provide systematic evidence on the relationship between Bitcoin and inflation. However, their study extend the analysis by including gold and market uncertainty. In their findings, by estimating a Vector autoregression model, the authors found that unlike gold, Bitcoin prices decline in the context of financial uncertainty. However, they also found that Bitcoin prices appreciates against positive inflation and inflation expectation shocks (Choi and Shin 2022). Their results provide empirical motivation to support the hedging capability of Bitcoin against inflation.

2.4 Research gap

A lot of research about hedging inflation has been done for assets such as gold, stocks, bonds, and T-Bills. Because of its recentness bitcoin has not been researched to such an extent. Furthermore, it is known that since its creation Bitcoin's relative dominance over other cryptocurrencies has been constantly decreasing. It could be interesting to investigate whether investing in indexes including other cryptocurrencies in addition to bitcoin might be still a good hedge against inflation in the long term. On the other hand, we can see that most of the research takes the US economy as a unit of observation, so it could be also interesting to analyze the hedging characteristics of bitcoin in different environments by analyzing different economies. Different countries imply different exposition to bitcoin and different inflation rates.

The objective of this research is to first investigate whether Bitcoin and Crypto Indexes have the hedging properties required to be considered potential inflation hedges. Then we want to analyze to what extent those hedging properties are more significant in different economical environments. This leads to our research objective and research question:

Research question: To what extent, under which format (only Bitcoin or including altcoins) and for which economies including cryptocurrencies in a portfolio can hedge against inflation?

3. METHODOLOGY

To investigate the relationship between inflation rates and cryptocurrencies returns, this study uses a variety of methods that can be used to assess the hedging capabilities of an asset. Pearson's correlations can be used to first quickly scan the hedging capabilities of cryptocurrencies. The following is the fisher coefficient which is used to describe the relationship between the expected nominal return of cryptocurrency assets and the expected inflation rate. This paper will apply the extended version of the Fisher hypothesis that was previously been studied by Fama and Schwert in which a distinction is made between expected and unexpected inflation. Such model will be modeled by means of the OLS regression model, which is used to determine the effect of inflation on cryptocurrencies returns. Each method will be apply to a vast number of variables. For a detailed overview of variables abbreviations see Appendix A..

3.1 Pearson correlation

The Pearson correlation ρ(rho) is applied to capture the general strength of a linear relationship between the inflation rate ${\pi_t}^k$ and nominal returns ${R_t}^k$ of an asset(Bodie 1979). This model usually requires the normality assumption to hold in order to completely characterize the relationship. However the measurement can still be useful to quickly scan the hedging capabilities of an asset even if the normality assumption is not assumed.

$$\rho(\text{rho}) = \text{Corr}(t)\,[{R_t}^k, {\pi_t}^k] \quad \textit{(Equation 1)}$$

Hypothesis 1: $\rho \neq 0$. The correlation between inflation and cryptocurrencies returns is significantly different from 0.

This hypothesis will be tested by means of P-Value first. Then the absolute value of the correlation coefficient in *Equation 1* determines the hedging capacity of an asset. A high absolute value of the correlation implies better hedging capacities.

3.2 Fisher coefficient

3.2.1 Fama and Schwert approach

The fisher coefficient can be applied to describe the relationship between the expected nominal return of an asset (Rt) and the expected inflation rate(E(πt)(Fisher 1930). This paper will apply the extended version of the Fisher hypothesis that was previously been studied by Fama and Schwert. An important distinction made by those authors is that it is necessary to distinguish between expected E(πt) and unexpected (πt-E(πt)) inflation (Fama and Schwert 1977). The asset return is the dependent variable and both expected and unexpected inflation are the independent variables, note that εt is an error term which are the residuals effects that are not explained by the data.

$$Rt = \alpha + \beta_1(E(\pi t)) + \beta_2(\pi t - E(\pi t)) + \varepsilon t \quad (Equation\ 2)$$

Interpretations of these coefficients are as follows: If $\beta_1 = 1$, an asset is said to be a complete hedge against expected inflation. If $\beta_2 = 1$ an asset is called a complete hedge against unexpected inflation. If $\beta_1 = \beta_2 = 1$, then an asset is said to provide a complete hedge against inflation. If the coefficients are 0, it means that no inflation abilities are present in the studied asset.

Hypothesis 2.1: $\beta_1 \neq 0$: The regression coefficient of expected inflation is statistically different from 0. Cryptocurrencies provide a hedge against expected inflation.
Hypothesis 2.2: $\beta_2 \neq 0$. Cryptocurrencies provide a hedge against unexpected inflation.

The underlying assumption of the fisher coefficient is that $\beta = 1$. If our null hypothesis is statistically rejected (P-Values), we can further analyze the sign of such coefficient. As stated by Laura Spierdijk and Umar $0 < \beta < 1$ implies a partial hedge, $\beta < 1$ is a "perverse hedge" meaning a decrease in value as inflation increases and if $\beta > 1$ is more than complete hedge (Spierdijk & Umar, 2010). In order to test these further interpretations we will estimate 95% confidence intervals for both parameters. If the parameter value lies outside the confidence interval there is enough evidence (with alpha level 5%) to reject the null hypothesis and to say that cryptocurrencies have hedging capabilities.

3.2.2 Proxy of expected inflation

As we previously mentioned, the Fama and Schwert approach differentiates expected and unexpected inflation. However, in the literature it has been shown that different methods can be assessed to proxy the expected inflation. In our study we will compare two approaches and compare their results.

The first approach follows Gultekin and assumes that expectations are perfect(Gultekin 1983). This approach implies that expected inflation equals the actual inflation so there is no distinction between expected and unexpected inflation, reducing the model from *Equation 2* to a simple regressive model:

$$Rt = \alpha + \beta\ (\pi t)\ \varepsilon t \quad (Equation\ 3)$$

The second approach is from Hamelink and Hoesli and expected inflation is represented by a linear regression model. In this model, expected inflation *E(πt)* is determined from past actual inflation rates making this model an Autoregressive of order one AR(1) . The model from Fama and Schwert approach from *Equation 2* becomes:

$$Rt = \alpha + \beta_1\ (E(\pi t\ )) + \beta_2\ (\pi t - E(\pi t\ )) + \varepsilon t \quad where:$$
$$E(\pi t) = \alpha + \beta(\pi t\text{-}1) + \varepsilon t \quad (Equation\ 4)$$

3.3 Assumptions

Both previously chosen models (*See equation 3 and 4*) will be studied by means of OLS estimators. Ordinary least squares (OLS) regression is arguably one of the most used methods for fitting linear statistical models (Hayes and Cai 2007). Such models require the validation of several assumptions. The first assumption is that the errors should be homoscedastic. The second assumption is that the disturbances shouldn't show signs of autocorrelation. The third assumption is that the error term should be normal distributed. It is important to precise that for consistently estimating our Beta coefficients normality and heteroscedasticity are not needed. However the assumptions are needed to interpret the p-values and confidence intervals (Damodar 2009). The following tables reveal the statistical evidences of each assumption, for an overview of the graphical representation see Appendix B.

3.3.1 Heteroscedasticity

The first assumption is that the residuals must be homoscedastic. If this assumption is violated we say that heteroscedasticity is present which could bias the outcomes of linear regression. A formal statistical test we can use to test this phenomenon is the Breusch-Pagan test. This test follows a Chi-Square distribution and if the null hypothesis is rejected we conclude that heteroscedasticity is present in the model. The following two tables show the results of the Breusch-Pagan test performed with the squared residuals of the returns for bitcoin (ΔBTC) and the CRIX index (ΔCRIX). The first table shows the results for monthly data with the different predictors CPI rates (ΔCPI) for every country for the first approach. For the second approach, the expected (EXP_INF) and unexpected inflation rates (UNEX_INF) were used for each country. The second table shows the results for daily data with the 10YIE as a predictor.

Table 1: Breusch-Pagan Test for Heteroskedasticity (Monthly results)

Approach	Dep.Variable	Predictor	Chi-Square	df	Sig.
1st	ΔBTC/CHF	ΔCPI_SW	0.183	1	0,669
	ΔBTC/USD	ΔCPI_US	1,163	1	0,281
	ΔBTC/TRY	ΔCPI_TU	1,107	1	0,293
2nd	ΔBTC/CHF	EXP_INF_SW + UNEXP_INF_SW	0,467	1	0.494
	ΔBTC/USD	EXP_INF_US + UNEXP_INF_US	0,582	1	0.446
	ΔBTC/TRY	EXP_INF_TU + UNEXP_INF_TU	1,046	1	0.306

Table 2: Breusch-Pagan Test for Heteroskedasticity (Daily results)

Approach	Dep.Variable	Predictor	Chi-Square	df	Sig.
1st	ΔBTC	Δ10YIE	49,979	1	<,001
	ΔCRIX	Δ10YIE	23,144	1	<,001
2nd	ΔBTC	EXP_INF + UNEXP_INF	63,989	1	<,001
	ΔCRIX	EXP_INF + UNEXP_INF	31,589	1	<,001

For monthly data, we can see that homoscedasticity can be assumed when using both approaches. All Significant values are above the alpha level of 5%, so we cannot reject the hypothesis that the residuals are homoscedastic. On the opposite, daily data show clear signs of heteroscedasticity since all significant values are below the alpha level of 5%.

In the presence of heteroscedasticity, if we persist in using the usual OLS formulas, the t and P-Value results will be misleading, resulting in erroneous conclusions (Hayes and Cai 2007). Consequently, since heteroscedasticity is detected in daily data, we will obtain White's heteroscedasticity-corrected standard errors of OLS estimators and conduct statistical inference for our *Equation 4* based on these robust standard errors.

3.3.2 Autocorrelation

Our model in *Equation 4* is based on a AR(1) model, which implies that the sample data have been collected over time. In such models, the errors in the model can be positively correlated over time, meaning that each error in time t is likely to be close to the previous one in time t-1. This event is called autocorrelation and can lead to inefficiently capturing the trends of regressive models. If we suspect first-order autocorrelation with the errors, we can use the Durbin-Watson (DW) test of the correlation parameter ρ. The null hypothesis implies that the error terms are not correlated between t and t-1. Rejecting this hypothesis at alpha 5% will imply that our errors are autocorrelated. As a rule of thumb if the Durbin-Watson value lies between 1.5 and 2.5 the data does not show autocorrelation. Both monthly and daily results didn't show any sign of autocorrelation since DW test were as follows: Table 3 shows the results for monthly data: 1,691, 1,669 and 1,659 respectively for the three chosen countries (Switzerland, United states and Turkey). In our table 4 we can see that our daily results also assume no autocorrelation with 2.111 for the errors of bitcoin returns (ΔBTC) and 2.047 for (ΔCRIX).

Table 3: Durbin-Watson test for monthly data (2nd approach)

Dependent Variable	Predictor	Durbin-Watson
ΔBTC/CHF	EXP_INF_SW + UNEXP_INF_SW	1,691
ΔBTC/USD	EXP_INF_US + UNEXP_INF_US	1,669
ΔBTC/TRY	EXP_INF_TU + UNEXP_INF_TU	1,659

Table 4: Durbin-Watson test for daily data (2nd approach)

Dependent Variable	Predictor	Durbin-Watson
ΔBTC*	EXP_INF + UNEXP_INF	2,111
ΔCRIX	EXP_INF + UNEXP_INF	2,047

3.3.3 Normality assumption

The second assumption to be tested is the normal distribution of the residuals. The residuals are the differences between the observed values and the values predicted by the regression model. This assumption can be tested by using the Jarque-Bera test. This test follows a Chi-Square distribution and if the null hypothesis is rejected we cannot assume normality. The following two tables show the results of the Jarque-Bera test with the residuals of the returns. Table 5 shows the results for monthly data with the different predictors CPI rates (ΔCPI) for every country and each approach. Table 6 shows the results for daily data with the 10YIE rate as a predictor variable.

Table 5: Jarque-Bera Test for Normality (Monthly results)

Approach	Dep.Variable	Predictor	Chi-Square	df	Sig.
1st	ΔBTC/CHF	ΔCPI_SW	5,137	2	0,076
	ΔBTC/USD	ΔCPI_US	4,720	2	0,094
	ΔBTC/TRY	ΔCPI_TU	2,719	2	0,256
2nd	ΔBTC/CHF	EXP_INF_SW + UNEXP_INF_SW	5,055	2	0,079
	ΔBTC/USD	EXP_INF_US + UNEXP_INF_US	4,738	2	0,094
	ΔBTC/TRY	EXP_INF_TU + UNEXP_INF_TU	2,738	2	0,254

For monthly data we can assume normality since all the significant levels are above alpha level (5%) meaning that we cannot reject that the data is normally distributed.

Table 6: Jarque-Bera Test for Normality (Daily results)

Approach	Dep.Variable	Predictor	Chi-Square	df	Sig.
1st	ΔBTC*	Δ10YIE	1.634,502	2	<,001
	ΔCRIX	Δ10YIE	313,668	2	<,001
2nd	ΔBTC*	EXP_INF + UNEXP_INF	1.588,835	2	<,001
	ΔCRIX	EXP_INF + UNEXP_INF	306,442	2	<,001

When it comes daily data, we can see that normality cannot be assumed when using the first approach with perfect inflation expectations. All Significant values are below the alpha level of 5%, so we reject the hypothesis that our returns are normally distributed. This assumption is not essential for our objective of estimating the parameter Beta via OLS. Therefore, we will proceed with the approach from Fama and Schwert regardless of the normality results.

4. DATA

This section provides an overview of which type of data will be used in this research and the reasons behind those choices. As stated in the introduction, the first goal of this research is to analyze the hedging capabilities of Bitcoin and cryptocurrencies in general. Therefore it is needed to extract the past return performances of Bitcoin and cryptocurrencies. The second goal of this research is to compare the hedging capabilities of such assets in three different economical environments those being US, Switzerland, and Turkey. Inflation rates will be selected for each of those three countries.

4.1 Sample period and frequencies

Following the research paper of Michele Modugno, high-frequency data improve forecast accuracy over models that use higher frequencies (Modugno 2013). Also, by the rule of thumb, the lower the frequencies are, the higher means and variances will be, which could also cause misleading results. Given the limitations when searching for daily inflation rates for Switzerland and Turkey, we will first compare the three countries by using monthly data. On the one side, for monthly results we will use the returns of bitcoin only. The reason behind is that we want to have the maximum number of data to have more reliable results. Unfortunately CRIX returns were only available from 2018 while bitcoin returns were available from 2014. Our first analysis using monthly data will be therefore from September 2014 until May 2022. On the other side, since we could find daily inflation indicators for united states we will also collect daily data from the US. 10-Year Breakeven Inflation Rate (T10YIE). Consequently in our second analysis we will use both returns from Bitcoin and CRIX from 19th March 2018 until 20th May 2022.

4.2 Sample selection:

As we previously mentioned, most of the literature about inflation hedging has taken The US economy as a unit of observation, however since inflation rates are significantly different depending on each country, it is decided to include 3 different economies which differ in terms of the amount of inflation and exposition to cryptocurrencies. USA economy will be used as it is the country in which Bitcoin and other cryptocurrencies are the most traded. Additionally, regulations in this country tend to be more flexible in comparison to other countries, and therefore the number of new projects are rising incredibly in the past years. Last but not least, inflation rates especially after Covid are being a topic of concern. The second economy to be analyzed will be Switzerland which similarly to the USA, investing in cryptocurrencies is something popular.

However, it is still interesting to compare both countries because of the difference in inflation rate and the fact that Switzerland is known to be an early adopter of new blockchain technology. The last economy to be considered in this research will be Turkey, this country is especially interesting to be studied because of its unstable authoritarian monetary policies causing an incredible increase in inflation over the past years.

4.3 Variables and Data collection

4.3.1 Inflation indicators

In accordance with the three countries of observation, three different indicators of inflation rates will be chosen. The most common measure of inflation is the CPI of a country which is a measure of the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services. This data was obtained from Refinitiv Eikon.

4.3.1.1 CPI

For the inflation indicator of US, we use the Consumer price index of all items (CPI) originally released by the Bureau of Labor statistics of the U.S Department of Labor. The price is not seasonally adjusted. For Switzerland the Price index was released by the Federal statistical Office of Switzerland (FSO) and the price is not seasonally adjusted. Finally, for Turkey we also use the consumer prices of all items by commodity not seasonally adjusted. This indicator is provided by “TurkStat”, the Turkish Statistical institute. After collecting each CPI, we make use of excel to compute the CPI change rate by month on month.

4.3.1.2 10TYIE

For daily data USA we will use the US. 10-Year Breakeven Inflation Rate (T10YIE). This indicator is a measure of expected inflation derived from 10-Year Treasury Constant Maturity Securities (BC_10YEAR) and 10-Year Treasury Inflation-Indexed Constant Maturity Securities (TC_10YEAR). In excel we first compute the rate of change of this indicator daily. Since some of the data was missing, we also use excel to exclude those missing cases.

4.3.2 Monthly return variables

For the first analysis in monthly frequency, we collect the price of bitcoin of the last day of every month and computed the return by comparing their prices with the price of the previous month. The price selected is the average between bid and ask prices. Prices of bitcoin are in dollars, but since our sample selection uses different currencies, a conversion is needed. For the ease of our analysis we will assume that the investors first change their local currency into USD before buying the asset. This assumption is also in line with most of the exchanges for such assets which also mainly work with US Dollars. It is known that the most famous exchanges for cryptocurrencies do not allow investors to purchase directly in local currencies. It is often needed to first buy a so called stable coin which is pegged to the US Dollar and only then buy the asset. The exchange rates between each local currency and dollar is retrieved the same exact day of bitcoin prices collections, namely last day of every month.

4.3.3 Daily Return variables

For the second analysis in daily we use both daily prices of Bitcoin and CRIX and then we compute their daily returns in excel. Some of the data was also missing so we also used excel to align the returns for Bitcoin, CRIX and the previously mentioned T10YIE. Bitcoin prices were obtained from Coinbase. CRIX returns were extracted from the global website.

5. RESULTS

5.1 Descriptive statistics:

5.1.1 Monthly results

The following table 7 represents the descriptive statistics for all variables used in this analysis from July 2014 until May 2022 meaning a total of n=95 monthly observations.

Table 7: Descriptives statistics (Monthly Results)

Note: N = 95	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
ΔCPI_SW	-0,615	0,659	0,028	0,260	0,000	-0,018
ΔCPI_US	-0,669	1,335	0,216	0,363	0,267	0,518
ΔCPI_TU	-1,443	13,575	1,449	2,077	3,657	16,751
ΔBTC/CHF	-36,690	69,440	6,796	23,493	0,575	0,085
ΔBTC/USD	-37,609	70,252	6,718	23,341	0,550	-0,001
ΔBTC/TRY	-41,331	69,809	9,047	23,685	0,436	-0,157

The first interesting point to notice is that bitcoin returns have been positive on average for the three economies of observation. For the US the mean is +6,718% we can also see that the higher average returns of bitcoin are for Turkey with an average of +9,047%. Concerning the average of inflation rates, we can see that they are also all positive on average. This can give us a first evidence that our research is meaningful since our research is based on the assumption that bitcoin returns increase with an increase of inflation rate.

We can notice significant differences between the inflation indicators among different economies. As expected, the mean ΔCPI for turkey is the highest one with an average monthly inflation rate of 1,449%, followed by United states with a mean of 0,216% and Switzerland with a low average of 0,028% over the past 8 years. As previously mentioned, these values were expected because the purpose of this study was to compare economies with significant different expositions to inflation. It is important to analyze the standard deviations of the mean inflation rates since it can gives us an prior idea about the variation of this estimate, which will be afterwards more precisely analyzed when running the estimates of the OLS models with robust standard errors. We can observe that in general the standard deviations are quite high, showing patterns of significant inflation variation over the selected period. The values of skewedness and kurtosis provide us an indication of how close our samples are from a normal distribution. The high value of skewedness of Turkey can be explained by the rapid increase in inflation rate the past years.

Concerning the descriptive of Bitcoin we can observe significant extreme values. Indeed, taking as an example the returns of Bitcoin with the USD pair, the maximum was of 70,252% and the minimum was -37,609%. These values are very characteristics for this type of assets due to their high volatility. Those extreme values are very similar for the returns with Swiss francs (BTC/CHR) and slightly more significant for the returns with Turkish lyra (BTC/TRY) which maximum return was 69,809% and the minimum was -41,331%.

5.1.2 Daily results

The following table 9 represents the descriptive statistics for all variables used in this analysis from March 19th 2018 until 20th May 2022. This should be a total sample of 1522 days, however a prior cleaning process needed to be done in order to align bitcoin returns, CRIX returns and daily information for the 10YIE inflation indicator. Since daily inflation is not posted on weekends and some of the data for bitcoin and CRIX was missing, the final sample size was reduced to 1045. For the purposes of our study, this sample size is more than enough to perform a reliable analysis.

Table 8: Descriptives statistics (Daily Results)						
Note: N = 1045	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Δ10YIE	-24,427	50,000	0,055	2,748	4,622	119,944
ΔBTC*	-37,414	23,361	0,228	4,599	-0,239	6,250
ΔCRIX	-23,857	20,851	0,199	4,657	-0,054	2,698

As opposed to monthly returns, the extreme values should be logically less significant because of the high frequency. However we can observe that bitcoin return decreased by 37,414% in a single day, looking back at the data set, this value refers to the day the global pandemic was announced publicly. By the time, the whole market crashed due to the uncertainty around this new virus. Apart from this specific extreme value we can see that the variance is intuitively less significant for every indicator. When comparing the average returns between the Crypto index and bitcoin we can see that the mean is relatively close due to the high percentage of bitcoin in the crypto index. Nevertheless, both indicators are still different to make this comparative study worthy. An important aspect revealed by this table is the high level of skewness and kurtosis for daily data in comparison to monthly frequency.

The overview of the descriptive graphical representations can be found on the Appendix C.

5.2 Results of OLS regression:

5.2.1 *Pearson's correlations*

The first chosen scan for inflation hedging capabilities was the absolute value of the Pearson's correlation.

Table 9: Pearson Correlations between bitcoin returns and inflation rates (monthly data)

N=95		ΔCPI_SW
ΔBTC/CHF	correlation (Sig)	0,064 (0,538)
		ΔCPI_US
ΔBTC/US	correlation (Sig)	-0,009 (0,927)
		ΔCPI_TU
ΔBTC/TRY	correlation (Sig)	-0,111 (0,285)

At an alpha level of 5%, the results from monthly data shows that no correlation coefficient was significantly different from 0. This quick scan already inform about low correlation between returns and inflation rates suggesting poor hedging capabilities of bitcoin with regards to the inflation indicators. The highest correlation was observed with Turkey with an absolute correlation of 0,111 followed by Switzerland with 0,064 and United states with 0,009. Analyzing the sign of such coefficients one can notice that it is positive only for Switzerland, when inflation increases returns also increase. However, this result is statistically not significant.

Table 10: Pearson Correlations between bitcoin returns and inflation rates (dailydata)

N=1045		Δ10YIE
ΔBTC*	correlation (Sig)	0,067 (0,030)
ΔCRIX	correlation (Sig)	0,074 (0,017)

The results from daily data show significant outcomes for both assets Bitcoin and CRIX. Both P-Values are less than alpha 5%. We can therefore reject our null hypothesis and state that bitcoin and CRIX returns have a positive correlation with the inflation rate. The returns of bitcoin show a positive correlation of 0,067 with the inflation rate. For the CRIX index such coefficient is higher with a correlation coefficient of 0,074. Although statistically significant both coefficients are still close to 0 showing that the hedging capabilities are not very strong. Nevertheless, this first scan provides us motivation to further examine the hedging capabilities of such assets by means of regression.

5.2.2 *1st approach for monthly data*

It is important to remember that this regression was performed under the assumption of perfect inflation expectations, meaning that no distinction between expected and unexpected inflation rates was made.

Table 11: Regression with perfect expectations (1st approach) for monthly data

Dependent Variable: ΔBTC				
Parameter	B	Std. Error	Sig.	R^2
Intercept	6,632	2,433	0,008	0,004
ΔCPI_SW	5,775	9,337	0,538	
Intercept	6,850	2,804	0,016	0,0001
ΔCPI_US	-0,610	6,665	0,927	
Intercept	10,878	2,965	<,001	0,012
ΔCPI_TU	-1,264	1,175	0,285	

The previous table 11 shows that any of the results is significant. Ranking them from the least significant to the most significant we have US, Switzerland and Turkey. For the US, with alpha 5% and with a P-value of 0,927 there is no enough evidence to reject the null hypothesis and state that the coefficient Beta is significantly different from 0. The same interpretation goes for Switzerland and Turkey with respective P-Values of 0,538 and 0,285 both significantly higher than alpha 5%. An additional value to interpret is the poor fit of the model with only 0,01% of the variance in returns of bitcoin explained by the CPI for United States. For the Switzerland the model is fitting slightly more (R^2=0,004) so it is for Turkey with (R^2=0,012).

5.2.3 *1st approach for daily data*

Table 12: Regression with perfect expectations (1st approach) for daily data

Dependent Variable: ΔBTC*				
Parameter	B	Robust Std. Error	Sig.	R^2
Intercept	0.222	0.143	0.122	0,005
Δ10YIE	0.113	0.093	0.224	
Dependent Variable: ΔCRIX				
Intercept	0.192	0.145	0.185	0.005
Δ10YIE	0.125	0.110	0.255	

Table 12 shows the regression results for the first approach using daily returns. Although there still no significant results, we can observe that the P-Values are much better than the ones form the previous table with monthly frequencies. We can also observe that estimates, explained variances and significances are very similar for both return variables.

5.2.4 *2nd approach*

5.2.4.1 *Proxy of expected inflation*

For the second approach we first proxy the expected inflation at time t from the actual inflation at time t-1. Following are the results of this inference.

Table 13: Proxy for expected inflation in monthly data					
Dependent Variables: ΔCPI_SW, ΔCPI_US and ΔCPI_TU respectively					
Country	Parameter	B	St.error	Sig.	R^2
Switzerland	Intercept	0,020	0,025	0,424	0,158
	ΔCPI_SW_L1	0,410	0,098	<,001	
United States	Intercept	0,081	0,034	0,018	0,398
	ΔCPI_US_L1	0,652	0,083	<,001	
Turkey	Intercept	0,523	0,197	0,010	0,424
	ΔCPI_TU_L1	0,652	0,079	<,001	

We can see that all lagged inflations ΔCPI for each country are significant and the explained variance R^2 of the regression are 0,158, 0,398 and 0,424 for Switzerland, United states and Turkey respectively. The positive sign of all Beta coefficient indicates that the higher the inflation is at t-1, the higher it's going to be at time t for each country.

Table 14: Proxy for expected inflation in daily data

Dependent Variables: Δ10YIE				
Parameter	B	St.error	Sig.	R^2
Intercept	0,052	0,085	0,543	0,004
Δ10YIE_L1	0,064	0,031	0,038	

For daily data, the lagged inflation is also significant and the explained variance R^2 of the regression of 0,004 is quite lower than the proxy previously done with monthly data. Same as before, the coefficient beta is positive, suggesting a positive inflation at time t when inferred by the inflation at the previous time t-1.

5.2.4.2 Regression from Fama and Schwert

Once the proxy for the expected inflation has been done, it is time to perform the regression proposed by Fama and Schwert in which the unexpected inflation equals to the errors from the previous regressive model. According to the theory of fisher, the beta coefficient for expected inflation should be one for the returns of all assets, namely bitcoin and CRIX for this research.

Table 15: Regression with expected and unexpected inflation rates (2nd approach) for monthly data

Dependent Varibles: ΔBTC/CHF ΔBTC/USD ΔBTC/TRY respectively						
		St.Error		95% Confidence interval		
Parameter	B		Sig.	lower	upper	R^2
Intercept	6,329	2,478	0,013			0,007
EXP_INF_SW	16,433	23,222	0,479	-29,082	61,947	
UNEX_INF_SW	3,778	10,053	0,707	-15,926	23,482	
Intercept	6,923	3,279	0,035			0,00011
EXP_INF_US	-0,951	10,452	0,927	-21,437	19,534	
UNEX_INF_US	-0,384	8,499	0,964	-17,044	16,275	
Intercept	11,106	3,530	0,002			0,012
EXP_INF_TU	-1,421	1,786	0,426	-4,921	2,079	
UNEX_INF_TU	-1,149	1,531	0,453	-4,150	1,853	

For monthly data, our beta coefficients for expected inflation are not significantly close to 0, all P-values above 0,05 provides us evidence for it. We can therefore state that bitcoin in monthly return does not provide hedge against expected inflation. Additionally, if we observe the sign of this coefficient is negative for United states and Turkey meaning that bitcoin could act as a reverse inflation hedge for those two countries. However, when we observe the confidence intervals, we can see that this value can be also positive and far from 0, which makes it hard to interpret anything from those beta coefficients. For Switzerland, we also have the same problem, although the estimates are positive, the high standard errors and therefore confidence intervals are not reliable enough to make any conclusion. Similar to the previous approach with perfect expectations, the model shows poor fit since all the R^2 are very low. Indeed the higher magnitude is for Turkey with only 1,2% of the variance in the returns of bitcoin that can be explained by this model.

Table 16: Regression with expected and unexpected inflation rates (2nd approach) for daily data

Dependent Variable: ΔBTC*						
		Robust St.Error		95% Confidence interval		
Parameter	B		Sig.	lower	upper	R^2
Intercept	0,175	0,156	0,262			0,006
EXP_INF	0,947	0,817	0,247	-0,657	2,527	
UNEX_INF	0,109	0,089	0,220	-0,065	0,283	
Dependent Variable: ΔCRIX						
Intercept	0,138	0,158	0,385			0,007
EXP_INF	1,111	0,915	0,225	-0,684	2,906	
UNEX_INF	0,121	0,106	0,255	-0,087	0,329	

For daily frequencies, since all P-Values are above the alpha level, we don't have enough evidence to state that bitcoin and or CRIX have hedging capabilities against expected inflation. As opposed to the same approach performed with monthly data, we can observe that the estimates are much closer than 1. In general this is because higher frequencies tends to improve the quality and reliability of the regression models. Indeed, the Beta coefficient of expected inflation for Bitcoin lies between -0,657 and 2,527 in 95% of the cases and between -0,684 and 2,906 for CRIX. According to the fisher theorem, in daily frequencies both assets does not show enough evidence to be considered a hedge against expected inflation. When analyzing the beta coefficients for unexpected inflation one can see that the results are very similar in terms of P-Values, showing no hedging capabilities against unexpected inflation either.

An overview of the regression graphical representations can be found on the Appendix D.

6. DISCUSSION

6.1 1st versus 2nd approach

After running all the tests for both monthly and daily data, one can notice minimal differences between using both approaches. The main difference was found in terms of the explained variances. Indeed, adding the error term as a predictor variable (the unexpected inflation) slightly increased the fit of the model (See differences in R^2 between tables 11 and 15 for monthly data and between 12 and 16 for daily data).

6.2 Daily versus Monthly frequencies

When comparing monthly and daily returns one can notice how the P-values become much more significant when using daily data. Taking as an example the second approach for the United States, the P-Values are 0,247 (expected inflation) and 0,220 (unexpected inflation) for daily data and 0,929 (expected inflation) and 0,956 (unexpected inflation) for monthly data. (See tables 15 and 16 with Bitcoin returns). As we previously mentioned, the choice of higher frequencies usually leads to higher reliability.

6.3 Outliers

An outlier is an extreme value and their presence need to be identified and managed properly in order to properly proceed with OLS estimators. In investor theory, the question about outliers are very relevant. Large positive or negative values are essential features of a return process. From an investor's perspective a large positive outlier might represent a potential chance to obtain high returns and a large negative might result into an incredible risk. In our research we have two distinguished type of variables: Returns of crypto and inflation indicators.

On the one hand, one could argue that when working with crypto returns, managing outliers might be contra intuitive. First of all, this type of asset is volatile by definition. Secondly, cryptocurrencies investors are aware of this volatility and are willing to take such risks. This is why we decided not apply winsorization for our return variables.

On the other hand we have an inflation indicator which is a slow moving economic time series. The presence of outliers in inflation is also essential in economic analyses and shouldn't be modified at large levels. This is why we decide to winsorize our independent variables at a 0,5% level for both monthly and daily data. Monthly inflation indicators don't show any outlier. However, after winsorization at a 0,5% (meaning that 0,025% largest 0,025% smallest observations are capped) for daily data we find a total of 6 outliers. Those outliers will therefore minimized and changed to the lower (-15,772%) or upper (+11,497%) borders of the 99,5% confidence interval.

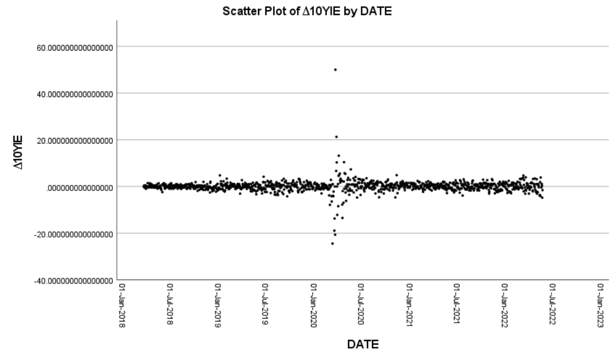

Figure 1: Scatter plot of Δ10YIE in daily frequency from 19th March 2018 until 20 may 2022. (Before winsorization)

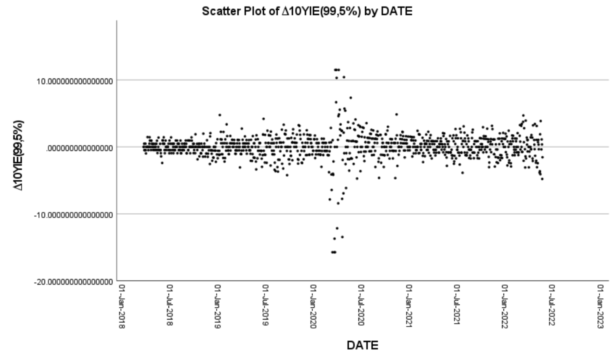

Figure 1: Scatter plot of Δ10YIE in daily frequency from 19th March 2018 until 20 may 2022. (After winsorization)

In figure 1, we can notice that all the outliers come from march 2020 when Covid-19 pandemic was announced. Looking back at the excel table used for winsorization one can see that all those outliers are between the 9th of march and 2nd of April of 2020. In the figure 2, after minimizing the effect of the outliers the values on the graph are more equally spread through 0.

6.4 Scenario with restricted inflation

As we previously mentioned, the second approach manifested better fit of the models. Additionally, daily frequency resulted in more significance in our P-Values. Last but not least daily data winsorized at 99,5% reveal the presence of 6 outliers, such outliers can have a massive effect on the OLS estimators. Given those reasons, it is decided to run again the second approach form Fama and Schwert for daily data. This new analysis with winsorized inflation represents the hedging ability of cryptocurrencies considering normal inflationary circumstances. This scenario will be compared with the previous analysis representing the turbulent inflationary times caused by the pandemic.

6.4.1 Descriptive

Table 17: Descriptives statistics (Daily Results pre and post winsorization)

Note: N = 1045	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Δ10YIE(99,5%)	-15,723	11,497	0,024	2,081	-1,374	17,142
Δ10YIE	-24,427	50,000	0,055	2,748	4,622	119,944
ΔBTC*	-37,414	23,361	0,228	4,599	-0,239	6,250
ΔCRIX	-23,857	20,851	0,199	4,657	-0,054	2,698

As one can expect, after minimizing the outliers, the kurtosis and skewedness from the inflation indicator has been drastically minimized from 119,944 to 17,142 for the kurtosis and from 4,622 to -1,274 for the skewedness. The difference in the mean rate evidences the importance of managing outliers. As we can see the mean is practically the half after winsorization, going from 0,055 to 0,024.

6.4.2 Proxy expected inflation

Table 18: Proxy for expected inflation in daily data

Dependent Variables: Δ10YIE(99,5%)

Parameter	B	St.error	Sig.	R^2
Intercept	0,019	0,063	0,764	0,033
Δ10YIE(99,5%)_L1	0,182	0,030	<,001	

The lagged inflation is significant and the explained variance R^2 of the regression of 0,033 which is much higher than the proxy previously done with original inflation rates (R^2 was 0,004, see table 14). This difference can be explained by the effect of minimizing the outliers when performing regression. The coefficient beta is positive, suggesting a positive inflation at time t when inferred by the inflation at the previous time t-1.

6.4.3 Regression from Fama and Schwert

Before running the OLS estimates, same as done previously we perform the Breush-Pagan test.

Table 19: Breusch-Pagan Test for Heteroskedasticity (Daily results post winsorization)

Dep.Variable	Predictor	Chi-Square	df	Sig.
ΔBTC*	EXP_INF(99,5%) + UNEXP_INF(99,5%)	83,041	1	<,001
ΔCRIX	EXP_INF(99,5%) + UNEXP_INF(99,5%)	44,439	1	<,001

The results reveals the presence of heteroskedasticity in the residuals. Therefore we proceed to run the regression by using the robust standard errors of the parameters estimates.

Table 20: Regression with expected and unexpected inflation rates (2nd approach) for daily data post winsorization

Dependent Variable: ΔBTC*

Parameter	B	Robust St.Error	Sig.	95% Confidence interval lower	95% Confidence interval upper	R^2
Intercept	0,220	0,144	0,128			0,007
EXP_INF(99,5)	0,328	0,409	0,423	-0,475	1,131	
UNEX_INF(99,5%)	0,172	0,107	0,109	-0,038	0,381	

Dependent Variable: ΔCRIX

Parameter	B	Robust St.Error	Sig.	95% Confidence interval lower	95% Confidence interval upper	R^2
Intercept	0,184	0,145	0,207			0,009
EXP_INF(99,5)	0,658	0,420	0,118	-0,167	1,483	
UNEX_INF(99,5%)	0,185	0,111	0,095	-0,032	0,402	

When analyzing the effect of expected inflation on cryptocurrency returns, we can see that none of the results are significant. For Bitcoin, with an estimate of 0,328 and 0,658 for CRIX we don't have enough evidence to say that the estimates are significantly different from 0. Although no significance, one can observe that the results for CRIX (P-Value = 0,118) are more significant than the ones from Bitcoin (P-Value=0,043). According to our confidence intervals, the beta coefficient for of expected inflation lies between -0,475 and 1,131 in 95% of the cases for Bitcoin. For CRIX, the coefficient lies between -0,032 and 0,402 which is clearly more narrow than the previous interval. These differences in estimates evidences that CRIX returns have more hedging capabilities that Bitcoin's.

When analyzing the beta coefficients for unexpected inflation one can see that any of the assets show significant results at alpha 5%. However at a p<0,1 level we can see that the effect un expected inflation is significantly different form 0 for CRIX returns. Looking at the 95% confidence interval we can see that for CRIX the parameter Beta = 1 is outside the confidence interval which suggest that CRIX could act as a hedge against unexpected inflation.

7. CONCLUSION

Apart from being an extraordinary technological innovation, cryptocurrencies can be also seen as an appealing investment. In times of rising inflation, investors are willing to diversify their portfolios in order to maintain their purchasing power over time. The largest market crapped cryptocurrency is the Bitcoin, but with the rise in popularity of the cryptocurrency market other cryptocurrencies were also considered in this study.

The first goal of this research was to investigate whether cryptocurrencies might have hedging capabilities against the rising inflation. We used the CRIX index in addition to Bitcoin in order to extend the research to other cryptocurrencies. Since different countries imply different inflation rates, our second goal was to compare hedging capabilities among different economical environments, for this purpose we chose to compare the returns of Bitcoin in Switzerland, United States and Turkey.

By providing an extended literature we could find different properties that makes an asset a potential hedge against inflation. We also learned several models to asses hedging capabilities. Following the extended version of the Fisher Hypothesis, the approach from Fama and Schwert, was chosen to analyze the hedging capabilities of cryptocurrencies. The results of such approach revealed whether cryptocurrencies returns statistically provide evidence to hedge the rising inflation and made it possible to answer the main research question: *To what extent, under which format (only Bitcoin or including altcoins) and for which economies including cryptocurrencies in a portfolio can hedge against inflation?* Unfortunately, the results of this study manifest that cryptocurrencies do not have hedging capabilities. All results were insignificant regardless the format of investment (Bitcoin or CRIX) and the different countries of observation (Switzerland, United States and Turkey).

With regards to the first goal, the empirical study indicated that either Bitcoin or CRIX have hedging capabilities against inflation. Due to the announcement of Covid and the chosen daily frequencies, our inflation indicator revealed turbulent inflationary times. In order to reduce this phenomenon, it was decided to create another scenario with normal inflationary circumstances. Within turbulent inflationary times, both assets didn't show much differences when inferred with inflation. However, considering a normal inflationary scenario, the estimates for the CRIX index surprisingly provided better results than Bitcoin. A reason behind these results could be the fact that within the selected period for daily frequencies, many altcoins have outperformed Bitcoin. As for our second objective, when using monthly data we could not find any significant result for bitcoin returns in any of the three chosen countries. Nevertheless, we could still find differences in the estimates within countries. The only estimate that was positive was the one for Switzerland. However, this result could not be reliably interpreted because of the high standard error. Among the three countries, Turkey revealed the most significant results probably due to their higher exposition to inflation during the past years.

Although the similarities between Bitcoin and Gold, our results differed from the ones found on the literature. The reason of these differences could be explained by the period selected. In his study, Ghosh, Levin et al. found hedging capabilities in gold only on the long term (Ghosh, Levin et al. 2004). However our study was mainly focus on the short term due to the recentness of bitcoin. When comparing with the previous research done on Bitcoin, M.Blau et al found evidences of the inflation properties of this asset. As opposed to them, our study was using OLS estimators while the authors used a Vector autoregressive model. The use of different models can drastically change the results of hedging properties for an asset.

7.1 Limitations

The most noticeable limitation to this paper is the fact that the results show no significant results. Different reasons could explain such results specifically the selected time horizon, the choice of variables used and the approach to define expected inflation.

Firstly, the short time frames of our analysis for both monthly and daily results is one of the main constraints. The recentness of such asset make it difficult to accurately analyze the regressive models. Using longer time horizon could lead to recognizing different trends.

Secondly, choosing different type of variables and their computation will definitely lead to different results. For monthly frequencies we computed Bitcoin returns by comparing the prices of the asset of the last day of the month with the previous month. With such volatile prices, monthly returns are incredibly biased. We tried to attenuate such limitation by using daily returns, but selecting high frequencies leaded to high skewedness and kurtosis which also influences the results of an OLS estimation. Additionally, for Turkey and Switzerland, we made the assumption that people would first change their local currency in USD and then purchase cryptocurrencies. However, it is known that some exchanges such as Bitpanda recently added the possibility to buy cryptocurrencies without having to first buy USD or any stable coin pegged with the US Dollar.

Last but not least, in our study it was decided to proxy expected inflation using two different approaches. However, and due to the turbulences in daily inflation rates we could have chosen a different approach. Developed by Engle Lilien and Robins this approach defines the expected inflation based on an ARCH-M model (Auto Regressive conditional heteroscedasticity in mean) (Engle, Lilien et al. 1987). The main difference of this approach is that inflation is determined from the variance of the period before instead of from the inflation rate of the period before (Hamelink and Hoesli 1996). As the name implies, the advantage of this model is that it controls the homogeneity of the variance which can be very useful in periods of high volatility.

7.2 Recommendations for future research

This research studied the relationship between inflation and cryptocurrencies returns. However, many questions still worth to be investigated regarding this topic. For example, this research only focuses on three economies and two of them have relatively low inflation rates. It could be interesting to include economies with hyperinflation such as Venezuela.

Another aspect that could be interesting to change is the time horizon for daily data. Our study was limited into 4 years (from 2018 to 2022) so it could be interesting to expand such time horizon in the future. Moreover, this study targets the CRIX index in order to include the hedging capabilities of altcoins. However, it could be maybe interesting to re-do the same experiments using another cryptocurrency such as Ethereum and compare its performance with bitcoin.

Finally, future research could be conducted using the same data but different models. As we previously mentioned in the literature, one could use Vector Autoregressive models. Advantages of such models are that it is a bi-directional model, meaning that the variables influence each other. In our study we study whether the predictor inflation influences cryptocurrencies returns, and not vice versa. However, given the nature of cryptocurrencies, it could be interesting to study whether the returns of cryptocurrencies not only depend on the past values of inflation but also on their own past returns.

8. REFERENCES

Ammous, S. (2018). The bitcoin standard: the decentralized alternative to central banking, John Wiley & Sons.

Blau, B. M., et al. (2021). "Inflation and Bitcoin: A descriptive time-series analysis." Economics Letters **203**: 109848.

Bodie, Z. (1976). "Common stocks as a hedge against inflation." the Journal of Finance **31**(2): 459-470.

Bodie, Z. (1979). Inflation risk and capital market equilibrium, National Bureau of Economic Research.

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

commission, U. S. S. a. (2022). FORM 8-K.

Damodar, N. (2009). Basic Econometrics Fifth Edition, McGraw-Hill.

Ely, D. P. and K. J. Robinson (1997). "Are stocks a hedge against inflation? International evidence using a long-run approach." Journal of International Money and Finance **16**(1): 141-167.

Engle, R. F., et al. (1987). "Estimating time varying risk premia in the term structure: The ARCH-M model." Econometrica: journal of the Econometric Society: 391-407.

Fama, E. F. and G. W. Schwert (1977). "Asset returns and inflation." Journal of financial economics **5**(2): 115-146.

Fisher, I. (1930). Theory of interest: as determined by impatience to spend income and opportunity to invest it, Augustusm Kelly Publishers, Clifton.

Ghosh, D., et al. (2004). "Gold as an inflation hedge?" Studies in economics and finance.

Gultekin, N. B. (1983). "Stock market returns and inflation: evidence from other countries." the Journal of Finance **38**(1): 49-65.

Hamelink, F. and M. Hoesli (1996). "Swiss real estate as a hedge against inflation: new evidence using hedonic and autoregressive models." Journal of Property Finance.

Hayes, A. F. and L. Cai (2007). "Using heteroskedasticity-consistent standard error estimators in OLS regression: An introduction and software implementation." Behavior research methods **39**(4): 709-722.

journal, T. w. s. (2021). "Tesla Buys $1.5 Billion in Bitcoin." from https://www.wsj.com/articles/tesla-buys-1-5-billion-in-bitcoin-11612791688.

Laidler, D. E. and J. M. Parkin (1977). Inflation: a survey. Surveys of Applied Economics, Springer**:** 169-237.

Lucey, B. M., et al. (2017). "Gold and inflation (s)–A time-varying relationship." Economic Modelling **67**: 88-101.

Meynkhard, A. (2019). "Fair market value of bitcoin: Halving effect." Investment Management and Financial Innovations **16**(4): 72-85.

Modugno, M. (2013). "Now-casting inflation using high frequency data." International Journal of Forecasting **29**(4): 664-675.

Nakamoto (2008). "Bitcoin: A Peer-to-Peer Electronic Cash System. 9."

Parkinson, J. (2020). "Senate scrambles to strike deal on $1T pandemic relief for businesses, families." abv NEWS. Retrieved March 17 2022, 2022, from https://abcnews.go.com/Politics/senate-scrambles-strike-deal-1t-pandemic-relief-business/story?id=69713460.

Salisu, A. A., et al. (2020). "The inflation hedging properties of gold, stocks and real estate: A comparative analysis." Resources Policy **66**: 101605.

Schär, F. (2020). Understanding the Bitcoin Halving, Crypto Finance Conference.

Schotman, P. C. and M. Schweitzer (2000). "Horizon sensitivity of the inflation hedge of stocks." Journal of Empirical Finance **7**(3-4): 301-315.

Spierdijk, L. and Z. Umar (2015). "Stocks, bonds, T-bills and inflation hedging: From great moderation to great recession." Journal of Economics and Business **79**: 1-37.

Statistics, U. S. B. o. L. (2022). "United States Inflation Rate." Retrieved March 05, 2022, from https://tradingeconomics.com/united-states/inflation-cpi

Trimborn, S. and W. K. Härdle (2018). "CRIX an Index for cryptocurrencies." Journal of Empirical Finance **49**: 107-122.

9. APPENDICES

9.1 Appendix A: Definitions and abbreviations of variables

Frequency	Variable	Abbreviation
monthly	Bitcoin returns in mothly frequency after conversion with USD pair	ΔBTC/USD
monthly	Bitcoin returns in mothly frequency after conversion with CHF pair	ΔBTC/CHF
monthly	Bitcoin returns in mothly frequency after conversion with TRY pair	ΔBTC/TRY
monthly	Consumer Price index rate change (computed month on month) for Switzerland	ΔCPI_SW
monthly	1st lag of the CPI rate change (month of month) for Switzerland	ΔCPI_SW_L1
monthly	Expected inflation for Switzerland in monthly frequency	EXP_INF_SW
monthly	Unexpected inflation for Switzerland in monthly frequency	UNEX_INF_SW
monthly	Consumer Price index rate change (computed month on month) for United States	ΔCPI_US
monthly	1st lag of the CPI rate change (month of month) for United States	ΔCPI_US_L1
monthly	Expected inflation for the United States in monthly frequency	EXP_INF_US
monthly	Unexpected inflation for the United States in monthly frequency	UNEX_INF_US
monthly	Consumer Price index rate change (computed month on month) for Turkey	ΔCPI_TU
monthly	1st lag of the CPI rate change (month of month) for Turkey	ΔCPI_TU_L1
monthly	Expected inflation for Turkey in monthly frequency	EXP_INF_US
monthly	Unexpected inflation for Turkey in monthly frequency	UNEX_INF_US
daily	Bitcoin returns in daily frequency	ΔBTC*
daily	Crix returns in daily frequency	ΔCRIX
daily	10-Year Breakeven Inflation Rate change (computed day to day) for the US	Δ10YIE
daily	1st lag of the 10YIE rate change for the US	Δ10YIE_L1
daily	Expected inflation for US in daily frequency	EXP_INF
daily	Unexpected inflation for US in daily frequency	UNEX_INF
daily	10YIE (computed day to day) for the US after winsomization at 99,5%	Δ10YIE(99,5%)
daily	1st lag of the 10YIE rate change for the US after winsomization at 99,5%	Δ10YIE_L1(99,5%)
daily	Expected inflation for US in daily frequency after winsomization at 99,5%	EXP_INF(99,5%)
daily	Unexpected inflation for US in daily frequency after winsomization at 99,5%	UNEX_INF(99,5%)

Note: Expected and unexpected inflations are obtained by inferring the actual inflation with the inflation at the first lag. Expected inflation represents the predicted values and the Unexpected inflation represents the error term of the inference

9.2 Appendix B: Graphical overview of the assumptions

9.2.1 Heteroscedasticity

9.2.1.1 Monthly results

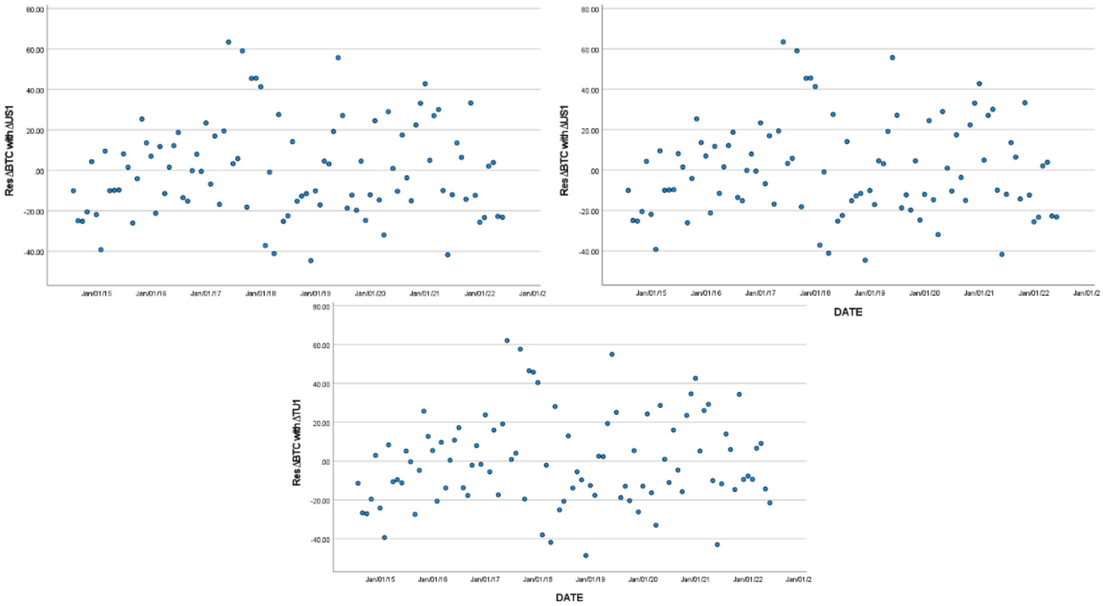

Figure 3: Scatter plots of the residuals of the regression for heteroscedasticity assumption for 1st approach. The figures represents the residuals of bitcoin for Switzerland, United States and Turkey respectively.

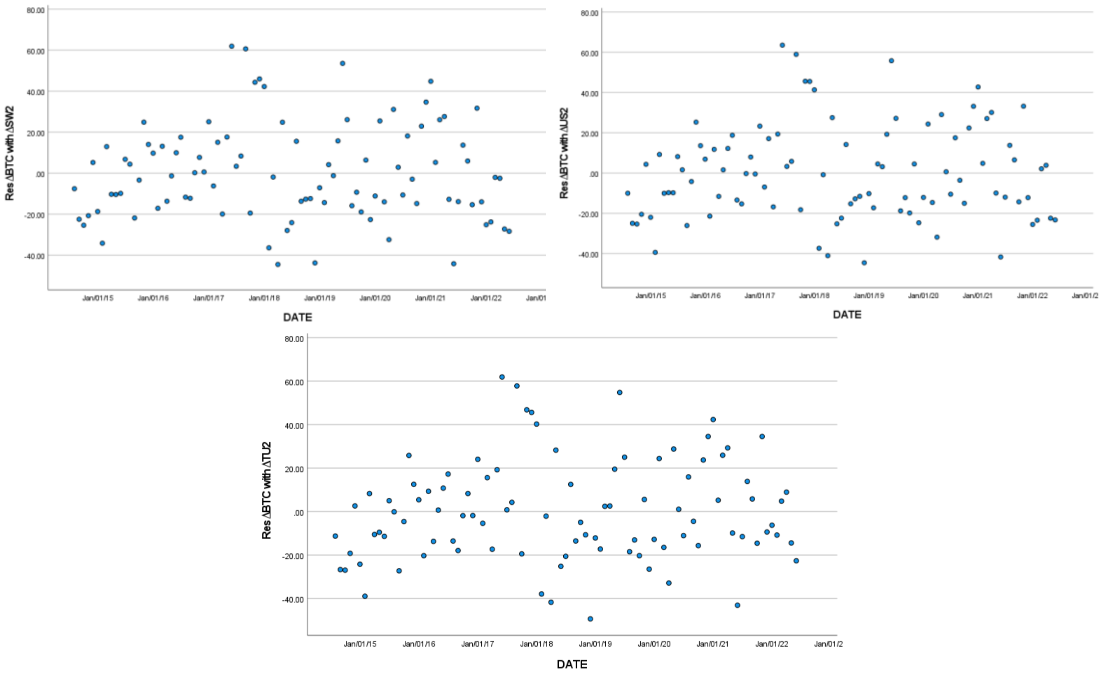

Figure 4: Scatter plots of the residuals of the regression for heteroscedasticity assumption for 2nd approach. The figures represents the residuals of bitcoin for Switzerland, United States and Turkey respectively

9.2.1.2 Daily results

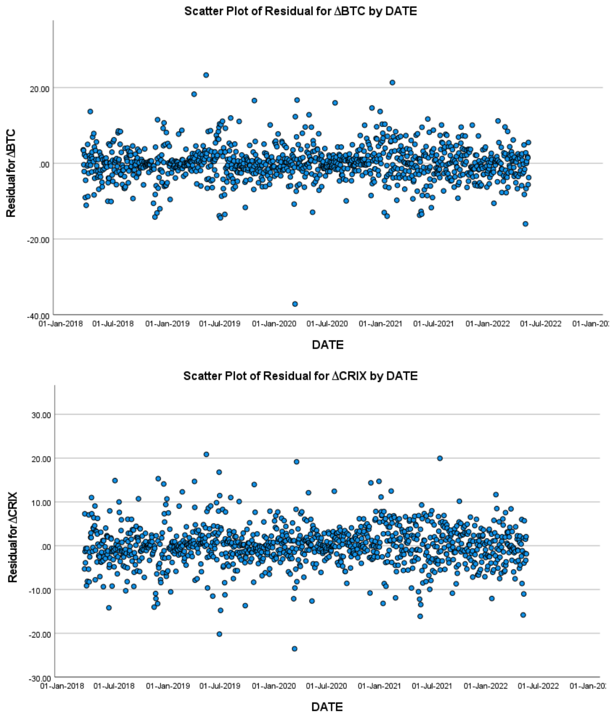

Figure 5: Scatter plots of the residuals of the regression for heteroscedasticity assumption for 1st approach. The figures represents the residuals of bitcoin and CRIX respectively.

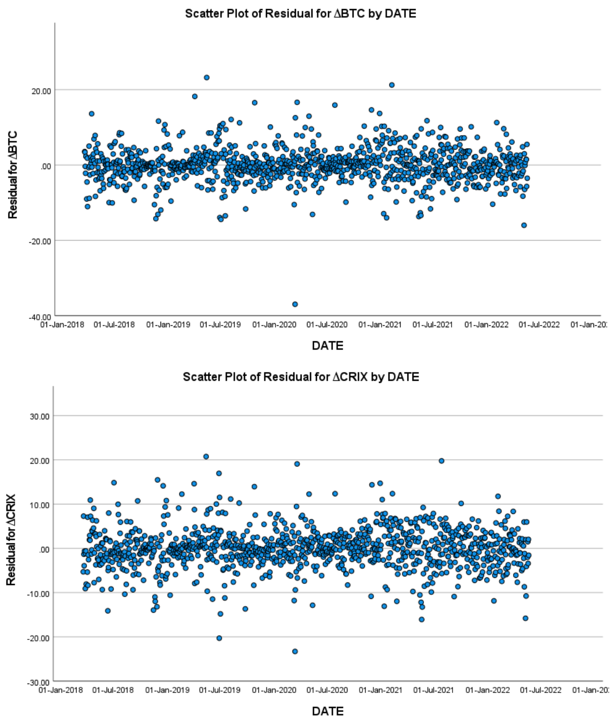

Figure 6: Scatter plots of the residuals of the regression for heteroscedasticity assumption for 2nd approach. The figures represents the residuals of bitcoin and CRIX respectively

9.2.2 Normality

9.2.2.1 Monthly results

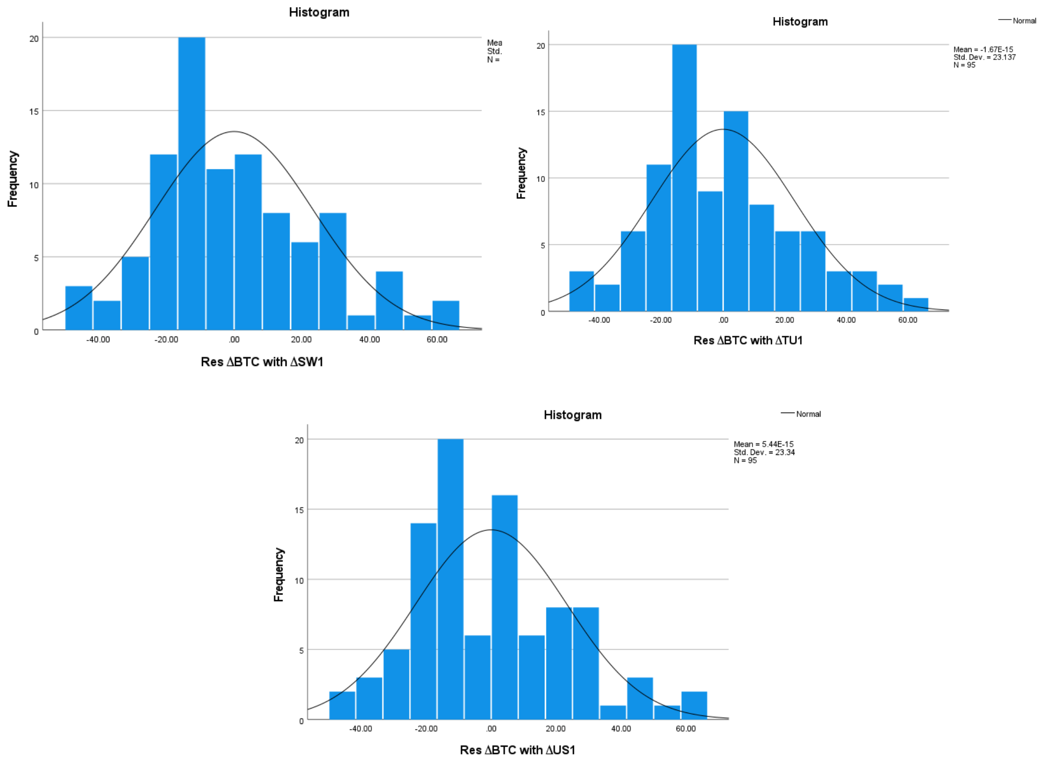

Figure 7: Histograms of the residuals of the regression for normality assumption for 1st approach. The figures represents the residuals of bitcoin for Switzerland, United States and Turkey respectively.

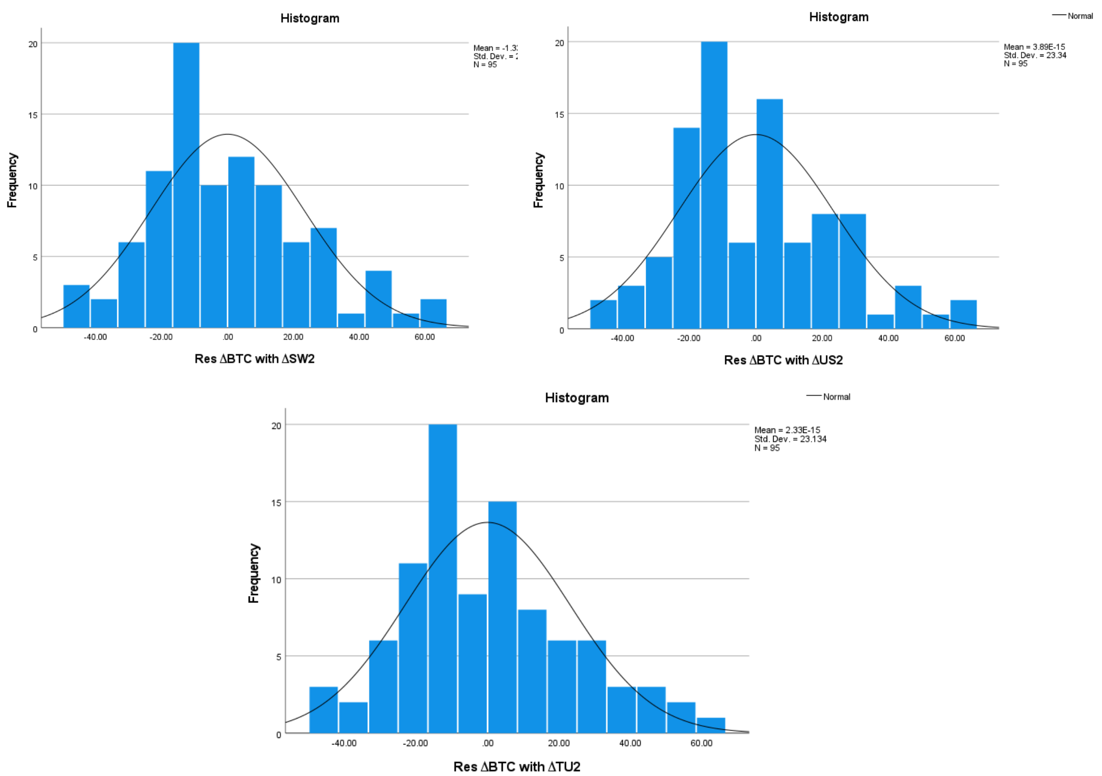

Figure 8: Histograms of the residuals of the regression for normality assumption for 2nd approach. The figures represents the residuals of bitcoin for Switzerland, United States and Turkey respectively.

9.2.2.2 *Daily results*

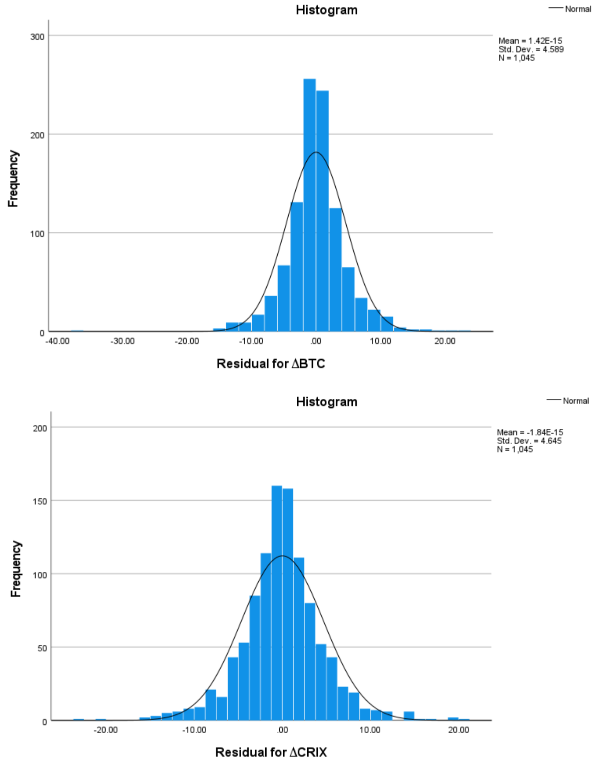

Figure 9: Histograms of the residuals of the regression for normality assumption for 1st approach. The figures represents the residuals of bitcoin and CRIX respectively

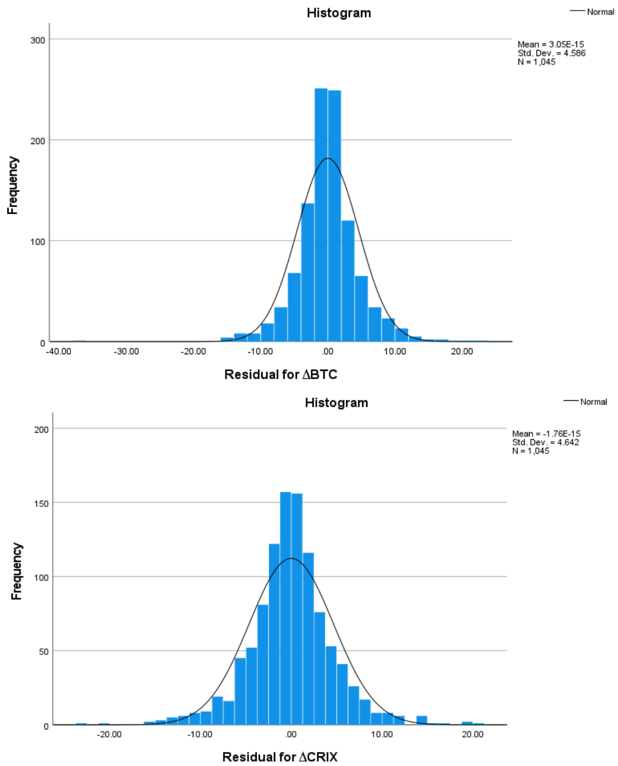

Figure 10: Histograms of the residuals of the regression for normality assumption for 1st approach. The figures represents the residuals of bitcoin and CRIX respectively

9.3 Appendix C: Graphical overview of the descriptive

9.3.1 Monthly descriptive

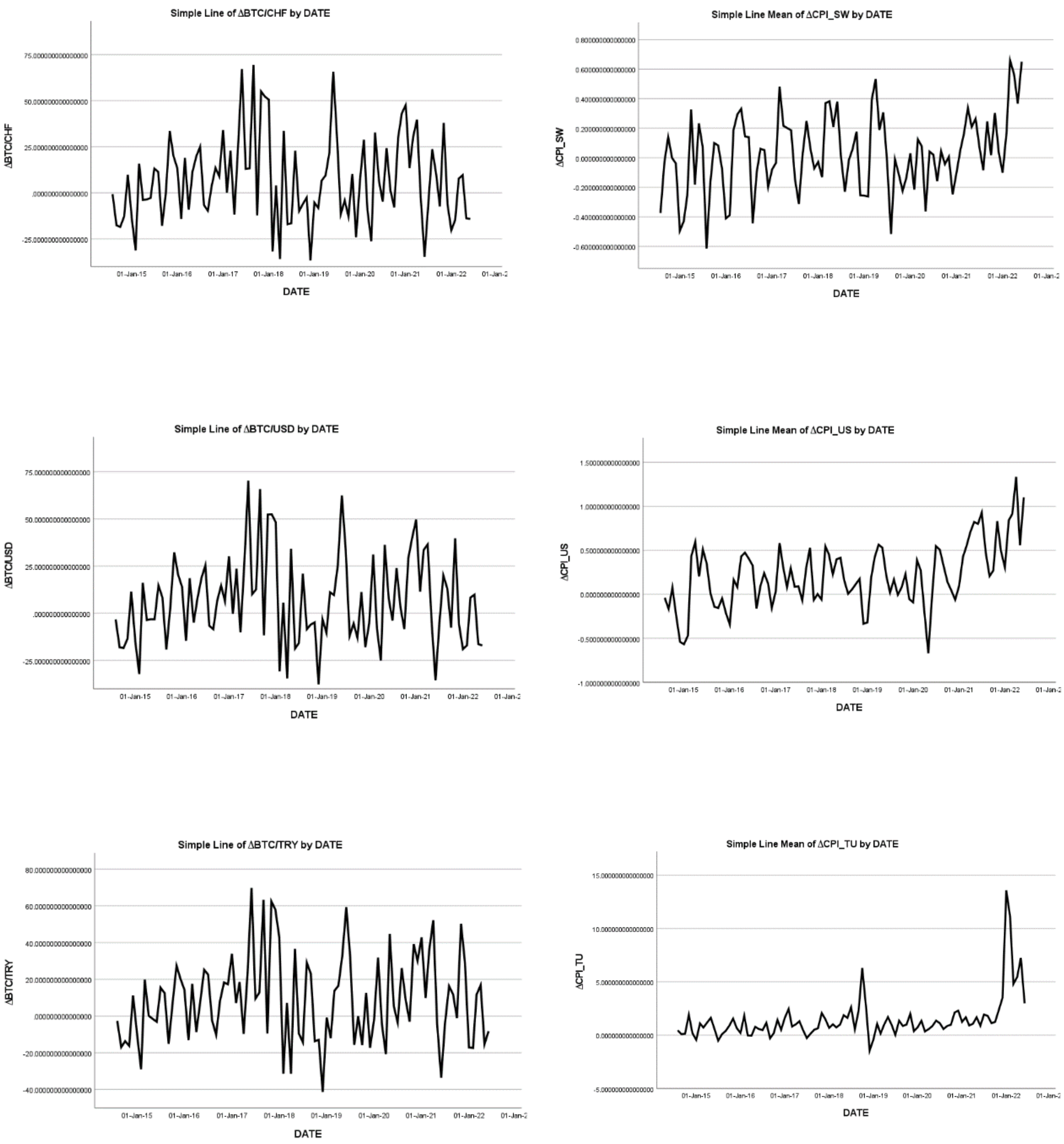

Figure 11: Trend lines of bitcoin returns and inflation rates in monthly frequency form July 2014 until May 2022 for the three economies Switzerland, United States and Turkey respectively

9.3.2 *Daily descriptive*

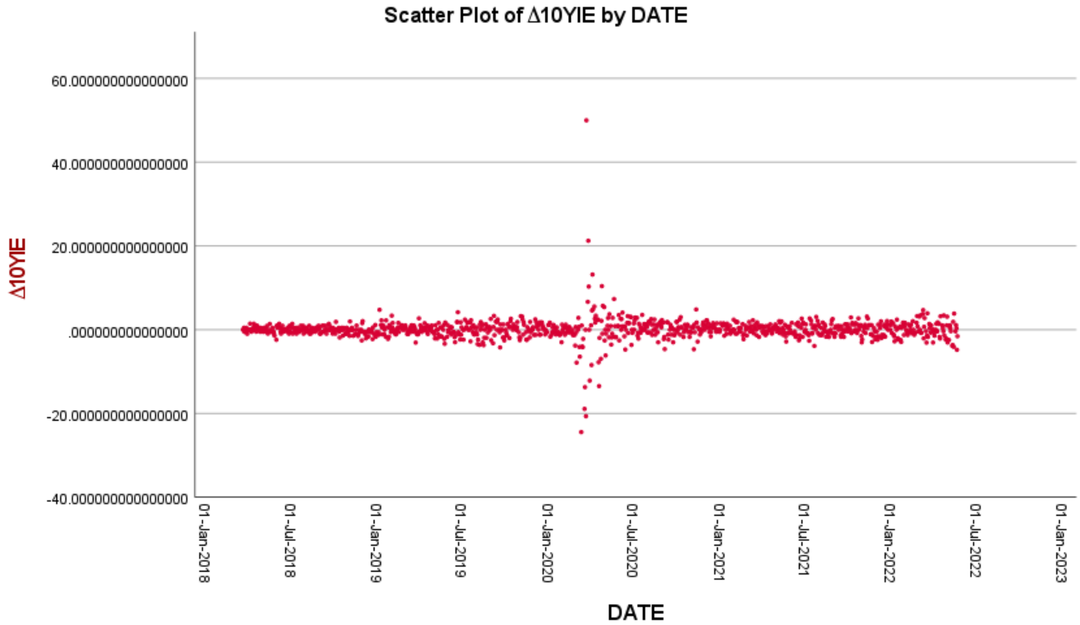

Figure 12: Scatter plot of the rates of the 10YIE in daily frequency from 19th March 2018 until 20 may 2022.

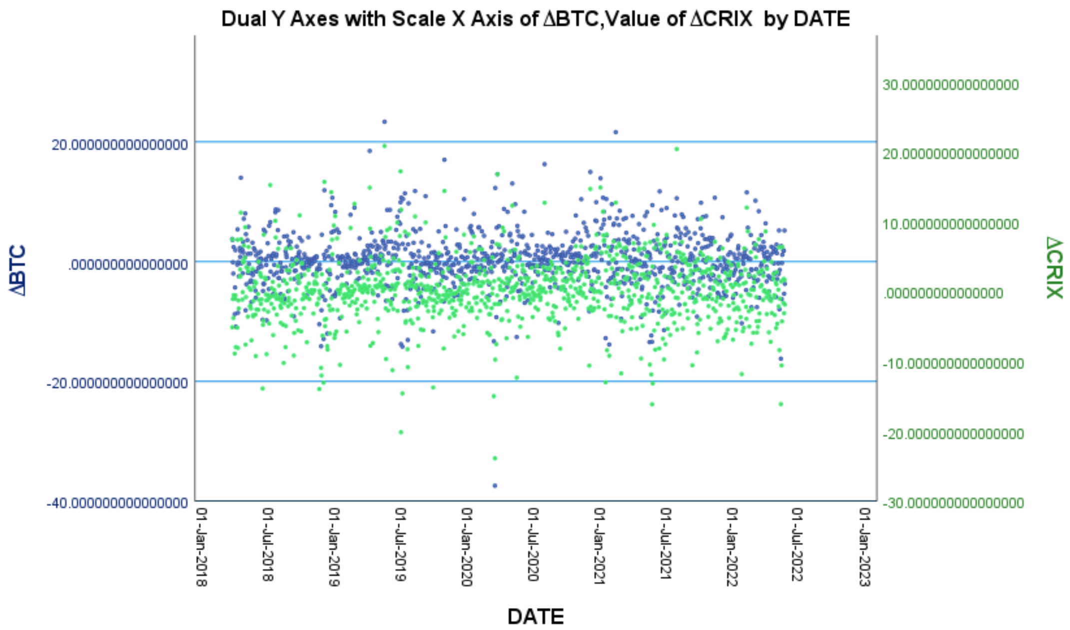

Figure 13: Dual scatter plot of the returns of the Bitcoin and CRIX in daily frequency from 19th March 2018 until 20 may 2022.

9.4 Appendix D: Graphical overview of the OLS estimates

9.4.1 Monthly

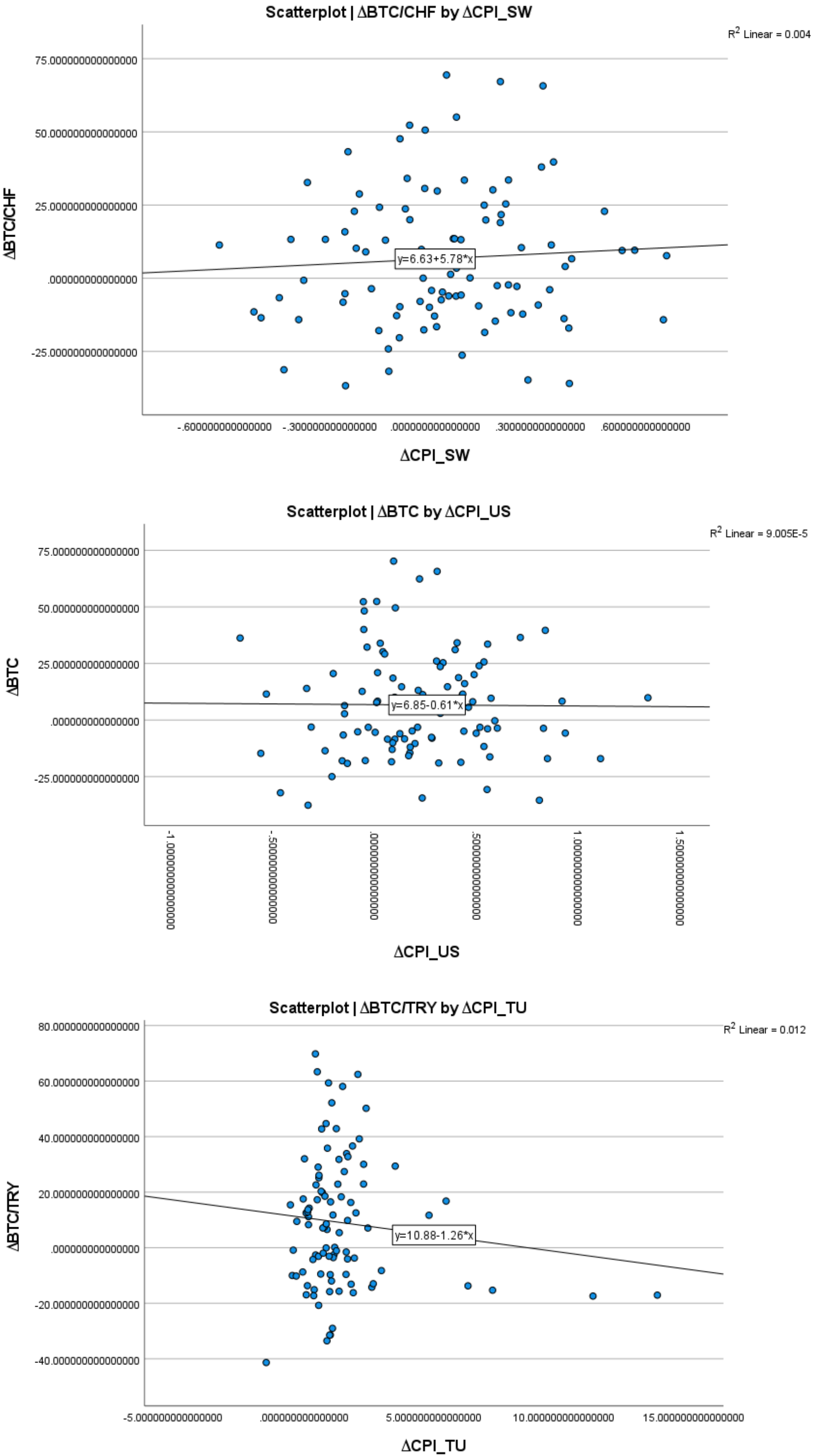

Figure 14: Scatter plot with trend lines for the regression when using the 1st approach of Bitcoin returns with Switzerland, United States and Turkey inflation rates respectively

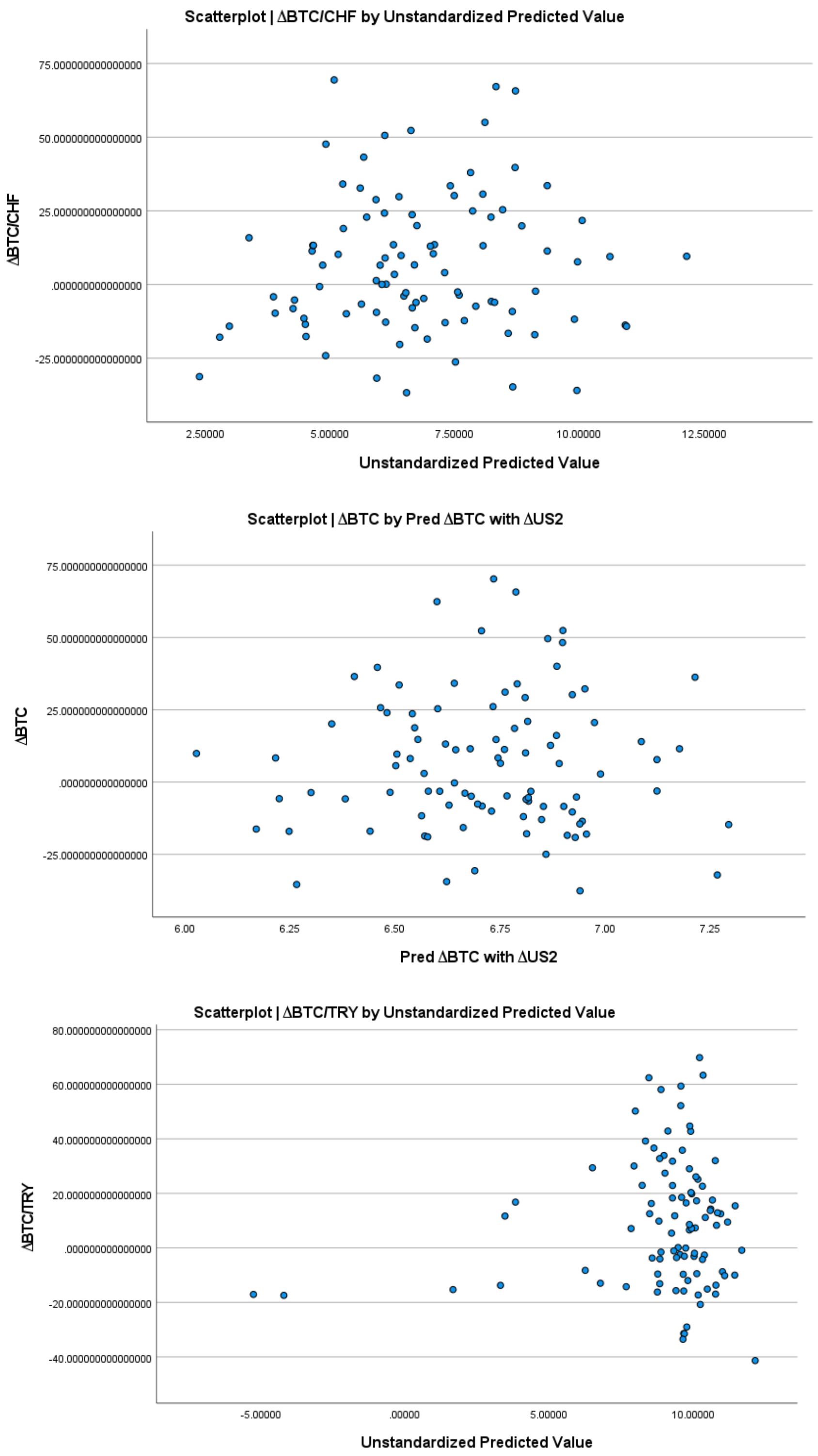

Figure 15: Scatter plot for the regression when using the 2nd approach of Bitcoin returns with Switzerland, United States and Turkey inflation rates respectively.

9.4.2 Daily

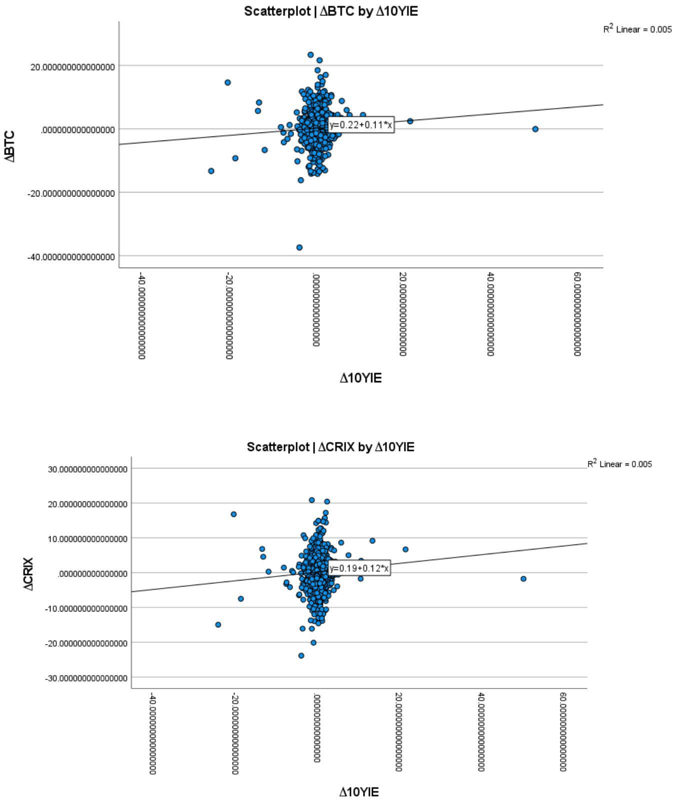

Figure 16: Scatter plot with trend lines for the regression when using the 1st approach of Bitcoin returns and CRIX returns respectively with the 10YIE inflation rate.

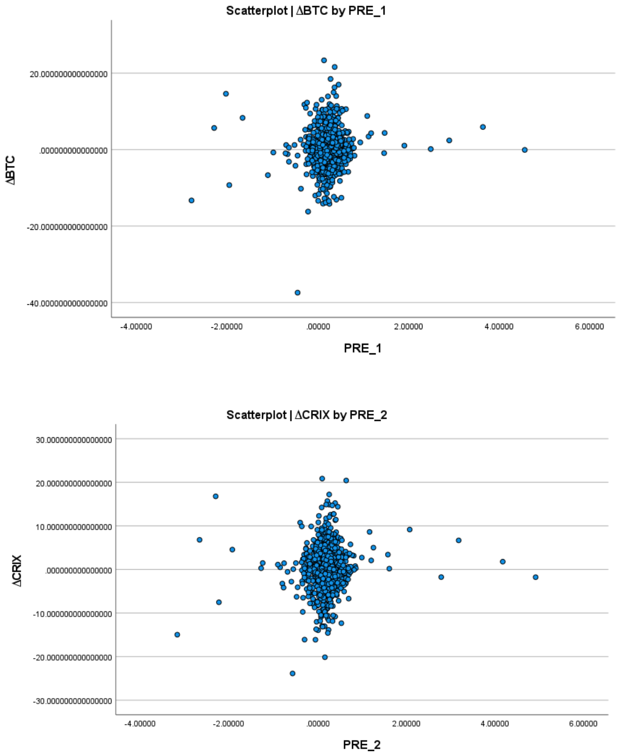

Figure 17: Scatter plot for the regression when using the 2nd approach of Bitcoin returns and CRIX returns respectively with the 10YIE inflation rate.