CHARLES UNIVERSITY IN PRAGUE
FACULTY OF SOCIAL SCIENCES
Institute of Economic Studies

Bachelor's Thesis

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Can Bitcoin serve as an inflation hedge asset in the US, Euro Area, and Czech markets?

Bachelor's Thesis

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Year of the defense:	2023

Declaration

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2. I hereby declare that my thesis has not been used to gain any other academic title.
3. I fully agree to my work being used for study and scientific purposes.

In Prague on 03.01.2023 Aleksandr Volkov

Abstract

Since the 1970s, economists have started studying the concept of inflation hedging as a way to protect investments. With the recent high inflation rates, investors might be interested if newly created assets such as cryptocurrencies can be effective against inflation. This thesis paper aims to find out whether the largest crypto asset Bitcoin can be used as an inflation hedge. To answer this question, Fisher coefficient estimation and hedging demand for the US, Euro Area, and the Czech Republic for the period between November 2014 and October 2022 will be analyzed. In addition, the vector autoregressive model (VAR) will be used for the US market in the same time frame. The results showed overall positive Bitcoin returns but all three methods indicated no or negative correlation between inflation rates in three regions and Bitcoin returns. The thesis paper concludes that Bitcoin cannot be used as an inflation hedge as not all requirements are met.

Abstrakt

Od 70. let 20. století začali ekonomové studovat koncept inflačního zajištění jako způsob ochrany investic. S nedávnými vysokými mírami inflace by investory mohlo zajímat, zda nově vytvořená aktiva, jako jsou kryptoměny, mohou být účinná proti inflaci. Tato diplomová práce si klade za cíl zjistit, zda lze největší kryptoaktivum Bitcoin použít k zajištění inflace. Abychom zjistili odpověd̆ na danou otázku použijeme Fischerův koeficient a headging demand pro USA, EU a Českou republiku na období od listopadu 2014 do října 2022. Dále pro americký trh bude také použit vektorový autoregresní model (VAR). Výsledky ukázaly celkově pozitivní výnosy bitcoinů, ale všechny tři metody ukazují, že mezi mírou inflace a návratnosti bitcoinu je bud̆ negativní korelace nebo zadna korelace ve všech třech regionech. Práce dochází k závěru, že bitcoin nelze použít k zajištění inflace, protože nebyly splněny všechny požadavky.

Keywords

Cryptocurrency, Bitcoin, gold, inflation, inflation hedge, Fisher coefficient, VAR model

Klíčová slova

Kryptoměna, Bitcoin, zlato, inflace, zajištění inflace, Fisherův koeficient, VAR model

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Název práce

Může bitcoin sloužit jako aktivum pro zajištění inflace na trzích v USA, eurozóně a v České republice?

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Chapter 1

Introduction

What is inflation? According to Mankiw (2009,p.90), it can be described as the overall increase in prices. This fundamental indicator has a big impact on the overall economy and financial markets. The Nobel Prize winner Milton Friedman wrote in his book that "inflation is always and everywhere"(Friedman,1963,p.39). Inflation can also be viewed as a falling currency value resulting in decreasing consumer purchasing power which means that fewer goods and services can be consumed (Arnold and Auer,2015).

There are a few ways in which inflation can be measured. One of the most common approaches is the Consumer Price Index (CPI). The United States Labor of Statistics describes it as "a measure of the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services". CPI is used in the USA but also in other countries around the world. In contrast, the Harmonised Index of Consumer Prices (HICP) is used within the European Union countries. Even though both indices measure the price change over time (including the same data source), they use different methods for calculation (Milecová, 2010). The first difference is geographical. On one hand, CPI includes domestic as well as abroad purchases of goods and services by the population of the given country. On the other hand, HICP applies the domestic method which includes the consumption of goods and services inside the country by both resident and non-resident population (Milecová, 2010). Secondly, both indices have baskets of goods and services that contain a different set of items.

In the last 30 years, financial markets have been developing and adjusting to the world's technological development. Since the financial crisis of 2008, it has taken a new turn with something that is known as Fin-Tech (A. Takeda and Y. Ito,2021). Many researchers tried to define "Fin-Tech". One of the most recent was stated by Peterson K. Ozili (2018) who explained it as the delivery of financial and banking services through modern technological innovation led by computer programs and algorithms. With the development of Fin-Tech, new technological tools assets and have been created.

The cryptocurrency which is digital money that is not backed by the government according to the United States Federal Trade Commission can be considered as one of the parts of the new financial world and market. There are hundreds of different cryptocurrencies available on the market with new ones being created every year. The first and the largest cryptocurrency is Bitcoin which was originally created in 2009 but only a year later the official trades were made. In May 2010, Bitcoin was traded at 0.004 USD per 1 BTC (Miller, The Ultimate Guide to bitcoin, 2015). As of October 1st, 2022, the price of Bitcoin was $19,312.10$ with a market capitalization of over 370 billion USD which is equivalent to 39.42% of the total crypto market capitalization. This is followed by Ethereum with 17.27% and Tether with 7.23% who are second and third on the list respectively.

The following characteristics can be used to describe the properties of Bitcoin (which are similar to other cryptocurrencies). Firstly, in comparison with fiat currencies (e.g. US Dollar, Euro), it is a limited supply of digital money. When originally designed by Satoshi Nakamoto (2008), the source code implied that there can only be a finite number of Bitcoin circulating in the market. As of early 2020, more than 90% has already been mined and it is expected that a maximum of 21 million will be reached by the year 2140. Secondly, Bitcoin is not backed by any state authorities (Yuneline, 2019). It is being generated by the mining process. Next, all transactions are stored in a series of recorded data blocks or records maintained on a distributed ledger which is known as a blockchain (Klaus,2017). This information is publicly available. Last but not least encrypting protocols as part of cryptography methods are used to oversee P2P (peer-to-peer) activities and transactions.

In the current market, Bitcoin and cryptocurrencies, in general, gained popularity among normal customers, businesses, and investors. According to the data from Blockchain.com, almost 242,000 transactions (trades and purchases) have been recorded on 1st October 2022. Looking at the business side of accepting Bitcoin as a means of payment, Deloitte in their article "Corporates using crypto" claims that over 2,300 individual US firms already can accept payments in cryptocurrency, and this number keeps growing. Moreover, some companies use Bitcoin as an investment. Based on the data, it is reported that 23 public companies have reported Bitcoin holdings on their Balance Sheets. The biggest company holder is MicroStrategy which is a US-based firm with over 2 billion USD worth of Bitcoin. In total, these companies hold 0.91% of the total BTC market supply.

Investors want to get a positive return when putting their financials into work. For this to happen, a change in the purchasing power affected by inflation has to be less than investment returns (Fama and Schwert, 1977). Given the fact that inflation is a key indicator, it needs to be taken into account. It is important to understand inflation, how it works and how to protect their returns. Investors might consider looking into inflation hedge assets which can protect the investment from increasing prices. Two characteristics are associated with such assets. Firstly, they should have zero or positive returns. Secondly, there should be a positive correlation between returns and inflation (Bekaert and Wang 2010).

Over time, there are some items that have been considered a hedge against inflation. Gold has been one of the oldest assets and is popular among investors as it provides value storage function and has limited supply resulting in its scarcity. Stocks and bonds investment are also view favorable against inflation, In particular, S&P500 (which includes top 500 American public corporates) and Treasury inflation-protected Securities (TIPS). The first one had relatively high annual returns in the past and diversification (one of the methods how to protect the investment from price increase) whereas the last incorporates an inflation index (both principal value and return). Real estate has been also considered as a price increase leading to higher property value.

With the creation of new assets such as cryptocurrencies, investors might be interested in getting higher levels of profit and protecting against inflation. Bitcoin being the largest asset in this category could be viewed as an inflation hedge.

Chapter 2

Literature review

Inflation hedging has been a topic of research for a few decades already starting from testing the capabilities of stocks in the 1970s and finishing with recent publications on cryptocurrencies. The section will be a summary of papers and studies related to the topics of inflation hedge assets.

2.1 Inflation hedging assets

Bodie (1976) and Jaffe and Mandelker (1976) published the first two papers in the same May publication of the "Journal of Finance" where both investigated the relationship between asset returns and inflation rates. The first one used common stocks and the second focused on the weighted portfolio for the New York Stock Exchange (NYSE) stocks. A year later, similar research was carried out by Fama and Schwert (1977) where they extended the number of assets, whose effectiveness as inflation hedge had been tested, adding long-term U.S bonds and short-term U.S treasury bills, real estate, and labor income. Their core analysis was based on the Fisher coefficient hypothesis which states that there is a correlation between nominal asset returns and inflation rate (Fisher,1930). These three independent research had concluded that with respect to stock returns, there is a negative relationship with inflation rates (all research focused on the same time period between 1953 and 1971). Additionally, Jaffe and Mandelker (1976) studied the 1876-1970 period. In this case, the results showed that stocks return were not related to the inflation rates. However, there was a limitation of the data for the CPI prior to 1953 as only in that year did the rate of inflation become more accurate and reliable with the improved data collection (Jaffe and Mandelker,1976). With regards to other assets, private real estate and state bills, and government securities, the data showed that these can be considered as an inflation hedge (Fama and Schwert,1977). Results for labor income as human capital were inconsistent and did not provide enough evidence during different time periods according to Fama and Schwert (1977).

A few years later, Chua and Woodward (1982) included gold in the analysis of inflation hedge capabilities for the first time as well as extended the research outside the United States (the three pieces of research above only focused on the US inflation rate). Based on the results, it was concluded that "gold has only been an effective hedge against US inflation"(Chua and Woodward,1982). On the other hand, the time frame was only 5 years (between 1975 and 1980) which can be seen as a limitation of their analysis. Further, Gultekin (1983) enlarged the geographical scope by analyzing 26 countries in total including a range of countries from Europe, Asia, and North and South America while still focusing only on the stock returns and using the Fisher coefficient as the analysis basis. His results showed that between 1947 and 1979 there was no strong positive relationship between inflates rates and stock returns with negative relation for most of the countries (Gultekin, 1983).

Boudoukh and Richardson (1993) continued the research by investigating stock returns as an inflation hedge. Similar to all previous papers, they stated that there is a negative relation between the inflation rate and stock returns in the UK and the US. However, this was only applicable to a short-term period of time. It has been shown that stock returns and inflation rates have a positive correlation in the long term and suggested that stocks can be used as a hedge against inflation (Boudoukh and Richardson, 1993). Gold and inflation continued to be studied by Mahdavi and Zhou(1997) who claimed that gold could predict inflation. According to the results, gold did not appear to be an inflation hedge. On the other hand, they found that gold tends to react to market changes faster than CPI implying that the behavior of gold prices can be used for inflation forecast (Mahdavi and Zhou, 1997). However, this only works for a short period. In the longer run, gold does not seem to be an efficient predictor for inflation. Additionally, Taylor (1998) provided a similar conclusion that gold cannot be an effective asset against inflation based on the research on the relationship between precious metals (gold, silver, and platinum) and inflation. Yet there were certain periods between 1914 and 1996 where gold as well as other commodities had shown inflation hedge capabilities in short runs (Taylor, 1998).

A negative short-term correlation between stock returns and the inflation rate has been also confirmed by Schotman and Schweitzer (2000). If the time period is increased to 15 or more years, stocks appeared to be efficient assets in terms of inflation hedging. However, this only applies to the U.S. market. Similar results have been found but only for gold, stating that it can be used for hedging inflation especially as time goes on (the longer the more effective gold can be) (McCown and Zimmerman, 2007). Y. Campbell, J. Shiller and M. Viceira (2009) analyzed a new asset in the inflation hedge research field - inflation-linked bonds. In particular, they have used Treasury Inflation-Protected Securities (TIPS). The main focus was to understand the history and environment of TIPS and its role in the U.S. and UK financial markets. During the research, they came to the conclusion that inflation-linked bonds such as TIPS can be considered as inflation hedge assets in the longer term (Y. Campbell, J. Shiller and M. Viceira, 2009).

Dhyrberg (2015) was one of the first to start investigating and analyzing Bitcoin's hedging abilities. She compared Bitcoin to gold in terms of hedging and diversifier in the investor's portfolio and concluded that this cryptocurrency is an effective hedge against the stock market (Financial Stock Exchange (FTSE) 100 Index) and it has uncertain results when it comes to hedging against U.S Dollar, even though Bitcoin showed some evidence of hedging characteristics in the short-term (Dhyrberg, 2015). One of the most recent research, Bitcoin has been investigated as an inflation hedge for the US, Eurozone, UK, and Japan (Matkovskyy and Jalan,2021). They studied the Bitcoin markets in each of the regions and compared them to respective inflation rates. Trading Bitcoin in the US market proved to be a not effective method to hedge against inflation while it is for the UK, Japanese, and Euro markets. One of the big reasons for this is changes in the inflation rate. Bitcoin appeared to be quite effective during increasing inflation and high peaks of inflation. Another potential explanation could be "exchange-rate arbitrage from the USD"(Matkovskyy and Jalan, 2021). Finally, Bitcoin has been studied as "digital gold" in the paper of Choi and Shin (2022). They have built a vector autoregressive model (VAR) to find out if Bitcoin has the characteristics of an inflation hedge asset. Gold, Bitcoin, S&P500, EPU, and VIX indices and inflation expectations were part of the model. The findings suggest that there is no correlation between gold and Bitcoin behavior claiming that the largest cryptocurrency on the market cannot be considered as "digital gold"(Choi and Shin,2022). However, their results were aligned with the research from Matkovskyy and Jalan (2021) on Bitcoin's increase during inflation-positive shocks.

2.2 Research gap

The majority of the available literature focused on non-crypto assets such as stocks, bonds, or gold. There is limited research on cryptocurrencies and their effectiveness as an inflation hedge. This new asset class has not been studied broadly yet. Moreover, the geographical scope was around the US market, and only in a few cases, it was extended to other continents (South America, Europe, and Asia). However, many countries were not part of the scope. For example, there is no study on Bitcoin and inflation in the Czech Republic. Additionally, each paper was using one methodology to test Bitcoin's capabilities for an inflation hedge. Most of the research was based on the Fisher coefficient and there are few studies with emphasis on other methodologies.

2.3 Research question

Based on the literature review and research gap, this thesis will focus on Bitcoin's effectiveness as an inflation hedge asset in the US, Euro Area (19 countries in the EU that use Euro as their official currency), and Czech Republic (CZ) for the period between November 2014 and October 2022 using three different approaches:

- Fisher coefficient effect in the US, Euro Area, and CZ
- Hedging demand in the US, Euro Area, and CZ
- VAR model in the US

Chapter 3

Methodology

There is a number of methodologies and approaches that can be used in analyzing the effectiveness of an asset as an inflation hedge. This section will introduce the three selected ones for this thesis paper as well as state any assumptions used in the models.

3.1 Inflation estimation

All methods and models below are going to be based on the expected inflation rate. To estimate it, a generalized Fisher hypothesis will be used. This approach is based on the assumption that markets are efficient and expectations are perfect. This means that expected inflation $E(\pi)$ at period n equals to the actual inflation (π) at period n:

$$E(\pi_n) = \pi_n$$

This method of inflation estimation has been used in various papers studying the effectiveness of different assets as an inflation hedge. One of the first was Gultekin (1983) in his research on the stock market returns and inflation in 26 countries. Additionally, Rubens, Bond, and Webb (1989) used the generalized Fisher hypothesis in their research (using the actual inflation rate as expected). Similarly, H. Wurtzebach, R. Mueller, and Machi (1991) have used the assumption of efficient markets and perfect expectations while investigating real estate as the hedging inflation asset. One of the most recent papers by Hofmann and Mathis (2016) where the same inflation estimation has been applied to their research of assets' inflation hedging capabilities.

For the actual inflation data, the year-over-year (y-o-y) rate will be used for all further calculations: monthly CPI rate for the US and monthly HICP for the Euro Area and the Czech Republic. Inflation at the beginning of the time series (November 2014) is denoted as π_n and π_i at the end of it (October 2022).

3.2 Fisher coefficient

The first methodology to determine if Bitcoin can be considered as an inflation-hedging asset is using the Fisher coefficient. It describes the relationship between the nominal interest rate and the inflation rate. Additionally, Fisher (1930) introduced the concept of the Fisher hypothesis where it is stated that interest rate adjusts to expected inflation. This method can be used to determine the relationship between Bitcoin returns as an asset and the expected inflation rate. For this purpose, the following regression model is computed:

$$R_n^i = \mu + \beta E(\pi_n^i) + \varepsilon_n$$

where R_n^i is the Bitcoin return in period n to i; μ is a constant;β is the Fisher coefficient; $E(\pi_n^i)$ is the expected inflation rate in period n to i; ε_n is the error term for the period that is not explained by the data.

As mentioned in Section 3.1, expected inflation is estimated by the actual inflation rate. This results in a new adjusted regression model:

$$R_n^i = \mu + \beta \pi_n^i + \varepsilon_n$$

Using the Ordinary Least Squares Regression (OLS), the Fisher coefficient (β) can be determined. $\beta = 1$ means that the asset is viewed as a perfect hedge against inflation. If $\beta < 0$, this means that the asset is inefficient for inflation hedging, whereas $\beta > 0$ indicates the positive correlation of asset returns with the inflation rate and that asset can be considered as an inflation hedge.

Fisher coefficient (β) will be additionally tested for determining the ability of Bitcoin to act as an inflation hedge. The following hypothesis is tested with 95% confidence level ($\alpha = 0.05$):

$$H_0 : \text{statistically insignificant}$$
$$H_1 : \text{statistically significant}$$

If from the results the $p - value < 0.05$, then the null hypothesis can be rejected and concluded that β is statistically significant and Bitcoin can be used for inflation hedging.

3.3 Hedging demand

The second methodology to determine if an asset has inflation hedge characteristics is using hedging demand. It represents the ability of an asset to hedge against price changes using the Pearson correlation coefficient and the relationship between inflation and asset returns' variances. This can be expressed in the following formula:

$$\Delta = \rho \sqrt{\left[\frac{Var_n \left(\pi_n^i \right)}{Var_n \left(R_n^i \right)} \right]}$$

where Δ is the hedging demand; ρ is the correlation coefficient; $Var_n \left(\pi_n^i \right)$ is the variance of inflation in period n to i; $Var_n \left(R_n^i \right)$ is the variance of asset return in period n to i.

The result heavily depends on the correlation between the bitcoin returns and inflation rate since the hedging demand is "a scaled version of correlation coefficient"(Wagenaar,2022). If the value of ρ is negative, it is expected that the hedging demand results would also be negative.

According to Schotman and Schweitzer (2000), using this formula, $\Delta > 0$ would mean asset returns and inflation are positively correlated whereas $\Delta < 0$ shows a negative correlation relationship between the two variables. The higher the hedging demand value the more efficient is the asset as an inflation hedge (in case of a positive relationship). In this case, this would mean that with higher inflation rates there are greater asset returns and satisfy one of the characteristics of the inflation hedge asset.

3.4 VAR Model

The third method to test the ability of Bitcoin to act as an inflation-hedging asset is the vector autoregressive model (VAR) (Spierdijk and Umar,2014). The advantage of using this approach consists of the ability to observe variables over time in the past. This model uses the concept of "lag" which helps to identify how many observations from the past should be included in the model. For this approach, a few more assets' returns are added - gold, Treasure Inflation-Protected Securities (TIPS), and S&P500. Each variable results are predicted by their own observations during the previous period of time.

In total, the VAR model would include 5 variables:

1. Bitcoin returns
2. Inflation rate
3. Gold returns
4. S&P500 index
5. TIPS yield

Based on this, the following models can be created for each of the variables:

$$R(BTC)_n = \mu_1 + \sum_i^l \pi_{n-i} + \sum_i^l R(Gold)_{n-i} + \sum_i^l y(TIPS)_{n-i} + \sum_i^l I(SP500)_{n-i} + \sum_i^l R(BTC)_{n-i} + \varepsilon_1$$
$$\pi_n = \mu_2 + \sum_i^l R(Gold)_{n-i} + \sum_i^l y(TIPS)_{n-i} + \sum_i^l I(SP500)_{n-i} + \sum_i^l R(BTC)_{n-i} + \sum_i^l \pi_{n-i} + \varepsilon_2$$
$$R(Gold)_n = \mu_3 + \sum_i^l \pi_{n-i} + \sum_i^l y(TIPS)_{n-i} + \sum_i^l I(SP500)_{n-i} + \sum_i^l R(BTC)_{n-i} + \sum_i^l R(Gold)_{n-i} + \varepsilon_3$$
$$y(TIPS)_n = \mu_1 + \sum_i^l \pi_{n-i} + \sum_i^l R(Gold)_{n-i} + \sum_i^l I(SP500)_{n-i} + \sum_i^l R(BTC)_{n-i} + \sum_i^l R(TIPS)_{n-i} + \varepsilon_4$$
$$I(SP500)_n = \mu_1 + \sum_i^l \pi_{n-i} + \sum_i^l R(Gold)_{n-i} + \sum_i^l y(TIPS)_{n-i} + \sum_i^l R(BTC)_{n-i} + \sum_i^l R(SP500)_{n-i} + \varepsilon_5$$

where $R(BTC)_n$ is the Bitcoin return at time n; π_n is the inflation rate at time n; $R(Gold)_n$ is the gold return at time n; $y(TIPS)_n$ is the TIPS yield at time n;$I(SP500)_n$ is the S&P500 index at time n; $\mu_1, \mu_2, \mu_3, \mu_4, \mu_5$ are the constant values for each model; l is the number of lags; $\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, \varepsilon_5$ are the error terms for the period that are not explained by the data.

In addition, test hypotheses will be performed to analyze the statistical significance of the independent variables with respect to dependable variables by conducting a two-sided test with 95% confidence level ($\alpha = 0.05$):

$$H_0 : \text{statistically insignificant}$$
$$H_1 : \text{statistically significant}$$

T critical value will be calculated using the formula below:

$$t_{n-k-1,1-\frac{\alpha}{2}}$$

where n is the number of observations; k is the number of regressors;α is the significance level.

If from the results, the absolute value of observed *tvavlue* is greater than the calculated *t critical value*, the null hypothesis can be rejected stating the insignificance of the independent variables. Otherwise, the null hypothesis will be accepted.

3.5 Heteroskedasticity and autocorrelation tests

To check on heteroskedasticity and autocorrelation for Fisher coefficient models and the Bitcoin return model from VAR, a Breusch-Pagan Test and a Durbin-Watson Test will be performed.

The first one is used to detect if there is heteroscedasticity (which means that there is no equal variance distribution for the residuals) in the regression model. To test it, the following hypotheses will be used with a 5% significance level:

$$H_0 : \text{Homoscedasticity is present}$$
$$H_1 : \text{Heteroscedasticity is present}$$

If the reported p-value is less than 0.05, the null hypothesis will be rejected.

The second test focuses on determining the availability of autocorrelation in the regression residuals. Similarly, it will be tested at $\alpha = 0.05$ with the below hypotheses:

$$H_0 : \text{Residuals are not autocorrelated}$$
$$H_1 : \text{Residuals are autocorrelated}$$

Chapter 4

Data

To use the stated methodology and before making any calculations, the data set needs to be collected. This section will summarize the key variables collected and provide a short overview of their basic statistics. It also covers additional calculations that are required before proceeding to the next steps.

4.1 Data collection

In order to use the Fisher coefficient and hedging demand methodologies and perform calculations, Bitcoin prices and inflation rates for the US, Euro Area and Czech Republic (CZ) needs to be collected.

The total number of observations for the used variables is 96. This number is limited due to two reasons. Firstly, data for inflation (both CPI and HICP) is available on a monthly basis. Secondly, since Bitcoin is a new crypto asset in the market, its prices have only been published since October 2014 using a reliable source of data. Given that, the period between November 2014 and October 2022 has been considered for calculations providing 96 observations in total due to the fact that to calculate the return previous month's data and there is none available for September 2014.

Bitcoin prices have been recorded on the first day of the month. Inflation rate data for all regions are collected during the month and are always published during the following month. As a result, the monthly rate is assumed and considered to be actual data for the entire given period.

Since Bitcoin is traded in USD and the data is reported and accessed in the same currency, the exchange rate for Euro (EUR) and Czech Koruna (CZK) need to be considered and taken into account. Given this fact, Bitcoin prices and returns for both non-US regions need to be calculated and converted with the use of exchange rates: USD-EUR and USD-CZK.

For the proposed VAR model, additional information is recorded only for the US region:

- Gold price in USD
- S&P500 index
- TIPS yield

In order to be consistent, all rates have also been downloaded for the first date of the month. In a few circumstances, this day was during the weekend or a public holiday. As a result, for the exchange rate, S&P500, TIPS yield, and gold prices data, some of those missing values have been replaced by the first working day of that given month.

There are 4 data sources used in total::

1. Yahoo Finance for gold prices, S&P500, and exchange rates
2. Federal Reserve Bank of St. Louis for TIPS yield
3. Eurostat for HICP for both Euro Area and the Czech Republic
4. U.S.Bureau of Labor Statistics for CPI for the US

4.2 Data preparation

Since the Bitcoin prices are recorded in USD, it is required to calculate the amount in local currencies for Euro Area and Czech Republic in EUR and CZK respectively using the exchange rates collected previously.

To be able to use the proposed methodology, a few additional calculations need to be computed. For S&P500, gold, and Bitcoin prices, the rate of return is required to be calculated since the raw data provides the actual value at the given period of time. This can be done using the formula:

$$R = \frac{x_n - x_{n-1}}{x_{n-1}}$$

where R is the asset return; x_n is the asset value at current month n; x_{n-1} is the asset value at previous month $n-1$.

4.3 Descriptive statistics

Bitcoin price has been recorded at the start of the time series on 1st November 2014 and at the end of it on 1st October 2022 respectively. The Table 4.1 summarizes the data:

	Novermber 2014	October 2022	% change
USA (USD)	325.75	19,312.09	5829%
Euro Area (EUR)	306.81	19,720.93	6328%
CZ (CZK)	8,521.21	484,119.32	5581%

Table 4.1: Bitcoin prices for three regions

Additionally, Figures A.1 to A.3 in the Appendix show the charts for each country separately over time. Based on this data, it can be observed that Bitcoin has a positive real return since the percentage change of the asset value is positive. It satisfies one of the characteristics of an inflation hedge. The second condition will be discussed later in the results of the Fisher coefficient, hedging demand, and VAR model.

Using R-studio, basic statistics have been calculated for both variables. The results show that the means for Bitcoin returns are almost identical and positive at around 0.07 which is equivalent to 7%. Min. and max. results are also similar to each other showing big differences in the range almost from -40% to nearly $+80\%$. Skewness results and histogram from Figures A.4 to A.6 in Appendix show that the right-skewed distribution with a mild intensity of skew to the right. Given the kurtosis results for Bitcoin returns in three currencies, it can be concluded that the distribution is leptokurtic (values are positive) with the presence of outliers within the data populations.

Table 4.2 below shows the summary of descriptive statistics for Bitcoin returns in three different currencies:

	BTC USD	BTC EUR	BTC CZK
Min	-0.375	-0.381	-0.387
Max	0.800	0.786	0.788
Mean	0.067	0.070	0.068
Median	0.039	0.051	0.038
St.dev	0.240	0.236	0.234
Skewness	0.595	0.529	0.524
Kurtosis	0.257	0.135	0.179
Observations	96	96	96

Table 4.2: Basic descriptive statistics for Bitcoin returns

Similarly to Bitcoin returns, inflation rates for the USA, Euro Area, and the Czech Republic have been collected within the same time frame. CPI is used for the US and HICP is for the other two regions. Table 4.3 below shows a quick overview:

	November 2014	October 2022
CPI US	1.3%	7.7%
HICP EU	0.4%	11.5%
HICP CZ	0.6%	15.5%

Table 4.3: Inflation rates for three regions

Additionally, Figure A.7 in the Appendix shows an inflation rate comparison between 3 regions over the given time period.

The data shows the mean inflation ranges between 2% and 3%. It can also be observed that for all three regions at some point, deflation had occurred (a general decrease in prices for goods and services). Maximum values show that the Czech Republic had the highest level of inflation at 17.8% (almost doubled the maximum level in the US). Comparing to the results for Bitcoin returns, it can be concluded that data for all three regions is highly skewed to the right (all values are > 1, and mean values are greater than respective medians). Kurtosis results are also different showing leptokurtic distributions for all regions suggesting the presence of outliers, especially for the Euro Area and the Czech Republic. This partially can be explained by the higher inflation rates in 2022 for the whole world including the three selected regions for this study. Histograms for 3 regions are shown in the Appendix section (Figures A.8 to A.10). The Table 4.4 below represents descriptive statistics for inflation rates:

	CPI US	HICP EU	HICP CZ
Min	-0.002	-0.005	-0.001
Max	0.091	0.115	0.178
Mean	0.026	0.021	0.033
Median	0.019	0.016	0.024
St.dev	0.024	0.026	0.041
Skewness	1.372	2.106	2.384
Kurtosis	0.779	3.806	4.923
Observations	96	96	96

Table 4.4: Basic descriptive statistics for inflation rates

For the VAR model methodology, the basic statistics for gold returns, S&P 500 index, and TIPS yield are shown in Table 4.5 below:

	Gold	S&P 500	TIPS
Min	-0.107	-0.201	-0.019
Max	0.121	0.146	0.016
Mean	0.004	0.008	-0.002
Median	0.002	0.014	0.000
St.dev	0.041	0.048	0.008
Skewness	0.200	-0.765	-0.640
Kurtosis	0.183	2.921	-0.441
Observations	96	96	96

Table 4.5: Basic descriptive statistics for gold returns,S&P 500 and TIPS

Data for gold returns shows that the mean is very close to 0 meaning that on average returns are small but positive. The lowest and highest returns are relatively close to each other (1.4% difference between the values in absolute terms). Skewness is in the range between -0.5 and 0.05 which means that the gold returns distribution is almost symmetrical with a slightly right skew distribution. A positive kurtosis value suggests heavy tails on the side showing the availability of the outliers.

S&P 500 mean value is higher than the one for gold returns but still remains close to 0. Min. and max. values show that at some points in the given period, the positive return almost reached 15% and there was a loss of 20%. The skewness value is negative but it is not less than -1 - S&P500 distribution is relatively skewed to the left but not highly. Kurtosis value being positive and high suggests the presence of large outliers (similar to gold returns results).

The results for TIPS yield show the negative mean which shows the negative returns on average. A low value of standard deviation means that the data are grouped around the mean. The distribution is shown as moderately left-skewed with flat tails and small outliers (both skewness and kurtosis are negative).

Histograms time series of gold returns, S&P 500 and TIPS can be found in Appendix under Figure A.11 to Figure A.13 and FigureA.17

Chapter 5

Results

Key results from the three methods used are going to be presented, discussed, and interpreted in the section down below.

5.1 Fisher coefficient

Based on the regression model, results for three regions have been computed and displayed below in Table 5.1:

Country	Variable	Estimate	Std.error	R^2	p-value
USA	μ	0.114	0.036		
	β	-1.803	1.004	0.023	0.076
Euro Area	μ	0.099	0.031		
	β	-1.409	0.921	0.014	0.130
CZ	μ	0.100	0.031		
	β	-0.968	0.582	0.018	0.100

Table 5.1: OLS models results - Fisher coefficient

Full linear regression outputs can be found in Figures A.14 to A.16 in the Appendix section.

From the results, it can be observed that for the three regions investigated (US, Euro Area, and Czech Republic) the Fisher coefficient is negative. This results that Bitcoin cannot be used as a hedge against inflation. Moreover, the R^2 value is very low for all three scenarios. This means that the designed model can explain only 2% or even less (e.g. Euro Area and CZ).

For the hypotheses testing, the results show that the p-value for all three regions is greater than 0.05. This means that there is not enough evidence to reject the null hypothesis H_0. This results in the β being statistically insignificant (Euro Area has the highest p-value).

Additionally, high standard errors are observed and reported in the model. 95% confidence intervals summarized in the Table 5.2 below and it shows big intervals at $\alpha = 0.05$ for β coefficients for the three regions, especially for the US and Euro Area:

	Std.error	CI ($\alpha = 0.05$)
USA	1.004	(-3.798, 0.190)
Euro Area	0.921	(-3.237, 0.420)
CZ	0.582	(-2.125, 0.188)

Table 5.2: Standard errors and 95% confidence intervals

The data suggest that Bitcoin cannot be used for inflation hedging in the USA, Euro Area, and Czech republic for the period between November 2014 and October 2022. However, the proposed model for this testing might not be the best-fit model.

5.2 Hedging demand

In addition to the Fisher coefficient, calculations for hedging demand have been computed and summarised below in Table 5.3:

	US	Euro Area	CZ
VAR BTC	0.057	0.056	0.055
VAR Inflation	0.001	0.001	0.002
ρ	-0.182	-0.156	-0.169
Δ	-0.018	-0.017	-0.029

Table 5.3: Summary of hedging demand calculations for US, Euro Area, and CZ

Firstly, the ρ results show that monthly Bitcoin returns have a weak negative correlation with the monthly inflation rates for three selected regions. The results are aligned with the expectations (a negative correlation coefficient leads to negative hedging demand). For the US, Euro Area, and CZ. For all three cases, $\Delta < 0$. This proves the negative correlation relationship between the two variables and means that Bitcoin does not have abilities to be used as a hedge against inflation since the requirement for the presence of a positive correlation between inflation and returns is not fulfilled.

5.3 VAR Model

Compared with the two previous methods, there are additional variables added: monthly gold returns, S&P500 index, and TIPS yield. All values are set as time series and graphically represented in Figure A.17 in the Appendix section

The number of lags for the model needs to be identified. Using RStudio, with the four different criteria of Akaike's An Information Criterion (AIC), the Hannan-Quinn (HQ), the Schwarz Criterion (SC), and the Final Prediction Error (FPE), it was proposed to use lag of 1 period which means that in the model l=1. Results for the Bitcoin returns model below are shown in Table 5.4:

$$R(BTC)_n = \mu_1 + \pi_{n-1} + R(Gold)_{n-1} + I(SP500)_{n-1} + \\ y(TIPS)_{n-1} + R(BTC)_{n-1} + \varepsilon_1$$

Variable	Estimate	Std.error	t value
$R(BTC)_{n-1}$	0.091	0.108	0.840
π_{n-1}	-2.789	1.117	-2.497
$R(Gold)_{n-1}$	-1.113	0.597	-1.865
$I(SP500)_{n-1}$	-0.317	0.536	-0.592
$y(TIPS)_{n-1}$	-4.899	3.306	-1.482
μ_1	0.133	0.038	3.506
R^2	0.055		
p-value	0.074		

Table 5.4: VAR Model results for Bitcoin returns with lag=1

From the results obtained, it can be observed that only Bitcoin returns for the previous month have a positive impact on the actual Bitcoin return whereas all others report a negative impact, especially the inflation rate and TIPS yield. To report the significance of the variables in the model with respect to Bitcoin returns, a two-sided test at 5% significance level can be performed (α = 0.05) (where rejecting the null hypotheses H_0 : would mean that the variable is statically significant and can influence the dependable variable which Bitcoin returns in this case):

$$H_0 : \text{statistically insignificant}$$
$$H_1 : \text{statistically significant}$$
$$t_{89,0.975} = 1.987$$

Comparing the *t value* of each variable with the calculated *critical t value*, it can be concluded that only the inflation rate from the previous month can be considered statistically significant in this model which means that it is the only variable to affect the Bitcoin returns. In addition, the value of R^2 is quite low, similar to the results from the Fisher coefficient model (in this case, it is slightly higher with $R^2 = 0.055$). As a result, only less than 6% of the Bitcoin return variable can be explained by this model.

	$R(Gold)_n$		$I(SP500)_n$		$y(TIPS)_n$	
Variable	Estimate	t value	Estimate	t value	Estimate	t value
$R(BTC)_{n-1}$	-0.009	-0.486	0.023	1.066	0.001	0.829
π_{n-1}	-0.208	-1.051	-0.446	-2.007	0.049	4.700
$R(Gold)_{n-1}$	-0.123	-1.164	0.152	1.284	0.009	1.627
$I(SP500)_{n-1}$	-0.073	-0.766	-0.230	-2.164	0.001	0.205
$y(TIPS)_{n-1}$	-0.014	-0.024	-1.103	-1.678	1.039	33.414
μ	0.012	1.757	0.017	2.195	-0.001	-3.155
R^2	-0.018		0.080		0.928	
p-value	0.644		0.029		$< 2.2e-16$	

Table 5.5: VAR Model results for gold returns, S&P500 and TIPS with lag=1

Looking at the results of the VAR model for other variables that are displayed above in Table 5.5, the following can be observed. Firstly, gold returns are negatively impacted by all other variables including its own input from the previous month. One-lagged inflation rate and gold returns have the biggest effect among the five variables. However, none of them appeared to be statistically significant ($t - value$ compared to the *t critical value* that is already calculated before). Moreover, the R^2 value is negative suggesting that this model is a poor fit for gold returns as a dependent variable.

Secondly, inflation rate, S&P500, and TIPS from the previous month have a negative effect on the S&P500 while Bitcoin and gold returns positively impact it with TIPS yield having the strongest influence (within the current model results). In terms of significance, only two variables are statistically significant: inflation rate and S&P 500). On the other hand, this model can only explain less than 8% of the variation of the S&P 500 index ($R^2 = 0.07962$).

The last dependable variable from the VAR model TIPS yield is positively impacted by all the independent variables. All estimates values are low except TIPS yield with 1 lag. The inflation rate and TIPS itself from the last month can be considered as statistically significant. On the other hand, this model seems to be a good fit with a high value of R^2 above 90% (0.9284).

Overall, it can be stated that Bitcoin doesn't have inflation-hedging abilities based on this VAR model. In addition, looking at the output above, the proposed VAR model might not be the best-fit model for testing Bitcoin capabilities as an inflation hedge due to the low statistical significance of the variables and low value of R^2. The same applies to models with S&P 500 and gold returns being the dependable variables being not the best fit. On the other hand, this model can be used for explaining the behavior of inflation rates and TIPS yields. However, these two are strongly dependent on their own one-lagged values.

Full VAR model results with lag 1 can be found in the Appendix - Figure A.18.

5.4 Heteroskedasticity and autocorrelation tests

Results from Breusch-Pagan and Durbin-Watson tests show that no residual heteroscedasticity or autocorrelation has been detected in any of the Bitcoin models for both Fisher coefficient estimation and VAR as per Table 5.6 :

Model	B reusch-Pagan	Durbin-Watson	Test $\alpha = 0.05$
BTC US	0.4672	0.1573	H_0 : accepted
BTC Euro Area	0.6448	0.2054	H_0 : accepted
BTC CZ	0.5377	0.2212	H_0 : accepted
BTC VAR	0.7443	0.5182	H_0 : accepted

Table 5.6: Breusch-Pagan and Durbin-Watson results

This means that the output results from regression models can be used and interpreted.

Chapter 6

Conclusion

This section summarizes the results of the thesis paper. It also includes limitations of the analysis, compassion the results with other similar research, and suggests how the analysis can be improved in future research.

6.1 Conclusion summary

To conclude and answer the thesis question if Bitcoin can be considered an inflation hedge, it needs to be checked if two main characteristics are fulfilled:

- Zero or positive returns
- Positive correlation between returns and inflation

Based on the data and results, it was shown that during the given period of time between November 2014 and October 2022, Bitcoin returns were positive for all three regions: the US, Euro Area, and the Czech Republic. The first criteria is met. The findings from the three methodologies show the following with regard to the second one.

Firstly, the Fisher coefficient approach provided the results that there is no positive correlation between the Bitcoin returns and inflation rates for all three regions. In fact, the model showed a negative relationship between the two variables. Based on this, the second characteristic is not satisfied. Secondly, the second method also showed the negative correlation between Bitcoin and inflation in the US, Euro Area, and CZ markets. As a result, hedging demand results does not prove a positive correlation between returns and inflation. Lastly, similar to the previous two methods, the VAR model proves that Bitcoin returns are not positively correlated with the inflation rate in the US.

Correspondingly, given the fact that only one of the criteria is fulfilled, it is not enough to claim that Bitcoin can be an effective hedge against inflation in the US, Euro Area, and CZ markets between November 2014 and October 2022. These results are partially aligned with the previous research on the inflation hedge capabilities of cryptocurrencies. Matkovskyy and Jalan (2021) reached the same conclusion with regard to the US market but had shown that in the Euro Area, it is the opposite. On the contrary, this conclusion is not aligned with the results from Choi and Shin (2022) who claimed that Bitcoin has a positive correlation with inflation rates.

6.2 Limitations and further studies

Since cryptocurrencies (including Bitcoin) are considered a relatively new asset class, there is a limitation in the data set available that can be used for the research and analysis. In the previous papers studying the effectiveness of other assets hedging against inflation, the minimum period of 15 years has been used while this thesis only had 8 years of the scope. Additionally, the data for inflation is on a monthly basis which results in the additional limitation of the analysis. With higher data collection frequency (weekly or even daily), it can result in more accurate results and better models. Next, the assumption of perfect information in the markets leading to the actual and expected inflation being the same has been used. Different estimations of inflation could be used. For instance, Fama and Schwert (1977) extension of the Fisher coefficient suggests that the asset return can be explained not only by the expected but also by unexpected inflation.

Additionally, there are other ways how the expected inflation rate can be estimated. In this thesis, a generalized Fisher hypothesis has been used assuming that expected inflation equals to actual inflation. For instance, expected inflation can be estimated based on the previous rates. In this case, a regression model can be built and it is assumed that there is a relationship between current and previous inflation rates. Inflation can also be predicted by already existing inflation estimation measurements. For the US market, there is data published on a daily basis for 1-Year and 5-Year Forward Inflation Expectation Rates or 5-Year Break-even Inflation Rates. Another approach could be by using the ARCH model which is focused on the conditional expected inflation and it can be calculated based on the variance from the previous periods.

Furthermore, the VAR model method only focused on the US data and inputs meaning that Euro Area and CZ markets were not studied. Lastly, only 5 variables have been used which could have resulted in poor models for some of them. With a higher number of other assets as variables, better results could be achieved.

Moreover, a wider geographical scope could be used when analyzing inflation hedging. There are still many countries from Europe, Central and South America, and Asia where there is limited or no research available on the topic of Bitcoin inflation-hedging capabilities.

As time goes on, there will be more data available for Bitcoin. This means that in the future, with a higher number of observations, inflation hedge effectiveness can be investigated further providing more accurate findings. Besides, other big cryptocurrencies such as Ethereum, Tether, or USD Coin can be studied as inflation hedge assets. In addition, other crypto assets could be compared to Bitcoin to find any relationship between each other and inflation rates.

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Appendix A

Appendix

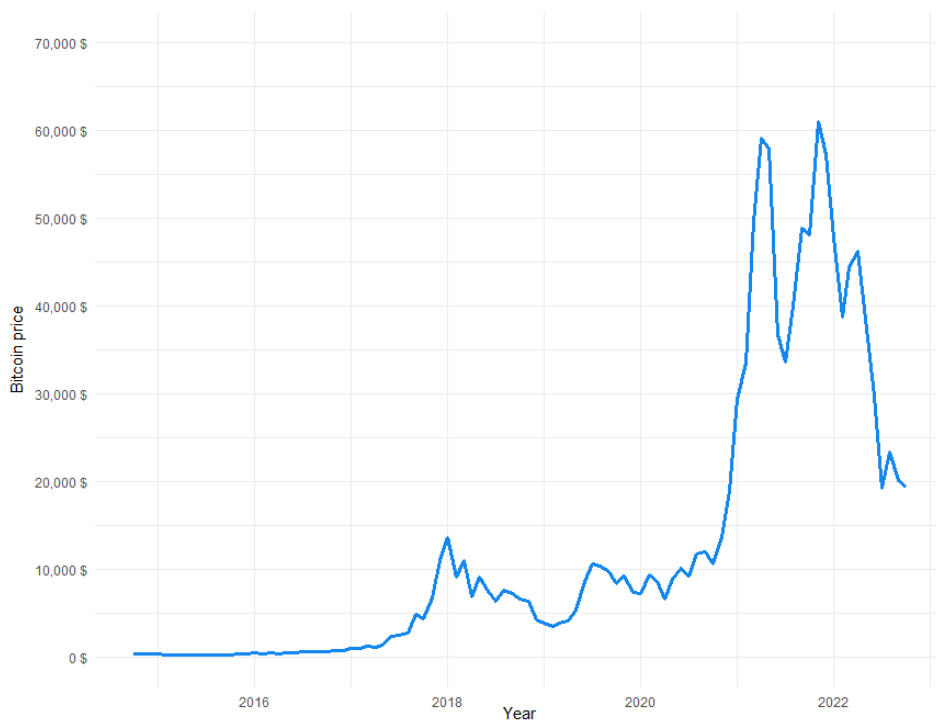

Figure A.1: Bitcoin price in USD for the period between October 2014 and October 2022

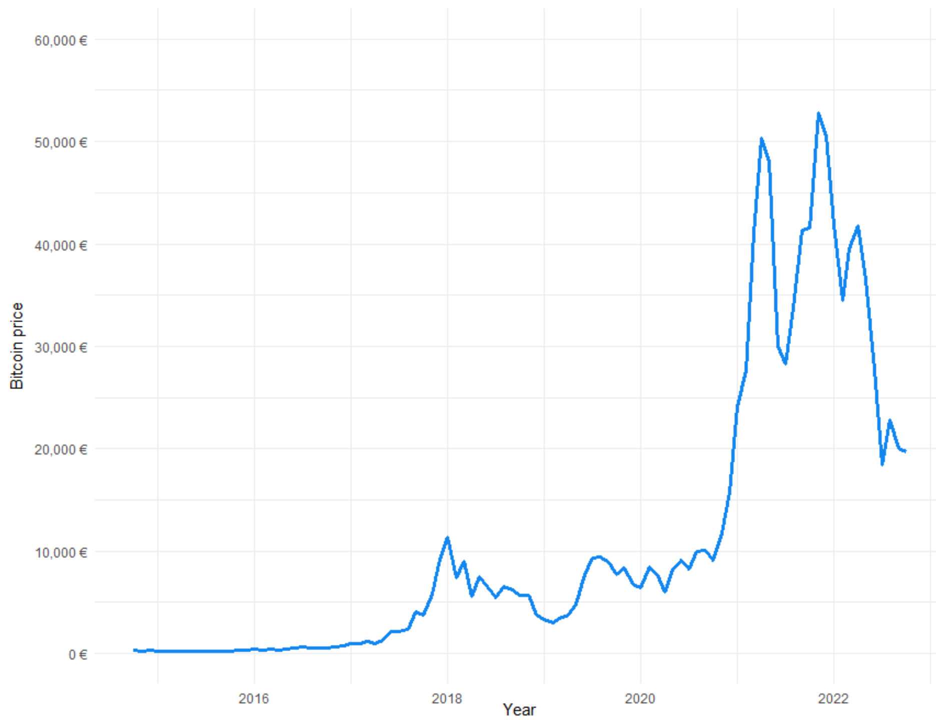

Figure A.2: Bitcoin price in EUR for the period between October 2014 and October 2022

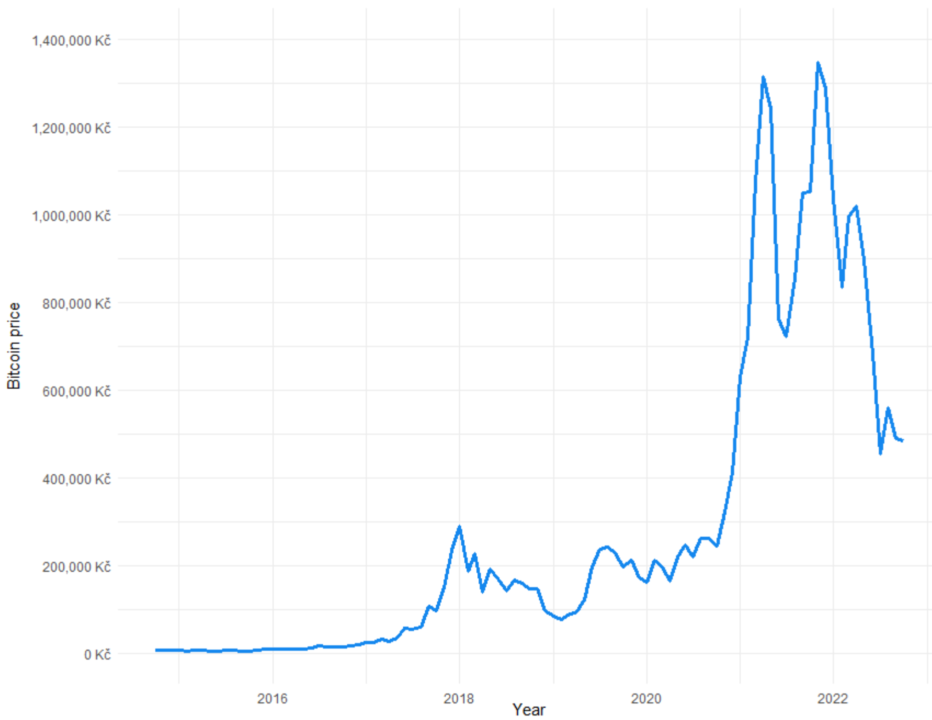

Figure A.3: Bitcoin price in CZK for the period between October 2014 and October 2022

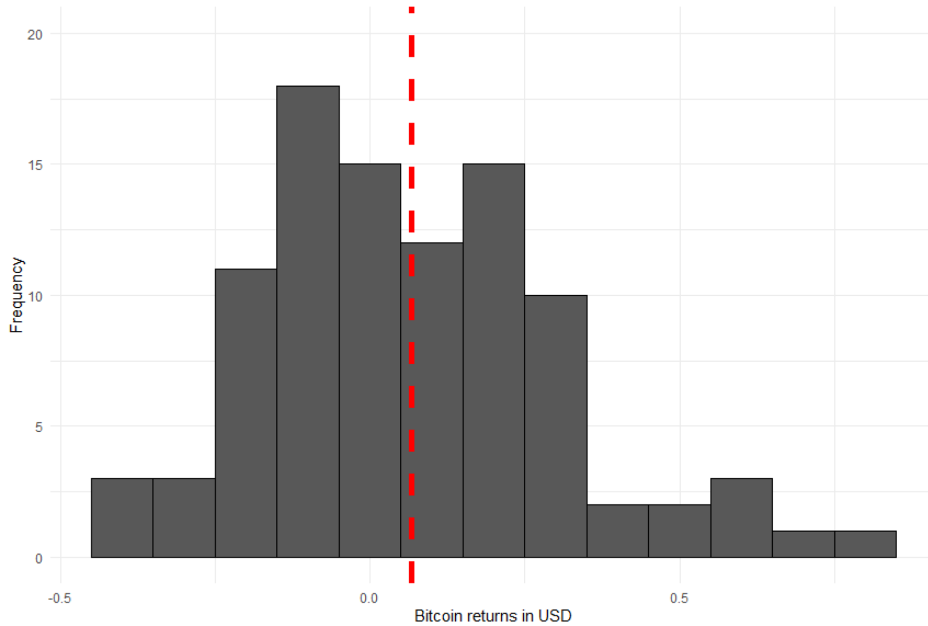

Figure A.4: Histogram for Bitcoin returns in USD

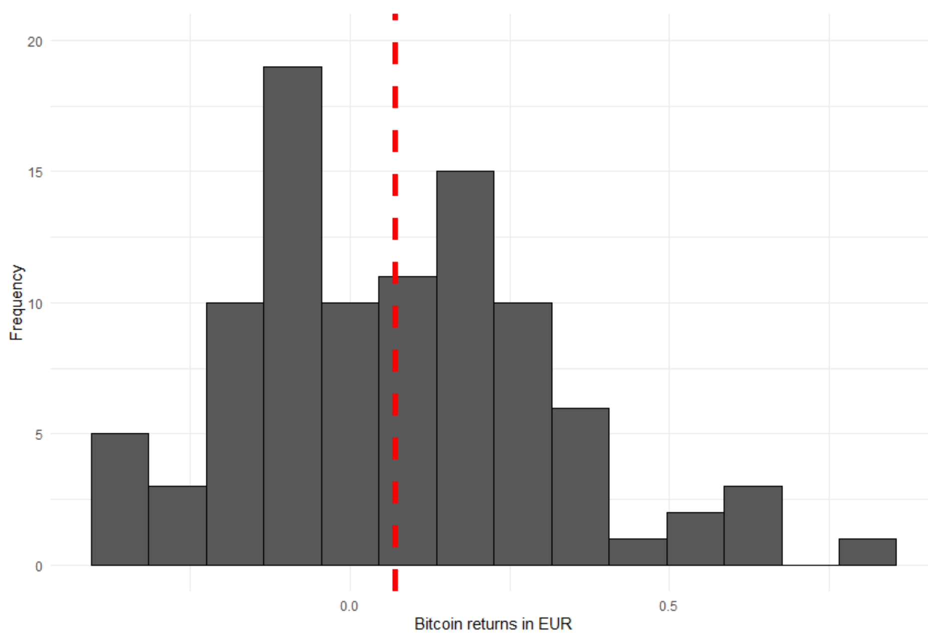

Figure A.5: Histogram for Bitcoin returns in EUR

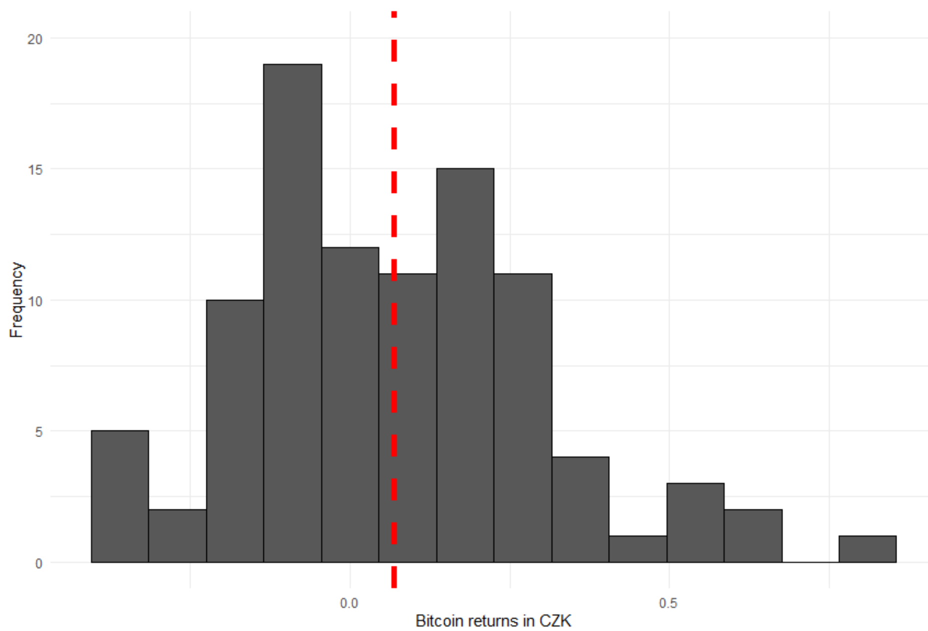

Figure A.6: Histogram for Bitcoin returns in CZK

Figure A.7: Inflation rates for US, Euro Area and CZ between 2014 and 2022

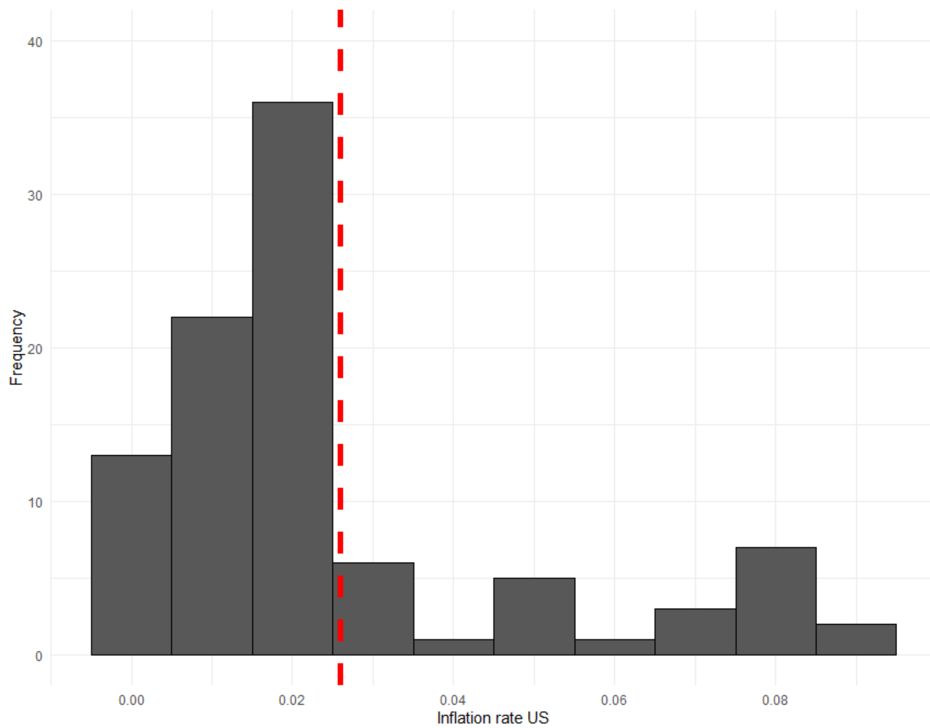

Figure A.8: Histogram for inflation rate in US

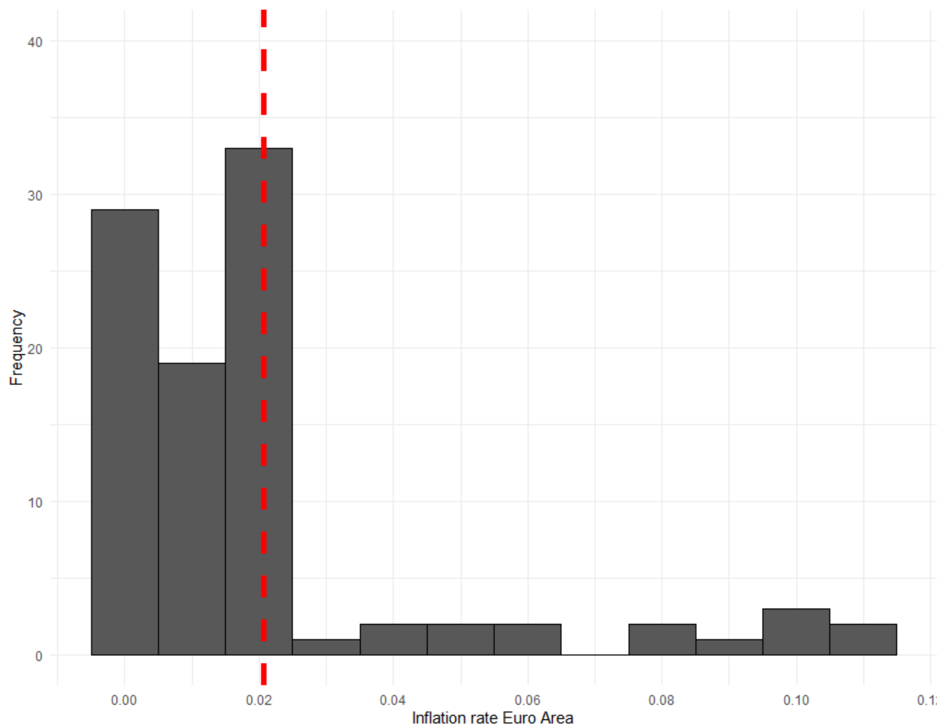

Figure A.9: Histogram for inflation rate in Euro Area

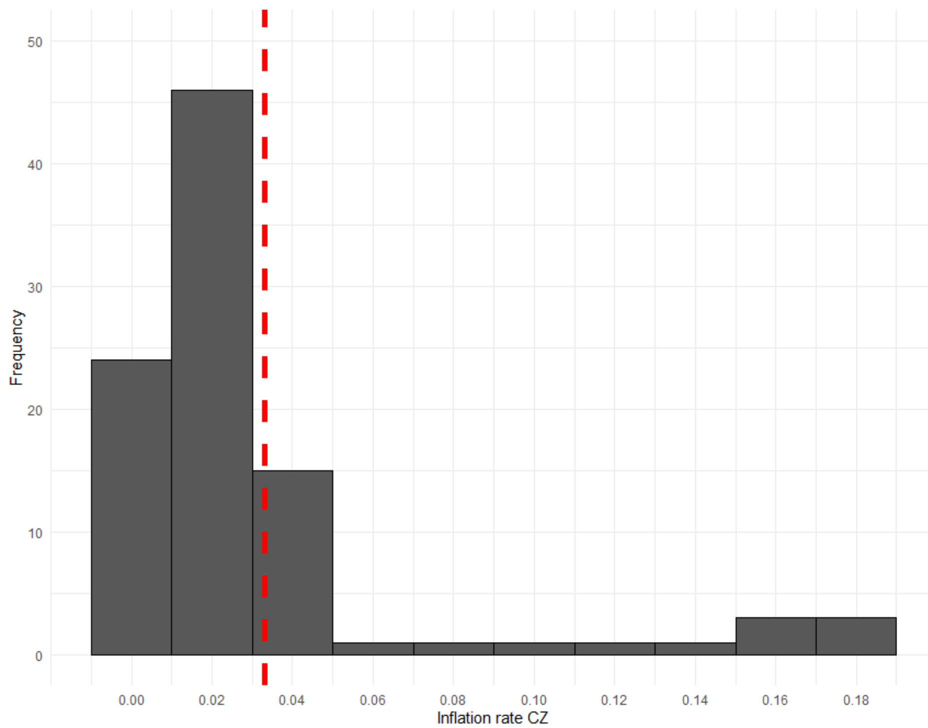

Figure A.10: Histogram for inflation rate in Czech Republic

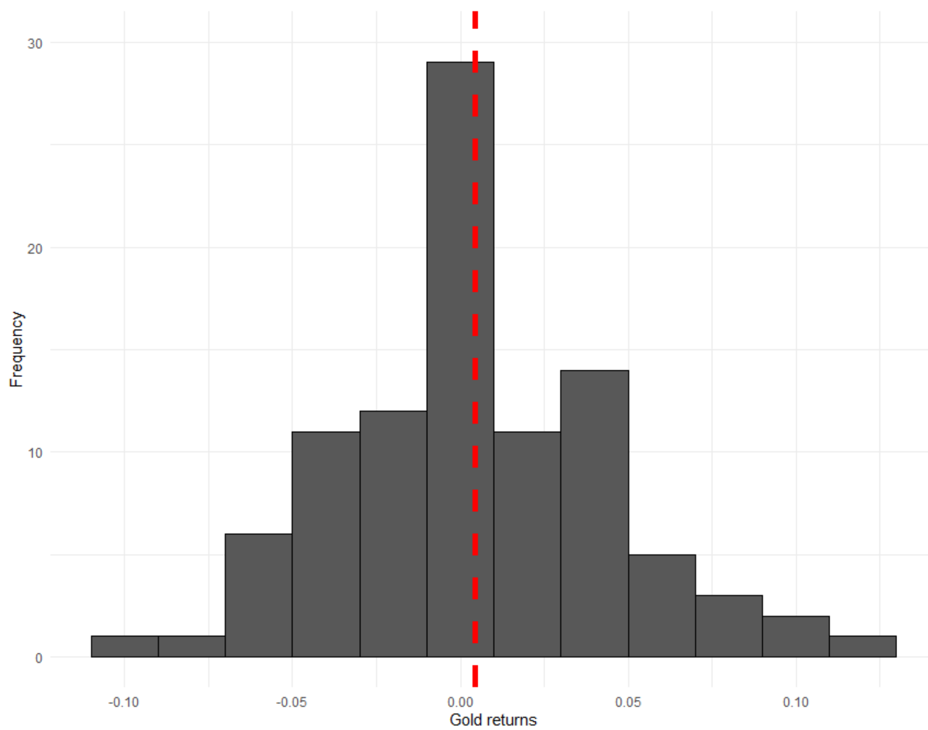

Figure A.11: Histogram for gold returns (US)

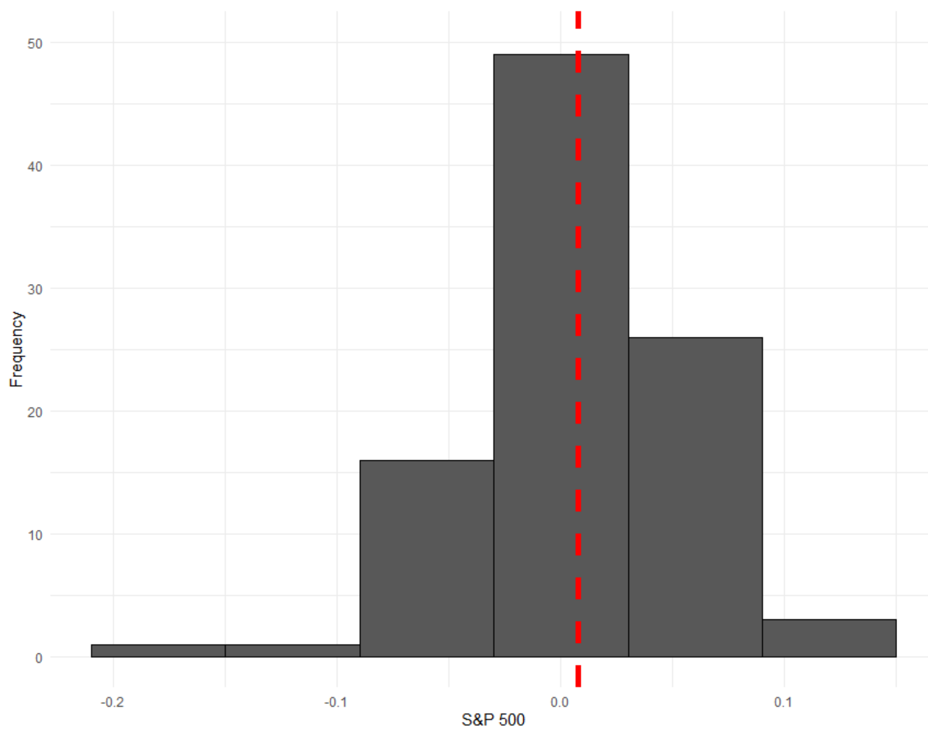

Figure A.12: Histogram for S&P 500 (US)

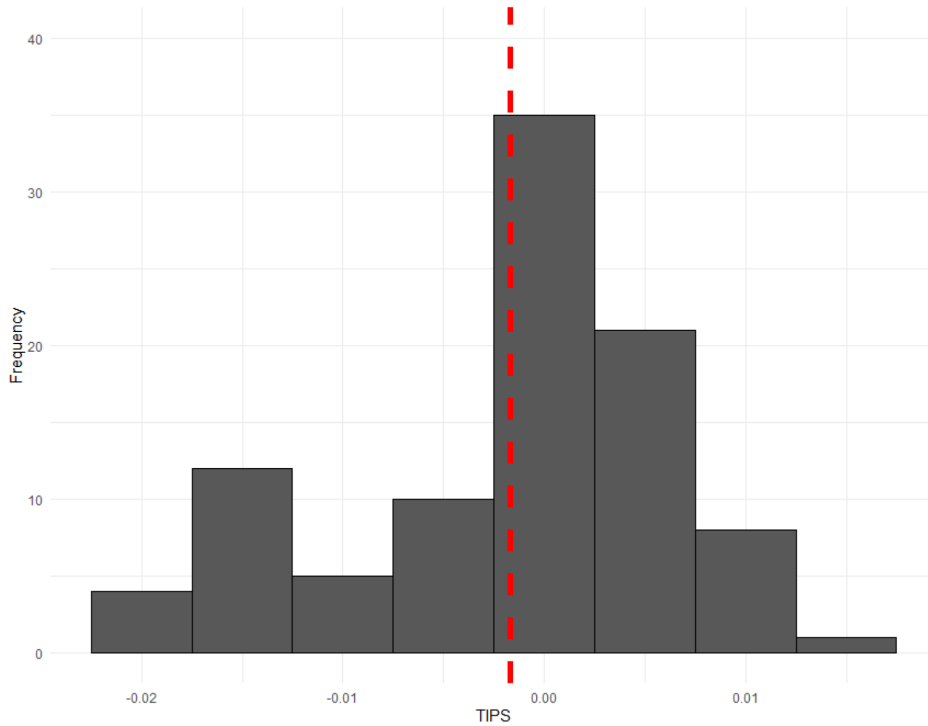

Figure A.13: Histogram for TIPS (US)

```
Call:
lm(formula = R_BTCUSD ~ USCPI)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.44423 -0.17402 -0.01964  0.16104  0.72505 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)   
(Intercept)  0.11431    0.03556   3.214  0.00179 **
USCPI       -1.80381    1.00418  -1.796  0.07566 . 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2369 on 94 degrees of freedom
Multiple R-squared:  0.03319,	Adjusted R-squared:  0.0229 
F-statistic: 3.227 on 1 and 94 DF,  p-value: 0.07566
```

Figure A.14: Linear regression model output for US

```
Call:
lm(formula = R_BTCEUR ~ EUHICP)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.4589 -0.1790 -0.0266  0.1443  0.7131 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)   
(Intercept)  0.09879    0.03058    3.23  0.00171 **
EUHICP      -1.40880    0.92088   -1.53  0.12941   
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2349 on 94 degrees of freedom
Multiple R-squared:  0.02429,	Adjusted R-squared:  0.01391 
F-statistic:  2.34 on 1 and 94 DF,  p-value: 0.1294
```

Figure A.15: Linear regression model output for Euro Area

```
Call:
lm(formula = R_BTCCZK ~ CZHICP)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.46397 -0.17099 -0.02718  0.14173  0.71175 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)   
(Intercept)  0.10013    0.03053   3.280  0.00146 **
CZHICP      -0.96854    0.58253  -1.663  0.09971 . 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.232 on 94 degrees of freedom
Multiple R-squared:  0.02857,	Adjusted R-squared:  0.01823 
F-statistic: 2.764 on 1 and 94 DF,  p-value: 0.09971
```

Figure A.16: Linear regression model output for Czech Republic

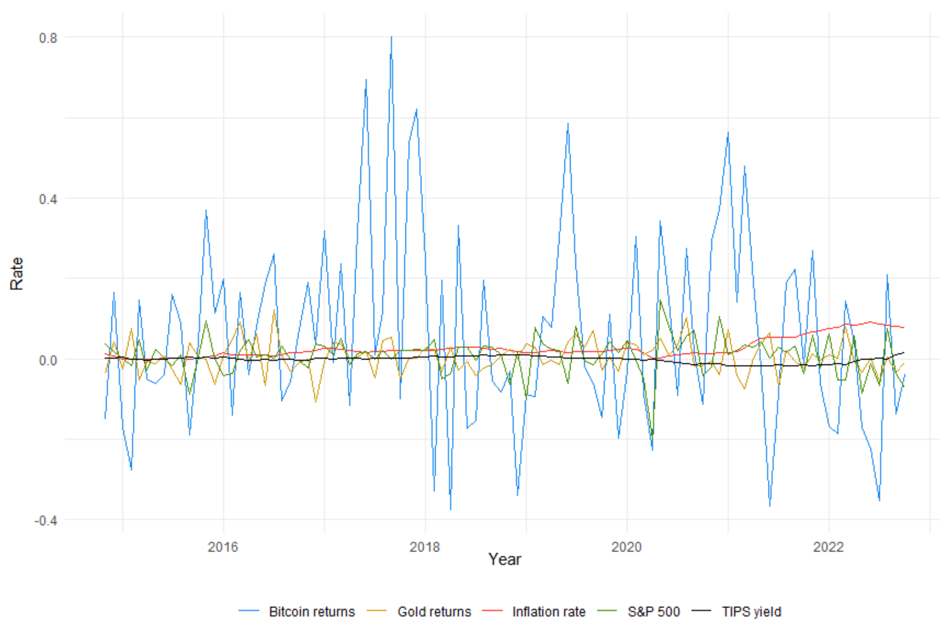

Figure A.17: Time series for 5 variables used in the VAR model

```
VAR Estimation Results:
=========================
Endogenous variables: tsBTC, tsCPI, tsGOLD, tsSP500, tsTIPS
Deterministic variables: const
Sample size: 95
Log Likelihood: 1221.956
Roots of the characteristic polynomial:
1.014 1.014 0.2359 0.2359 0.1364
Call:
VAR(y = varlags, p = 1, type = "const", exogen = NULL)


Estimation results for equation tsBTC:
======================================
tsBTC = tsBTC.l1 + tsCPI.l1 + tsGOLD.l1 + tsSP500.l1 + tsTIPS.l1 + const

           Estimate Std. Error t value Pr(>|t|)
tsBTC.l1    0.09078    0.10806   0.840 0.403120
tsCPI.l1   -2.78948    1.11719  -2.497 0.014370 *
tsGOLD.l1  -1.11272    0.59654  -1.865 0.065434 .
tsSP500.l1 -0.31686    0.53558  -0.592 0.555608
tsTIPS.l1  -4.89930    3.30550  -1.482 0.141828
const       0.13308    0.03796   3.506 0.000716 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.2332 on 89 degrees of freedom
Multiple R-Squared: 0.105,	Adjusted R-squared: 0.05471
F-statistic: 2.088 on 5 and 89 DF,  p-value: 0.07423
```

```
Estimation results for equation tsCPI:
======================================
tsCPI = tsBTC.l1 + tsCPI.l1 + tsGOLD.l1 + tsSP500.l1 + tsTIPS.l1 + const

             Estimate Std. Error t value Pr(>|t|)
tsBTC.l1    0.0006342  0.0016205   0.391   0.6965
tsCPI.l1    0.9858705  0.0167526  58.849  < 2e-16 ***
tsGOLD.l1  -0.0175214  0.0089452  -1.959   0.0533 .
tsSP500.l1  0.0074182  0.0080311   0.924   0.3581
tsTIPS.l1  -0.2083066  0.0495668  -4.203 6.26e-05 ***
const       0.0006163  0.0005693   1.083   0.2819
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.003497 on 89 degrees of freedom
Multiple R-Squared: 0.9804,    Adjusted R-squared: 0.9793
F-statistic: 889.6 on 5 and 89 DF,  p-value: < 2.2e-16


Estimation results for equation tsGOLD:
=======================================
tsGOLD = tsBTC.l1 + tsCPI.l1 + tsGOLD.l1 + tsSP500.l1 + tsTIPS.l1 + const

            Estimate Std. Error t value Pr(>|t|)
tsBTC.l1   -0.009276   0.019100  -0.486   0.6284
tsCPI.l1   -0.207618   0.197460  -1.051   0.2959
tsGOLD.l1  -0.122761   0.105435  -1.164   0.2474
tsSP500.l1 -0.072543   0.094661  -0.766   0.4455
tsTIPS.l1  -0.013735   0.584233  -0.024   0.9813
const       0.011787   0.006710   1.757   0.0824 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.04122 on 89 degrees of freedom
Multiple R-Squared: 0.03647,   Adjusted R-squared: -0.01766
F-statistic: 0.6737 on 5 and 89 DF,  p-value: 0.6444
```

```
Estimation results for equation tsSP500:
========================================
tsSP500 = tsBTC.l1 + tsCPI.l1 + tsGOLD.l1 + tsSP500.l1 + tsTIPS.l1 + const

           Estimate Std. Error t value Pr(>|t|)
tsBTC.l1    0.02292    0.02149   1.066   0.2891
tsCPI.l1   -0.44599    0.22219  -2.007   0.0478 *
tsGOLD.l1   0.15235    0.11864   1.284   0.2024
tsSP500.l1 -0.23049    0.10652  -2.164   0.0331 *
tsTIPS.l1  -1.10292    0.65740  -1.678   0.0969 .
const       0.01657    0.00755   2.195   0.0308 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.04638 on 89 degrees of freedom
Multiple R-Squared: 0.1286,   Adjusted R-squared: 0.07962
F-statistic: 2.626 on 5 and 89 DF,  p-value: 0.02909


Estimation results for equation tsTIPS:
=======================================
tsTIPS = tsBTC.l1 + tsCPI.l1 + tsGOLD.l1 + tsSP500.l1 + tsTIPS.l1 + const

             Estimate Std. Error t value Pr(>|t|)
tsBTC.l1    0.0008426  0.0010168   0.829  0.40946
tsCPI.l1    0.0494080  0.0105114   4.700 9.42e-06 ***
tsGOLD.l1   0.0091303  0.0056127   1.627  0.10733
tsSP500.l1  0.0010326  0.0050391   0.205  0.83811
tsTIPS.l1   1.0391956  0.0311006  33.414  < 2e-16 ***
const      -0.0011270  0.0003572  -3.155  0.00219 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.002194 on 89 degrees of freedom
Multiple R-Squared: 0.9322,   Adjusted R-squared: 0.9284
F-statistic: 244.9 on 5 and 89 DF,  p-value: < 2.2e-16
```

Covariance matrix of residuals:

	tsBTC	tsCPI	tsGOLD	tsSP500	tsTIPS
tsBTC	5.438e-02	5.629e-05	7.328e-04	3.266e-03	-6.153e-05
tsCPI	5.629e-05	1.223e-05	-9.550e-06	6.025e-05	-6.363e-07
tsGOLD	7.328e-04	-9.550e-06	1.699e-03	-6.167e-05	-4.454e-05
tsSP500	3.266e-03	6.025e-05	-6.167e-05	2.151e-03	-2.019e-05
tsTIPS	-6.153e-05	-6.363e-07	-4.454e-05	-2.019e-05	4.814e-06

Correlation matrix of residuals:

	tsBTC	tsCPI	tsGOLD	tsSP500	tsTIPS
tsBTC	1.00000	0.06902	0.07624	0.30195	-0.12025
tsCPI	0.06902	1.00000	-0.06625	0.37149	-0.08293
tsGOLD	0.07624	-0.06625	1.00000	-0.03226	-0.49246
tsSP500	0.30195	0.37149	-0.03226	1.00000	-0.19836
tsTIPS	-0.12025	-0.08293	-0.49246	-0.19836	1.00000

Figure A.18: VAR model results for Bitcoin returns