The inflation hedging properties of cryptocurrencies

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ABSTRACT,
When the inflation rate increases, the purchasing power of individuals diminishes. In the worst cases, it can make it virtually impossible to save up money for later consumption. This being said, cryptocurrencies are growing in interest and also being adopted all around the world. Especially in countries with high inflation rates and unstable economies, individuals seem to turn to cryptocurrencies to hedge the inflation. Implementing the Fama and Schwert (1977) methodology based on the Fisher theory (1930), the inflation hedging capabilities of the cryptocurrency index CRIX is analyzed for the USA, Eurozone, Turkey, and Argentina. The regression coefficients show different results, depending on the country and its respective inflation rates. Nevertheless, all the regression coefficients are statistically not different from zero, at a p-level of 0.05. The results show that the CRIX index cannot function as an inflation hedge since the significance of the coefficients was not at an acceptable level.

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1. INTRODUCTION

Inflation is a very actual topic in many countries, and one of generalized interest. For the last years, we have experienced a very low inflation rate in most parts of the world. In Europe and in the USA, inflation rates have been at a very low level, reaching even the negative. Nevertheless, some other countries in Africa, Asia, and South America have been experiencing high inflation rates year after year.

The inflation rate is basically the rate of increase of general prices, in a given time frame, which is usually on a yearly basis. In 2022 the inflation seems for many out of control and factors related to the COVID pandemic aggravated by supply-side distortions seem to be responsible for that.

With rising inflation, the need for inflation hedges for well-diversified portfolios gains in importance. Moreover, during these times of low-interest rates, investors seem willing to take higher risks in exchange for returns. Investors are also increasingly concerned about the sustainability of this low-interest-rate period as a result of the rapid increase in prices since 2021.

The cryptocurrency asset class is a relatively new one. Bitcoin was released in 2009 by an unknown person, who released the project as an open-source software. This was the first record of cryptocurrency protocols. This being said, Bitcoin or any other cryptocurrency have coexisted already with high inflation, in some countries, since it´s invention.

The highest inflation numbers in the years between 2000 and 2021 in the USA have been of less than 4%. Different is in other countries of the world, where cryptocurrencies have been used as a value of store and inflation hedge when inflation rates were comparably high.

The question arises though, to which extent cryptocurrencies can actually work as inflation hedges. As popularity grows and the adoption continues, more investors could consider an investment in the cryptocurrency asset class. Nevertheless, the volatility of such cryptocurrencies might make them unviable as a serious hedge for risk-averse investors.

This paper aims to provide some clarity into the inflation hedging capabilities of cryptocurrencies, with an extended scope of countries, compared to the most common ones such as the U.S. and European countries. Moreover, there is a need for more clarity on the functioning of cryptocurrencies as inflation hedges and their statistical relationship.

The paper will discuss first the existing literature on inflation, inflation hedging, cryptocurrencies, and also cryptocurrencies as hedges. With the help of the Fama and Schwert methodology, the hedging properties will be statistically tested in order to test the hypothesis that cryptocurrencies can actually act as inflation hedges (Fama and Schwert, 1977).

2. LITERATURE REVIEW

2.1 Inflation hedging

In Bodie´s paper on inflation hedging with common stocks, three definitions of the word "inflation hedge" are presented. These three different definitions do not have to be mutually exclusive though (Bodie, 1976).

The first definition is the elimination or reduction of the possibility that real returns on the stock/ security will fall below some floor value, such as zero (Cagan, 1974). In the second definition, we might say that inflation hedging is the proportional reduction in the variance of real returns. This being said, taking into account that real returns are excess returns compared to the nominal interest rate and since the variance of stocks and cryptocurrencies is high compared to other investment opportunities, risky assets such as these might not fulfil this definition of inflation hedging (Reilly et al., 1970)

The third one is the most common definition and is used mostly for studies as the main assumption. This assumption is followed by Fama and Macbeth (1974). This applies to stocks and risky assets, and it represents an inflation hedge if the real asset returns are completely independent of the rate of inflation.

One main theory on which this paper is based on, is the Fisher Effect. A very commonly recognized theory is the Fisher theory, which presented a hypothesis about the relationship between asset prices and inflation. The equation that he developed consisted of: nominal interest rate = expected real return + expected interest rate (Fisher, 1930).

The Fisher equation states that the real rate of interest is equal to the difference between the nominal rate of interest and the expected rate of inflation (Fisher, 1930). It is also stated, that if the efficiency of the market is high, the price of an asset will be influenced by the nominal return expectations and the inflation expectations. These conclusions from Fisher are the basic theory for this research paper and also the framework used by Fama and Schwert to later create an empirical test of inflation hedging (Fama and Schwert, 1977). It is accepted that when the Fisher hypothesis holds, the asset functions well as an inflation hedge (Spierdijk, 2013).

The Fama and Schwert regression model, referring to the adaptation of the Fisher hypothesis into an empirical test, is a broadly accepted measure for inflation hedging capabilities in research. This is helpful since it allows to statistically analyze the data with a regression model. A benefit of using the adaptation of Fama and Schwert is the possibility to differentiate between unexpected and expected inflation for further understanding of the hedging properties of the assets. The Regression model creates two regression coefficients ß1 and ß2, which when they are statistically identical to 1, the inflation hedging capabilities can be confirmed respectively for both expected and unexpected inflation. Further explanation about the regression model and coefficients is found later, in section 4.

In fact, a negative relationship was found in 1981, when Fama stated that the relationship between stock prices and inflation was possibly caused by a real factor, implying that the relationship was not direct. This means that the negative relationship could be a result of the inflation, which then leads to lower economic output, which in the end influences the stock prices (Fama, 1981). As stated by Cochran and Defina (1993), this statement has been both supported and rejected in several research. It was found that inflation has a time-limited negative effect on stock prices and inflation is not able to predict changes in the economic output alone, therefore supporting Fama´s hypothesis that economic output is directly related to real economic factors such as productivity (Cochran and Defina, 1993)

On the other hand, Bodie (1976) concluded that stocks were negatively correlated with both expected and unexpected inflation and that as per the theory, stocks should be shorted for inflation hedging

2.2 Cryptocurrencies

Cryptocurrencies have been a topic of research in past years, as blockchain technology has become more popular and relevant to the mainstream public. The functioning and nature of blockchains have been researched. Bolt and Ooordt (2016) and Kristoufek (2015) have analyzed the economics of bitcoin. Different cryptocurrencies have differences among them, e.g.: underlying technology, proposal, and use case. In the cryptocurrency environment, one could argue that the intended and actual use case can be seen as the "business models" of the different cryptocurrencies (White, 2014) The deflationary nature of the tokens and the limited supply design of the Bitcoin technology has also been analyzed(Foley et al., 2018).

Bitcoin is designed in a decentralized way, that no governmental body needs or can control the network. Moreover, with the limited maximum supply of 21 million BTC, this cryptocurrency is not subject to inflationary development as fiat currencies do (Van Alstyne, 2014).

In present times, central banks might inject more money into the supply, which is not possible with BTC. Moreover, Bitcoin works via a "proof-of-work" system, which means that "miners" have to solve complicated mathematical problems with help of computing power and are rewarded some BTC for it. The "halving is an event, where these block rewards are cut in half each four years approximately. Bitcoin supply has also been compared to the rate at which gold is being mined. This shows the comparison that BTC is a finite good, which's rate of supply growth declines over time in the long term (Struga and Qirici, 2018).

Trimborn and Härdle (2018) developed a cryptocurrency index called CRIX. It was found that BTC was the dominating currency/coin, but is not able to direct the market completely, as returns from different cryptocurrencies were not found to be correlated to each other (Elendner et al., 2017). Since the cryptocurrency environment is highly dynamic, an index trying to represent the ecosystem needs to be dynamic as well, to react to the changes in the market, as many projects are born and others stop existing. This index can and has been used in order to research the cryptocurrency market returns. (Trimborn and Härdle, 2018)

It is worth mentioning that research has shown that cryptocurrency adoption is not faster in developing countries or less developed countries. Bhimani et al. found that there was a positive relationship between cryptocurrency adoption and several development measurements, such as the HDI, the level of democracy and the GDP(Bhimani et al., 2022).

2.3 Inflation hedging with cryptocurrencies

Regarding inflation and inflation hedges, several questions with different quantitative analyses have been done. Over time, different measures for inflation hedging have been presented. Assets that have been analyzed include Commodities, stocks, forestry investments, real estate, bonds, and T-bills (Spierdijk, 2015). Cryptocurrencies have been analyzed as well but not to such an extent as other asset classes.

There is still not much research done on cryptocurrencies as inflation hedges, partly as a result that there is also not a very long time frame of available data still. There is more focus on conventional hedges for inflation, though some research has been done regarding alternative investments as well.

The effectiveness of cryptocurrencies as inflation hedges has not been widely recognized or proven. Nevertheless, some research has been done into BTC, both statistical analysis and also research on Bitcoin´s nature and technological design. A time-series model for the relation between cryptocurrency prices and forward inflation expectations was developed to analyze the relationship. The analysis which consisted of Bitcoin and Ethereum found no statistical evidence for inflation hedging properties (Conlon et al., 2021). Choi developed a vector autoregression model to test the inflation hedging capacity of Bitcoin, finding that It could function as an inflation hedge since BTC appreciated in value in the long term against inflation. Nevertheless, major differences were found, since BTC valuation decreased in periods of economic uncertainty, making it not such a "safe-heaven" as believed (Choi and Shin, 2021). A CNN-based multivariate data analysis for bitcoin trend prediction was also developed, where this predictive model for bitcoin was successful in improving returns in positive trends and minimizing losses while negative trends (Cavalli and Amoretti, 2021).

Moreover, further research needs to be done, if cryptocurrencies are good hedges for individuals in countries with very high inflation rates, where stocks and other alternatives may not be that efficient. In general, cryptocurrencies are bought using US dollars, but this paper will also focus on other countries' inflation rates as well as the US inflation.

3. RESEARCH OBJECTIVE / HYPOTHESIS

3.1 Research question

Can the cryptocurrency asset class work as an effective inflation hedge, especially in countries experiencing high inflation rates?

3.2 Research objective

The research objective is to answer the research question of whether the asset class of cryptocurrencies can act as an inflation hedge, especially for individuals in countries experiencing high inflation rates. The focus lies on individual investors as the regulations regarding alternative assets are less complicated and they are subject to fewer restrictions. Institutional investors may be prevented from investing in these assets directly and would need to wait for the regulatory framework to be more favourable for them. Moreover, individual investors do not have the knowledge and access to more complex investment vehicles. This leads to individuals to continuously lose their purchasing power and makes it impossible for normal citizens to be able to save capital for later consumption. This leads to immediate consumption of goods that are needed and the search for a safe refugee for the remaining capital.

3.3 Hypothesis

The hypothesis is that cryptocurrencies are effective inflation hedging instruments, and to a greater extent in countries experiencing high inflation rates. In order for this hypothesis to be confirmed, the regression coefficients ß1 and ß2 of the Fama and Schwert regression must be statistically indistinguishable from 1.

4. METHODOLOGY

In this paper, the main measure for inflation hedging will be the Fisher hypothesis presented in his book "Theory of interest" of 1930. As stated in the literature review, the Fisher hypothesis shows a hypothetical relationship between asset prices and inflation expectations. Moreover, the adaption of Fisher's hypothesis in an empirical test will be used (Fama and Schwert, 1977). A substantial part of the literature on inflation hedging states a good inflation hedge is an asset for which the Fisher hypothesis holds (Spierdijk, 2015). The paper consists of one regression model for the approximation of expected inflation and the Fama and Schwert regression model then, both followed by a statistical test on the regression coefficients.

Also with the help of descriptive statistics, some insights into the characteristics of cryptocurrencies will be analyzed. For the analysis part, the test will be realized with the help of SPSS analytics software.

4.1 Fama and Schwert regression model

The Fama and Schwert regression differentiates for expected and unexpected inflation, which means that this test will show if the cryptocurrency asset class can work as a hedge for any type of inflation. Moreover, the Fama and Schwert regression is considered to be a standard test for inflation hedging in the literature, which is widely accepted and used to analyze the hedging characteristics of various types of assets.

4.1.1 Expected and unexpected inflation

Since the Fama and Schwert regression allows for differentiation between expected and unexpected inflation, one must obtain a proxy for the expected inflation for time t. Research has been done as well using the assumption that inflation expectations are perfect, this meaning that unexpected inflation was not existent. The other possibility that one can apply is a model by Hamelink and Hoesli (1996). To obtain the expected inflation rate, Hamelink and Hoesli used a linear function of the rate at time t-1 for the expectations of the rate at time t. (Hamelink and Hoesli, 1996). With this approximation for the expected inflation rate, one can then calculate the unexpected inflation rate, this being the difference between the actual inflation at time t and the expected inflation. The linear regression equation consists of:

(F1) $$\pi_t = \alpha + \beta(\pi_{t-1)+} \varepsilon_t$$

Where:

π_t:	inflation rate at time t
α:	regression Constant
β:	regression Coefficient
$\pi_{(t-1)}$:	inflation rate at time t-1
ε_t:	error term

For the inference of the expected inflation, there are assumptions for linear regressions. These are: Linearity, Homoscedasticity, Independence, and Normality.

Linearity means that the data seems to change at the same rate, which can be checked by a Scatterplot to see if the data is linear. Homoscedasticity is the assumption that the error terms of the model are the same across the data. In order to check for that, then a scatterplot (P-P plot) with the residuals can be used as well. One can then check if the residuals are acceptable or if the data both fulfils the linearity and homoscedasticity assumptions.

The assumption of independence is also fulfilled in this case. Using the Chi-square tests for respectively the inflation and lagged inflation variables. In all cases, the p-value was not at an acceptable level of <0.05, which means that the assumption of independence is fulfilled.

Normality is the assumption that the data is normally distributed. This is when the e.g. returns residuals are plotted in a distribution graph and the data has a kind of bell-shaped graph. One can also test this by the Shapiro-Wilk Test. If the Sig. result of the Shapiro-Wilk test is over 0.05, then the data can be considered normal. Nevertheless, the normality assumption is not needed always for linear regression, if one assumed that the model is correct one wants to estimate the regression coefficients. It is important to mention that one has to test the residuals for normality and not the raw data.

Table 1 shows the results for the normality testing of the residuals, utilizing both the Shapiro-Wilk Test and the Kolmogorov-Smirnov test. Usually, the Shapiro-Wilk is the standard testing method, but since the SPSS software presents both the Kolmogorov-Smirnov test will also be shown.

Table 1: Test of Normality

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Stat.	df	Sig.	Stat.	df	Sig.
INF_USA	.378	49	<.001	.656	49	<.001
INF_EU	.392	49	<.001	.324	49	<.001
INF_TR	.411	49	<.001	.328	49	<.001
INF_AR	.173	49	<.001	.953	49	.050

Since the values for Sigma for the Shapiro-Wilk test are not over 0.05, one can reject the hypothesis that they are all normally distributed. This being said, inflation and return data are in reality not normally distributed at all.

With the results from the previous regression for the approximation of expected inflation, one then has all the data required for the Fama and Schwert regression. In order to get the expected inflation data, one can use the Casewise diagnostics of the regression. The residual should be equal to the unexpected inflation since this is the difference between the actual inflation and the predicted value/expectation.

4.1.2 Fama and Schwert regression

This regression model is the backbone of the analysis and it consists of:

(F2) $$r_{it} = \alpha_i + \beta_1 \pi_{it}^{exp} + \beta_2\left(\pi_{it} - \pi_{it}^{exp}\right) + \varepsilon_{it}$$

Where:

r_{it} :	nominal return of Index/Asset i at time t
π_{it}^{exp}:	expected inflation rate
π_{it}:	inflation rate
α_i:	time-constant term
ε_{it}:	error term

This is the main regression that is used in this analysis and the one that yields the final results that constitute the inflation hedging properties.

In this regression, π_{it}^{exp} stands for the expected inflation rate which one calculated, as stated in 4.1.1. In this case, ß1 is the regression coefficient related to the expected inflation rate. On the other hand, ß2 is the coefficient related to the unexpected inflation rate, which consists of the terms inside the parenthesis: $(\pi_{it} - \pi_{it}^{exp})$. This represents the difference between the actual inflation rate at time t and the expected inflation for the same period.

The results relevant for the Fama and Schwert model are the regression coefficients β_1 and β_2. The asset is a hedge against expected inflation if $\beta_1 = 1$ and a hedge against unexpected inflation if $\beta_2 = 1$. If both $\beta_1 = \beta_2 = 1$, then the asset is a complete hedge against inflation. If the coefficients are 0, then no inflation hedging abilities are demonstrated by the asset.

As stated by Fama and Schwert, when the regression coefficient ß1 = 1, this is consistent with the hypothesis stating that the exp. nominal return on the asset varies together with the expected inflation rate. If ß1 = ß2 = 1, then the nominal return on the asset varies together with both expected and unexpected inflation rates. This means that the "ex-post real return on the asset is uncorrelated with the ex-post inflation rate" (Fama and Schwert, 1977)

It is worth mentioning that these coefficients might adopt a negative value, representing a "reverse hedge", which would imply a possibility to short/sell the assets in order to hedge against inflation. Evidence for this type of relationship has been found by Bodie when analysing the inflation hedging properties of common stock. (Bodie, 1976)The hypothesis tested in this paper states/ expects these regression coefficients to be ~ 1 and statistically relevant. In order to test this, statistical tests on the regression coefficients need to be done in order to be able to accept the reliability and fitting of the regression model.

4.1.3 *Gültekin: Inflation expectations perfect*

As the Fama and Schwert model differentiates between expected and unexpected inflation, the regression coefficients strongly depend on the approximation method and reliability. Since the approximation is done with the help of a linear regression, which can deliver results that are not perfect, one can test alternatively with the assumption that the inflation expectations are perfect. This assumption follows the opinion that inflation expectations are indeed the real inflation rates and therefore perfect. (Gültekin, 1983)

In this case, the basis is equivalent to the Fama and Schwert model, but simplified to a simple linear regression with only independent variable. The regression consists of:

(F3) $$r_{it} = \alpha_i + \beta(\pi_{it}) + \varepsilon_{it}$$

Where:

r_{it} :	nominal return of Index/Asset i at time t
π_{it}:	inflation rate
α_i:	time-constant term
ε_{it}:	error term

The regression includes only one regression coefficient ß, compared to the two coefficients found in the original Fama and Schwert regression. This is due to the fact that only one single inflation data is used, which is at the same time the actual inflation and also the expected inflation. Therefore in this case, the "unexpected inflation" is always zero.

This is a step taken also by Hamelink and Hoesli (1996) when studying the inflation hedging properties of real estate in Switzerland.

In order to have more comparable results, this will also be tested and contrasted to the results found with the original Fama and Schwert regression. Due to the fact that approximating the expected/unexpected inflation is not necessary with this approach, the relationship between asset returns and inflation could become more clear.

5. DATA

The data used in this analysis consists of cryptocurrency returns, exchange rates and inflation rates (%MoM). The analysis focuses on four different countries/regions, these being: USA, Eurozone, Turkey and Argentina.

The choice of countries was done in order to have several results that could be comparable. First of all, the USA is the most commonly researched country and therefore it was included in the analysis. This can help to compare results more easily with previous research or also help for further research.

Since the research was undertaken in the European Union, it was also wise to take it into account. To do this, the Eurozone data was used as a representation of the whole EU´s economy and inflation rates. It also makes sense if one takes into account that all these countries in the Eurozone share the same currency, the Euro.

When considering other countries, to bring some variation into the analysis, countries from other continents are chosen. Turkey has experienced high inflation rates in the last years and therefore was interesting to adopt into the analysis. Argentina experiences something similar, with high rates of inflation for already long periods of time. In both of these countries, cryptocurrencies are actively used to try and hedge individuals´ wealth from erosion caused by inflation.

Several advantages of cryptocurrencies include not being under the control of a central government, thus being mostly decentralized (Moreno, C., 2016) Moreover, it is an opportunity for people who did not have an access to financial services, since every individual is able to access such networks with only internet connection.

The exchange rates for the computation of returns in these currencies were the official exchange rates, with exception of Argentina, where an "unofficial" exchange rate was chosen, as this is the one accessible to individuals in the country. More is explained under 5.1.1. The data sample is on a monthly measure basis and consists of 50 observations between March 2018 and March 2022.

5.1 Cryptocurrency

As for usual research, stock indexes are the standard type of data taken for such research papers, I will also use the CRIX, a cryptocurrency index developed by Trimmborn and Härdle. This is an index which is not rigid, meaning that the index can contain different cryptocurrencies depending on the dynamics of the market, as the model uses weights for dominance in the ecosystem and also based on trading volume, which might indicate some trends. Since the transaction costs of the crypto assets are very low, no considerable costs are associated with the rebalancing of the index (Trimborn, Simon & Härdle, Wolfgang Karl, 2018).

Monthly data starting from March 2018 will be used for the Royalton CRIX index. This is the earliest available data for this specific index. The official data will be taken from the S&P Down Jones Indices (SPDJI) Website.[1] Even though the data is only available from 2018, this index is preferable compared to other indices computed in a more simple way and with less accuracy.

5.1.1 *Cryptocurrency return in foreign currency*

The return data from the CRIX index is in USD, so in order to compare it in each of the local countries, the return will have to be converted to local currency. For the ease of the analysis, the assumption is going to be made, that these individual investors in these countries have access to USD and first seek to change their local currency into USD and then with Dollars buy assets.

This means that for the returns of Argentina, Eurozone and Turkey, computation of returns in local currency will be done – on monthly basis, the same frequency as the returns observations used. This creates theoretical complications since in Argentina there are many different exchange rates, both official and

[1] https://www.spglobal.com/spdji/en/custom-indices/royalton-partners-ag-rpag/royalton-crix-crypto-index/#overview

unofficial, which are part of the daily hustle of these people to escape from inflation. Two of those exchange rates are interesting for this study, the “Dolar Blue” and the “Dolar MEP”, the first one being the unofficial exchange rates available to the inhabitants and the second one being the exchange rate used by investors to purchase Dollars without restrictions (Lanier and Brunson 2014). The ”Dolar MEP” exchange is a result of buying a bond with Argentinian pesos and selling it in USD. Both of these exchange rates are virtually the same, as if one was comparably favourable every individual would exchange their local currency that way. As a basic assumption for the calculation, the “Dolar Blue” and the “Dolar MEP” will be the same.

As stated before, this research is focused on private investors and not institutional or professional investors, since they might have to comply with regulations regarding alternative assets such as bitcoin. This being said, for the exchange rates of Argentina, the “Dolar Blue” is going to be used as the standard, since that is indeed the rate that local inhabitants look at the most. Historical data for the “Dolar Blue” is impossible to find from an official source and for that reason, this data will be retrieved from ambito.com [2], the most well-known financial newspaper in Argentina.

5.2 Inflation

Four different inflation rates will be used for this analysis. The countries/areas chosen are: the USA, EU zone, Argentina and Turkey. The higher inflation rates of countries such as Turkey and Argentina make it interesting to analyze such countries as well as the most common ones, which are the USA and the Eurozone. The same as for the cryptocurrency returns, the inflation rate will be calculated at a monthly simple rate of return.

5.2.1 USA

For inflation data in the USA All Urban Consumer Price Index (CPI) from the US Bureau of Labor Statistics will be used. This is one of the most used inflation measures and is usually the basis for research. The data is also reliable from Refinitiv Eikon, In the time frame from March 20218 and March 2022, the biggest decrease registered (%MoM) in inflation was of -0.67% and the highest positive change of 1.34%.

5.2.2 Eurozone

For the inflation data from the Eurozone, the Harmonized Index of Consumer Prices all items (HICP) will be used. This is the standard measure for consumer prices inflation. In the time frame from March 20218 and March 2022, the highest decrease registered (%MoM) in inflation was of -1.04% and the highest positive change of 2.43%. The inflation data for the Eurozone was also taken from Refinitiv Eikon.

5.2.3 Turkey

In Turkey, the HICP is the standard measure for inflation. This data will be taken from Refinitiv Eikon. In the time frame from March 20218 and March 2022, the maximum registered (%MoM) decrease in inflation was of -1.44% and the highest positive change of 13.58%.

5.2.4 Argentina

The standard measure for inflation in Argentina is the IPC, (Spanish for CPI). This will be retrieved for the periods between March 2018 and March 2022. In the time frame from March 20218 and March 2022, the minimum registered (%MoM) change in inflation was of 1.40% and the biggest positive change of 6.60%.

2 https://www.ambito.com/contenidos/dolar-informal-historico.html

5.3 Descriptive statistics

5.3.1 Cryptocurrency returns

Table 2 depicts the results for the descriptive statistics for the monthly CRIX returns in the different currencies.

When analyzing the returns in different currencies, one can observe some differences between these. The mean for USD and EUR are very similar to each other. The mean monthly return in USD and EUR is of respectively 5.79 and 5.95 %. The standard deviation of USD and EUR are also almost equal with respectively 24.55% and 24.36%.

Table 2: Descriptive Statistics CRIX

Var.	N	Min	Max	Mean	SD	Skewness		Kurtosis	
		Stat.	Stat.	Stat.	Stat.	Stat.	Std. Error	Stat.	Std. Error
Ret_US	49	-38.29%	60.50%	5.79%	24.55%	.359	.340	- .717	.668
Ret_EU	49	-38.32%	63.74%	5.95%	24.36%	.390	.340	- .553	.668
Ret_TR	49	-42.42%	64.82%	8.89%	25.45%	.163	.340	- .845	.668
Ret_AR	49	-35.61%	91.08%	10.96%	26.54%	.618	.340	.374	.668

When talking about returns in Turkish Lira and Arg. Pesos, one can see that the statistical mean is much higher than those of the more stable currencies. The mean monthly return in Turkish Lira was of 8.89% and the mean return in Argentinian Pesos was of more than 10.9%. Nevertheless, the Standard deviation is only marginally higher in these last two cases compared to the SD in USD or EUR.

When taking Skewness into account, one can see that the returns in this case are more or less symmetrical, maybe with the exception of the returns in pesos, where Skewness has a value of > 0.5. This being said, all variables have values for Skewness and Kurtosis of less than 1, which indicates that the distribution is not outside the normal range. It is indeed worth mentioning that stock or asset returns are not normally distributed in most cases, so these results are somewhat surprising.

Figure 1.

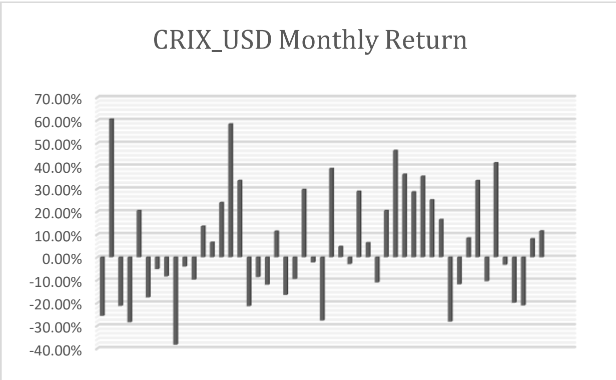


Figure 1 shows the CRIX Index monthly returns in USD. Only the USD chart is being shown here since the visualization of the data when including the returns in the foreign currencies is very poor. When comparing the USD returns to the foreign currencies, one can state that the variability of the monthly returns is more extreme, in the cases of Turkey and Argentina especially.

Nevertheless, even though only the USD returns are shown in Figure 1, the graph helps to visualize the high variability of monthly returns of the cryptocurrency asset class itself and provides a more visual representation of the volatility investors should expect.

5.3.2 Inflation rates (MoM)

Table 3 shows the results of the descriptive statistics for the inflation rate data. It is important to remember that this data is based on "Month on Month" inflation rates.

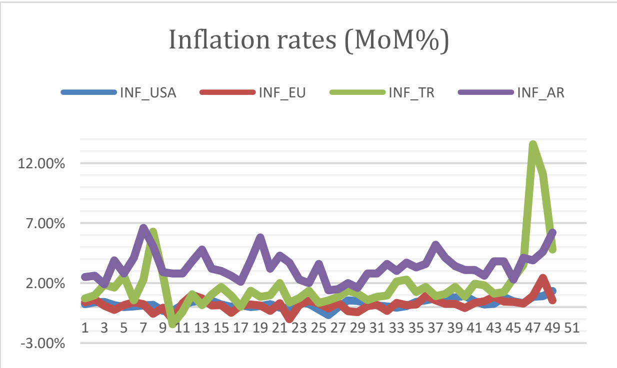
When analyzing the Inflation rates in these different countries, one can quickly differentiate between the two more stable currencies (USD; EUR) from the more unstable (TRY; ARS). The mean of the stable currencies is between .23% and .29%, whereas the mean for Turkey lies at 1.8% and for Argentina at 3.38%. This is quite interesting, since the % inflation rate used in this analysis is on a monthly basis. One can therefore state that the inflation in Argentina on a monthly basis since March 2018 has been at a mean of 3.3%, which is similar to the yearly inflation rates of other countries in this analysis such as the USA or the Eurozone.

Table 3: Descriptive Statistics Inflation Rate

	N	Min	Max	Mean	SD	Skewness		Kurtosis	
		Stat.	Stat.	Stat.	Stat.	Stat.	Std. Error	Stat.	Std. Error
INF_US	49	- .67%	1.34%	.295%	.371%	.237	.340	-0.735	.668
INF_EU	49	-1.04%	2.45%	.23%	.541%	.918	.340	5.291	.668
INF_TR	49	-1.44%	13.58%	1.849%	2.511%	3.351	.340	12.795	.668
INF_AR	49	1.40%	6,60%	3.38%	1.151%	.728	.340	0.693	.668

The skewness of these results is somewhat surprising, nevertheless also understandable since Turkey´s inflation data is very irregular which leads to turkey´s inflation rate being highly skewed, with a skewness coefficient of more than 3. Such high coefficients show that the distribution is skewed to the right. This means that the mean of 1.84% lies well above the median of 1.13%, which is probably caused by extreme high outliers.

Figure 2



In Figure 2 all the inflation rates in a month-on-month percentage change of the 4 countries/regions. One can see that the inflation rates in the Eurozone and the USA are quite similar, with almost the same behaviour.

The Argentinian inflation rate on a monthly bases is consistently higher than the ones from the other countries, with the exception of one observation, where turkey had a big outlier with 13.5% in a single month.

It is interesting mentioning that even though the inflation data are quite extreme, with a quite big standard deviation compared to the mean statistic, the inflation data is still relatively stable compared to the high volatility of the cryptocurrency returns.

6. RESULTS

6.1 Results for expected inflation approximation

In Table 4 the results for the expected inflation approximation are seen. The variables which include an "L" at the end are the lagged variables, with which the regression model is conducted for the approximation of the expected inflation, following Hamelink and Hoesli´s (1996) methodology. It is based on a simple regression model, using inflation data from time t-1. The total number of observations is 50.

Table 4 : Simple Regression Model: Expected Inflation inference

Variable	**INF_USA**	**Sig.**	**R Square**
Constant	.091	.083	.455
INF_USA_L	.737	< .001	
Variable	**INF_EUR**	**Sig.**	**R Square**
Constant	.158	.058	.094
INF_EUR_L	.300	.032	
Variable	**INF_TR**	**Sig.**	**R Square**
Constant	.729	.043	.388
INF_TR_L	.632	< .001	
Variable	**INF_AR**	**Sig.**	**R Square**
Constant	1.867	< .001	.185
INF_AR_L	.458	.002	

The regression model was done for the approximation of the expected and the calculation of the unexpected inflation rates. In this case, we can see all regression coefficients are positive, which indicates that if inflation rises in a month, the probability is high that it rises in the next month as well. The highest coefficient was the USA coefficient, followed then by the Turkish, then the Argentinian and European. In all these cases, the p values were < 0.05, resulting in the conclusion that these results are statistically significant.

The highest coefficient being 0.737 for the inflation approximation for the USA is surprising since the data did not seem to indicate that increases in the inflation rate would contribute to further increases in the next month.

6.2 Results Fama and Schwert regression

The next table shows the results of the four regression models for each of the relations between the inflation rate and the rate of return.

Table 5: Linear Regression Model (Fama and Schwert)

	Ret_US		**Ret_EUR**		**Ret_TR**		**Ret_AR**	
	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.
Const.	6.346	.256	3.904	.524	11.377	.053	12.690	.631
Exp. Inf.	-1.855	.897	8.884	.681	-1.346	.570	-.5110	.947
Un. Inf.	12.464	.338	4.423	.527	-1.336	.480	-6.022	.107
R Square	.020		.012		.017		.056	

Because of the significance, which in all of the observed cases the p-value is not < 0.05, one cannot say that the regression coefficients are statistically different from zero.

The highest significance is the one of ß2 for Argentina, with a p-value of ~0.1 for the variable Ret_AR. Still are these results not convincing.

On the other hand, when ignoring the significance and looking only at the coefficients ß1 and ß2, one can see that for Turkey and Argentina, these coefficients are negative. These 2 countries were the ones from the analysis with the highest inflation rates and also the highest volatility in these inflation rates.

For the Eurozone, both ß1 and ß2, respectively for expected and unexpected inflation, were positive, which would indicate the viability of cryptocurrencies as inflation hedges.

All these results are not significant, as mentioned before, and are therefore not statistically different from zero. This means that the hypothesis that Cryptocurrencies can be used as an inflation hedge can not be confirmed.

6.3 Results Assumption of perfect expectation

The next table shows the results of the regression model for each of the inflation rates respectively with the returns of the cryptocurrency index. Important to remember that in this case, the assumption of perfect inflation expectations was made, which makes a differentiation between expected and unexpected impossible, thus actual inflation being the only independent variable.

Table 6: Linear Regression Perfect Expectation Assumption

	Ret_US		Ret_EU		Ret_TR		Ret_AR	
	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.
Const.	4.011	.380	4.835	.219	11.366	.016	22.888	.021
Inf.	6.048	.531	4.844	.462	-1.339	.365	-5.003	.134
R Square	.008		.012		.017		.047	

In this case, for the US and the Eurozone, the coefficients are both positive, but with respectively a Sig. of 0.531 and 0.462 still statistically insignificant.

For Turkey, the regression coefficient is -1.339 and for Argentina, the coefficient is -5.003. Remarkably both these coefficients are negative. Nevertheless, as in all other cases, the significance is not at an acceptable level of $p<0.05$.

6.4 Estimates with robust standard error

Tables 7 and 8 show the parameter estimates with robust standard errors for both the Fama and Schwert regression model and for the regression with perfect expectations assumptions.

When utilizing a regression model, the data might infringe the assumption of homoskedasticity. When the data is heteroskedastic, the standard errors are not constant, and the reliability of the regression model decreases.

Table 7: Parameter Estimates with Robust St. Errors*
(Fama and Schwert Regression)

	Ret_US		Ret_EUR		Ret_TR		Ret_AR	
	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.
Const.	6.346	.235	3.904	.513	11.377	.065	12.690	.642
Exp. Inf.	-1.855	.879	8.884	.639	-1.346	.638	-.511	.950
Un. Inf.	12.646	.426	4.423	.381	-1.336	.603	-6.022	.158

*HC3 Method

With the help of the Parameter Estimates with standard errors, one is able to get results which are robust against the heteroskedasticity of the data. . In theory, the data used in this paper does is not heteroskedastic, which should translate into similar estimates, even with robust standard errors This being said, it is nevertheless still interesting to include these coefficients.

Table 7 shows the Parameter Estimates for the standard Fama and Schwert regression. These results are comparable with the results shown in Table 5. The coefficients are indeed exactly the same, being the p-value the only thing that changes. This being said, the p-values are minimally different, still all being not significant at a p-value < 0.05.

The same thing happens in Table 8., where the results are very similar to the ones in Table 6. Since there is not much difference between the coefficients, and still are not significant, one can state that heteroskedasticity is not the main concern in the data used for this research.

Table 8: Parameter Estimates with Robust St. Errors*
(Perfect Expectation Assumption)

	Ret_US		Ret_EUR		Ret_TR		Ret_AR	
	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.
Const.	4.011	.457	4.835	.186	11.366	.015	27.888	.043
Inf.	6.048	.580	4.844	.310	-1.339	.350	-5.003	.141

*HC3 Method

The HC3 method is a calculation for the standard error and its robust coefficients. It is said that HC3 should be used when the sample size of the research is smaller than 250, which is the case in this paper. Moreover, it is also concluded that the HC3 method is better functioning, compared to others, when the data is "affected by heteroskedasticity" (Long & Ervin, 2000).

In this case, the HC3 method was the best-fitting model to test the estimates with the robust standard errors. This being said, it is good to include estimates with robust standard errors to further test the regression model.

7. DISCUSSION

The results for the regression coefficients were in all cases not significant as stated, this leads to the conclusion that the regression model did not fit the data appropriately.

There may have been different reasons for this result. The first one could be a relatively small sample size, but this should not be the main problem in this case.

More plausible seems to be that there is in reality no relationship (at least linear) between cryptocurrency returns and inflation rates. It is worth mentioning that both expected and unexpected inflation yielded the same results in the regression model.

When comparing the results from the Fama and Schwert regression (Table 5) with the results of the regression with the assumption of perfect expectations (Table 6), one can see that the results are not very different. In most cases the regression coefficients have the same symbol before (+/-).

It is worth mentioning that the coefficients of the perfect expectations regression (Table 6) are very similar to the coefficients in the Fama and Schwert regression for the unexpected inflation. This is interesting to see, since the assumptions were different, the inflation expectation being perfect, thus the real inflation being the expectation. The similar results seem to indicate that even without the unexpected factor, the utility as cryptocurrencies as inflation hedges can not be confirmed.

It is worth comparing all the countries in this research. There are two main groups, one being the USA and the Eurozone together and the other Turkey and Argentina.

As stated before, the coefficients for USA and Eurozone are all positive but one. This means that for these countries there is the possibility that cryptocurrencies actually act as an inflation hedge.

On the other hand, there is Turkey and Argentina, where the results show completely the opposite functioning of cryptocurrencies. These two countries are both the ones with the highest inflation rates from the country sample, and might therefore yield different results. When ignoring the significance, in this case, the negative symbol could represent a reverse hedge, meaning that the cryptocurrencies must be shorted in order for them to act as inflation hedges. This is interesting since the same assets are showing different behaviours, depending on the evolution of the inflation rates. Nevertheless, this does not have a statistical significance with which one can state any hedging capabilities.

The R-squared of all the regression models is very low, also in both cases with different assumptions. The R-squared of the models lies between 0.008 in the worst case, and 0.056 in the best one. This means that in the best case, 5.6% of the variability in the return data is explained by the regression model.

Nevertheless, as all these results are not complying with the significance level of p-value < 0.05, nor p-value < 0.1, one can reject the hypothesis that these cryptocurrencies can act as inflation hedges.

7.1 Theoretical implication

This case of no significant results has similarities with the results found by Hofmann and Mathis (2016), while studying the inflation hedging abilities of REIT investments in Switzerland, where the inflation hedging properties of these REITS can not be proved, as a result of poor significance. (Hofmann and Mathis

Similar results were found by Hamelink and Hoesli (1996), who found a positive relation for stocks, bonds and real estate with inflation rates, but the significance of the results were non-existent. The hypothesis that assets need a certain time to adapt to "inflation shocks" could give some insight into why these relationships are not clear in this research as well. It is worth mentioning that Hamelink and Hoesli´s research was conducted with data on a yearly basis, which did not yield good results either.

7.2 Practical implication

The practical application of cryptocurrencies as inflation hedges is not as simple as displayed in theory. In reality, the extreme volatility of the asset class makes the variability of returns too high, for investors to reliably implement cryptocurrencies as hedges. With max drawdowns of more than -30% in a single month, wiping out 1/3 of the asset value, risk-averse investors should not consider the cryptocurrency asset class. This might indeed change when more data is available and the time frame for the analyses is longer. Long-term trends might be identified and can be used for practical implementation. In the real-world implementation, the already mentioned volatility is too extreme.

7.3 Limitations and further research

The main problem in this research paper would be the data limitations. Not only due to the restricted amount of data, but also the quality of the data.

The short time frame for the analysis is one constraint. The short time since the creation of indexes for cryptocurrencies and the asset class itself makes the analysis more difficult than if more data would be available. With more data, some segmentation would be possible to maybe recognize other trends.

The cryptocurrency returns are highly volatile, even when taking a look at a cryptocurrency index, where one could expect less variability. These fluctuations in price are in comparison to the fluctuations in the inflation rate enormous, which also handicaps the implementation of crypto assets as inflation hedges.

With inflation in both Europe and the USA at very high levels, compared to the last 40 years, the need for further research on possible inflation hedging properties of other alternative assets must possibly be intensified. Alternative investments as collectables, alcohol or LEGO, and also investments in renewable energy might be of interest.

Due to the not long existence of this asset class, and still ongoing mainstream adoption, the cryptocurrency asset class might evolve differently than it has until now. This being said, longer time frames could yield different results, since the behaviour of cryptocurrencies return might change and new patterns might be recognized.

One last recommendation for future research is to compare Bitcoin with the broad cryptocurrency market, and their inflation hedging properties respectively. Due to Bitcoin´s deflationary nature, it could make Bitcoin especially interesting in the long term. The design of Bitcoins network with block rewards decreasing each "halving", might make BTC act as a store of value (Baur, Dimpfl, 2021). This would also work better with a longer time frame, since the decrease of the block rewards happens approximately every 4 years, the first one happening in 2012.

7.4 Methodology discussion

There are other possibilities to test for inflation hedging, for example with the help of vector autoregression models (VAR) or also GARCH models. Both of these methodologies have been used in the literature in order to test for hedging properties.

In this case, one can discuss if a vector autoregression model had yielded better results. In the case of Choi (2016), the inflation hedging properties of BTC were tested via the VAR model. The relation between the cryptocurrency, inflation, and uncertainty was calculated. (Choi 2021)

GARCH models are similar, the acronym standing for Generalized Autoregressive Conditional Heteroskedasticity model. In the case of cryptocurrencies where the data might not be linear, and therefore not well-fitting with a regular simple regression, the GARCH model can be of help when analysing it.

One can therefore discuss if other methodologies would have been better fitting in this case, since the cryptocurrency data is very irregular and is difficult to explain through simple regression models.

8. CONCLUSION

In conclusion, one must reject the hypothesis that cryptocurrencies function as an inflation hedge. The results, which are all not significant and therefore not statistically different from zero, show that this asset class is not the most appropriate for inflation hedging.

The hypothesis also stated that the hedging abilities would remain intact or even improve in countries with higher inflation rates, which can also be rejected, as these show no better characteristics than in other countries.

The significance of the regression coefficients are all not relevant at a p-value < 0.05. Even when considering a higher acceptance level of p-value < 0.1, the results are still insignificant.

This theoretical answer must not reflect the practical implementation of CC as inflation hedges but is a good indicator of the difficulty. This being said, it is not possible to state that cryptocurrencies are good inflation hedges, at least not in the short term.

It is worth mentioning that the different assumptions tested did not influence the result positively, meaning that the regression coefficients were all insignificant. This was worth trying, as the regression without the proxy for expected/unexpected inflation was much simpler.

To further understand the capabilities of this asset class as inflation hedges, further research must be conducted. (See 7.3)

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