EXPLORING THE RELATIONSHIP BETWEEN BITCOIN AND INFLATION EXPECTATIONS: AN EMPIRICAL ANALYSIS

By

Ross H. Krakower

An Undergraduate Thesis Submitted as Part of the

WHARTON RESEARCH SCHOLARS

Faculty Advisor:

Shimon Kogan

Adjunct Associate Professor, Finance

THE WHARTON SCHOOL, UNIVERSITY OF PENNSYLVANIA

MAY 2023

ABSTRACT

This paper explores the relationship between Bitcoin and inflation expectations. More specifically, this paper seeks to understand how inflation expectations impact and move with Bitcoin prices and returns. As cryptocurrencies soared in both popularity and value over the last three years to become a mainstay in global macroeconomics, it remains important to understand how macroeconomic factors such as inflation expectations impact this asset class. Bitcoin is worth examining in particular because of all cryptocurrencies it has the greatest market capitalization and is also the most frequently traded. Using historical data on Bitcoin prices and relevant measures for inflation expectations, this study uses regression analyses and cointegration tests to explore the relationship between Bitcoin and inflation expectations. The regression analyses reveal that inflation expectations are a statistically significant predictor of Bitcoin prices. Cointegration tests reveal that inflation expectations and Bitcoin prices share a long-term equilibrium relationship, albeit one that is not relatively strong.

I. INTRODUCTION

The aim of this research is to explore how certain macroeconomic factors — namely inflation expectations — impact Bitcoin. The conceptual question at hand driving this research is: how do Bitcoin prices and returns move with changes in inflation expectations? It goes without saying that cryptocurrencies are no longer just a fad, but a major part of our global economy and a wildly popular investment vehicle. As evidenced by the roughly two trillion USD in value wiped from the cryptocurrency markets over the past year, investors — retail and institutional alike — have suffered *serious* financial losses. Additionally, Bitcoin has the largest market capitalization of all cryptocurrencies, and is also the most frequently traded crypto asset. Therefore, it is important to explore how our greater macroeconomic environment — moving from a low rate regime to an inflationary and rising rate system — has impacted the Bitcoin market as a whole. A clearer understanding of the macroeconomic factors impacting cryptocurrencies will better prepare and educate investors interested in this space. Additionally, many policymakers are unsure how to regulate these digital assets. Regulators are hampered because they do not know how cryptocurrencies function and how they are correlated with other investments or macroeconomic factors. The recent events in the cryptocurrency markets provide a valuable laboratory of data. Overall, a thorough investigation of how macroeconomic factors impact Bitcoin is *absolutely* necessary, as current literature does not thoroughly address this.

Relatively new, the cryptocurrency industry possesses a considerably small body of literature. Currently, the majority of macroeconomic literature regarding the impacts of interest rates, inflation expectations, and inflation rates covers the public equity markets. In fact, there is a thorough body of literature on that specific topic, which has greatly guided this research. As cryptocurrencies become increasingly popular, a deeper understanding of the macroeconomic factors, which impact their returns, is necessary to explore. The body of literature covering cryptocurrencies is rapidly evolving given increased interest and curiosity from investors and regulators. The emerging literature explores how coverage of macroeconomic news impacts cryptocurrency prices (Corbet et al., 2020), how cryptocurrency prices move with gold and oil prices (Teker et al., 2020), and how cryptocurrency trading volume impacts prices (Sovbetov, 2018), to name a few. This paper will inform both investors and regulators about the cryptocurrency space. It will be useful to investors — retail and institutional alike — since it aims to help them make more informed investment management decisions. Additionally, this paper will be useful to regulators because it will facilitate a deeper comprehension of the fiscal or monetary policy decisions influencing this asset class.

Given the explosive popularity and interest in the cryptocurrency space, further research must be conducted in order to deeper understand how macroeconomic factors impact Bitcoin prices and returns. The following sections in this paper provide background information on the cryptocurrency industry, a review of the relevant prior research driving this study, an explanation of the methodology, an explanation of the results and concluding remarks. To determine the impact inflation expectations have on cryptocurrencies, this research uses historical data of Bitcoin prices, global inflation forecasts from OECD participating nations, the S&P Global Developed Sovereign Bond Index and the S&P Global Developed Sovereign Inflation-Linked Bond Index. Regression analyses and cointegration tests run in R Studio will be used to determine the underlying relationship between these variables.

Through regression analyses, this study found that monthly and quarterly inflation expectations are statistically significant predictors of monthly and quarterly Bitcoin prices, respectively. Additionally, the analyses revealed that changes in monthly and quarterly inflation expectations are statistically significant predictors of Bitcoin prices. Further, regression analyses did not reveal any significant relationship between Bitcoin returns and inflation expectations. Unit root tests revealed that only monthly Bitcoin prices, quarterly Bitcoin prices, monthly inflation expectations, and quarterly inflation expectations were non-stationary. Cointegration tests require time series to be non-stationary. Through cointegration tests, this study found that monthly Bitcoin prices and monthly inflation expectations share a cointegrated relationship, though this relationship appears to be relatively weak. Also, cointegration tests revealed that quarterly Bitcoin prices and quarterly inflation expectations share a cointegrated relationship. The largest eigenvalue of this test indicates that the relationship between quarterly Bitcoin prices and quarterly inflation expectations is moderately strong. Overall, this paper will contribute to the current field of cryptocurrency literature because it will help both regulators and investors better understand the space, while adding to a significantly growing body of literature that is fairly new.

II. BACKGROUND

2.1 Background Section Introduction

The cryptocurrency space is a revolutionary movement within the Financial Technology (FinTech) industry. Cryptocurrencies have exploded in recent years, becoming an incredibly popular investment opportunity for both retail and institutional investors. Some examples of popular cryptocurrencies are Bitcoin, Ethereum, Litecoin, and Dogecoin, to name a few; though there are many more than just those. Notwithstanding industry setbacks such as the collapse of several prominent firms (Three Arrows Capital, Celsius, FTX, Genesis and more) and increased regulatory scrutiny, the global market capitalization of cryptocurrencies still exceeds $1 trillion USD, according to Yahoo Finance and Statista. Research to date regarding the macroeconomic factors that drive cryptocurrency prices is scarce. More specifically, scholars in the field of macroeconomics have not conducted enough research on the implications of macroeconomic factors (such as interest rates and inflation rates and expectations) for cryptocurrency prices. The majority of research conducted on the impact of interest rates, inflation expectations, inflation rates has focused on the public equity markets. The common barometers for interest rate measurement are treasury bills or the federal funds target rate. For inflation, the rate is most usually expressed using the Consumer Price Index (CPI), which is a measurement of the weighted average of the most common goods and services purchased by consumers. Changing rates are of significant importance because they not only influence the investment decisions of both institutional and individual investors, but have pricing implications for investable assets. Further, the implications of interest rates, inflation rates, and inflation expectations on the pricing of cryptocurrency is very important as more and more investors — both institutional and retail alike — enter this space. This review suggests that inflation rates, inflation expectations, and interest rates have significant implications for publicly traded stocks, but that more research is needed on their implications for cryptocurrencies.

2.2 Methods

In the field of macroeconomics, a main topic of research is how macro factors such as interest rates, inflation expectations, and inflation rates impact the value of an asset. The majority of research has focused on the impact these factors have on the returns of publicly traded equities. For example, one study was conducted using ten years of monthly returns from the Karachi Stock Exchange (KSE) 100 Index, interest rates for 6-month treasury bills, and CPI reports for inflation (Khan et al., 2012). In a multiple regression conducted by the researchers, the KSE 100 Index returns was the dependent variable, whereas inflation, measured via CPI, and interest rates, measured via the rate of 6-month T-bills, were the independent variables (Khan et al., 2012). Another study used data spanning from 1988 to 2003 to demonstrate the empirical relationship between stock returns and interest rates for 15 developed and developing countries (Alam et al., 2009). These researchers used both time series and panel regressions to explore the relationship between stock returns and interest rates, and changes in stock returns and changes in interest rates (Alam et al., 2009). Another study used statistical tools such as cointegration regression, linearity, and granger causality tests (Eldomiaty, et al., 2019). Researchers conducted their studies using the returns of the DJIA30 and NASDAQ1000 indices as the dependent variable, and quarterly data on United States (US) inflation and T-bills was used as the independent variables (Eldomiaty, et al., 2019). One study sought to explore the relationship between unexpected changes in the federal funds target rate and stock prices, using an exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model (Lobo, 2002). Scholars have explored the relationship between inflation rates, interest rates, and stock returns — how these macroeconomic variables impact equity returns over a period of time — because the implications are significant for all types of investors.

2.3 Macroeconomic Impact of Inflation Rates, Inflation Expectations, & Interest Rates

Inflation — commonly demonstrated via the CPI — is a measurement of either how general prices are increasing or the purchasing power of a dollar decreases. The impact of inflation as a macroeconomic variable has been the subject of extensive research. More specifically, many have studied the effects of inflation on stock prices. For example, one study argued that the relationship between inflation and stock prices is negative: increasing inflation corresponds to decreases in stock prices (Fama, 1981). Furthermore Fama (1981) argued that this relationship is a reflection of stagflation, that the negative correlation between inflation rates and real gross domestic product (GDP) can explain the negative correlation between inflation rates and stock returns. Another study — taking into account both supply and demand of stocks — argued that inflation negatively impacts stock prices and returns (Quayes, 2008). One study, which sought to determine how macroeconomic information impacts stock prices, found that there was no evidence against the expected inflation hypothesis (Hardouvelis, 1987). Hardouvelis (1987) wrote that the expected inflation hypothesis “claims that stock prices decrease because the inflation premium in nominal interest rates increases, which decreases the after tax real dividends.” Another study, which examined the Athen Stock Exchange (ASE) Index, sought to explore how inflation impacted stock returns over a period spanning from 1988-1999 (Apergis et al., 2001). This study argued that in the case of the ASE Index, stock prices are negatively correlated with movements in inflation — as measured by the CPI — and that a reduction in economic inflation will significantly increase stock prices (Apergis et al., 2001). Finally, Feldstein (1983) argued that there is a significant difference between the impact a high, yet constant inflation rate has on stock prices and the impact increases in future expected inflation rates has on stock prices. For example, the study argued that while share prices are increasing proportionally with high constant inflation rates, increases in the expectation of future inflation rates causes a decrease in the price to earnings ratio of public stocks (Feldstein, 1987). Overall, across the field of macroeconomics, scholars have widely agreed that the rate of inflation has a relationship, usually negative, with stock returns.

An interest rate is the cost a borrower pays to the lender each period, as a percentage of the overall principal. Interest rates are one of the most important macroeconomic variables as they affect borrowing costs and the returns on savings and many other investments. The impact of interest rates as a macroeconomic variable has been the subject of extensive research. Most commonly, the research to date has focused on the impact interest rates have on stock prices or returns. For example, the study exploring the impact of interest rates in 15 developed and developing countries found that in all countries there was a negative relationship between interest rates and stock prices (Alam et al., 2009). Further, the researchers found that in six of the countries there was a negative correlation between changes in interest rates and changes in stock prices (Alam et al., 2009). Another study pointed out that lower interest rates increase expectations for stock returns and the capital flows to public equity markets, while rising interest rates incentivizes more saving in banks and decreases capital flows to public equity markets (Eldomiaty et al., 2019). From a policy perspective, the researchers suggested that in order to achieve stability in the stock market — less volatility — stability in real interest rates is required, in turn also requiring strong control over rates of inflation (Eldomiaty et al., 2019). Lobo (2002) explored the relationship between interest rate surprises and stock prices. Using survey data on interest rate expectations, the 3-month T-Bill yield, and the S&P 500 index, Lobo (2002) found that surprises associated with decreases in the federal funds target rate caused increases in stock prices, while surprises with increases in the target rate caused same-day market volatility to increase with volatility returning to pre-surprise levels within a day. In the ASE Index study, the researchers found that the relationship between stock prices and inflation rates was greater than the relationship between stock prices and interest rates, contrary to much of the literature covering the latter relationship. Overall, across the field of macroeconomics, scholars have widely agreed that the interest rates tend to have a negative relationship with stock prices, though there is some literature that suggests otherwise.

Inflation expectations — or forecasts — are forward looking measurements of the CPI. More specifically, inflation expectations indicate the anticipated changes in future inflation rates, representing inflation that individuals and institutions expect to occur. Inflation expectation is an important macroeconomic factor because it has significant implications on economic activity, behavior, and outcomes. For example, if an individual anticipates high levels of inflation in the future, then they might increase spending in the present in order to avoid a loss of purchasing power down the line. The impact of inflation expectations as a macroeconomic variable has been the subject of extensive research. Much of the literature focuses on exploring the relationship between inflation expectations and stock returns. For example, Chaudhary and Marrow (2022) determined that stocks presented positive returns in response to higher expected inflation. The researchers used treasury-inflation protected securities to determine the underlying expected inflation rate (Chaudhary and Marrow, 2022). Ultimately, Chaudhary and Marrow (2022) argued "that since the 2000s, stocks have provided a hedge against changes in inflation expectations. In another study, Solnik (1983) argues that "the interest rate remains the best single prediction of the inflation rate," so he uses "interest rates as proxies for expectations of inflation." This study *rejects* Fisher's assumption that returns do not impact expectations of inflation (Solnik, 1983). More specifically, the study postulates that the relationship between stock returns and inflation is driven by inflation expectations. In another study, Kupfer (2018) examines the inflation risk premia using inflation-linked bonds. Inflation risk premium is the required additional return that an investor seeks given the risk that inflation will decrease the value of a given investment. To a certain degree, the inflation risk premium can reflect inflation expectations because it is the difference between a nominal interest rate and the expected rate of inflation. Moreover, if an investor expects inflation to increase or become more volatile, then they might demand a greater risk premium. Lastly, inflation-linked bonds are debt securities adjusted to reflect changes in inflation rates. Kupfer (2018) uses inflation-linked bonds to determine the inflation risk premium, implying that the breakeven inflation rate for these securities reflects market inflation expectations. The breakeven inflation rate is determined by calculating the difference between yields on a nominal bond and an inflation-linked bond. Overall, across the field of macroeconomics, scholars have widely agreed that there is a relationship between inflation expectations and asset returns. Additionally, much of the literature uses inflation-linked bonds to determine inflation expectations.

2.4 Overview of Cryptocurrencies

Cryptocurrencies have become an increasingly popular investment vehicle and an important factor in the world global economy. A paper covering the macroeconomics of cryptocurrencies defined cryptocurrencies as “a digital representation of value, not necessarily issued by a central bank or other traditional financial institution…where cryptography secures transactions and issuance of currency units" (Noam, 2018). The technology powering cryptocurrencies is known as distributed ledger technology (DLT), which is a shared database that eliminates the necessity of a trusted central authority to authorize or secure the stored data and information (Noam, 2018). Blockchain is an example of DLT that is both decentralized and a peer-to-peer ledger (Noam, 2018). Inherently, cryptocurrencies are useless tokens, deriving their value from enough people believing they actually have value as an asset (Noam, 2018). The predominant cryptocurrency is Bitcoin, created in 2008 by a person self-identified as Satoshi Nakamoto. In his white paper on Bitcoin, Nakamoto (2008) expresses his frustrations with the current financial system: transaction costs resulting from financial intermediaries, impossibility of perfectly non-reversible transactions, and financial institutions requiring too much private information. Noam (2018) argues that some advantages of cryptocurrencies include the ease of sending payments, security and anonymity, ability to be linked to smart contracts, and transparency of current supply. On the other hand, Noam (2018) some disadvantages are the volatility in value, low scalability, negative environmental impact, potential use in illegal activities, technological problems, and low acceptability. Nonetheless, cryptocurrencies have continued to attract investors, with the once niche FinTech space now being more popular than ever.

The most well known cryptocurrency is Bitcoin, created by Satoshi Nakamoto. Bitcoins are only exchanged if the transaction criteria is added to the blockchain, its public ledger. It is important to note that Bitcoin is not backed by any central authority, financial institution, or government. Additionally, Bitcoin's technology adequately addresses the issue of double-spending. Farell (2015) explained that "double-spending occurs when an asset is duplicated, and thus can be sent multiple times…this problem does not exist in physical currencies, since transactions involve changing possession of property." Systems within the technology of the blockchain offer safeguards against the threat of digital copying, thus "without fear of double-spending, because the entire network becomes informed of which wallet the coin currently resides in" (Farell, 2015). Bitcoins popularity has significantly increased in recent years, as it was once valued at less than one USD, but now hovers around the $19,000-$20,000 range with an all time high of roughly $69,000. Though there is a scarcity of literature covering the cryptocurrency industry, such research is needed now more than ever.

2.5 Existing Literature on Cryptocurrencies

To date, literature covering cryptocurrencies has been scarce, however, research coverage has risen in recent years. For example, some studies have sought to explore the relationship between macroeconomic factors and cryptocurrencies. One study examined the factors influencing the prices of the five most cryptocurrencies: Bitcoin, Ethereum, Dash, Litecoin, and

Monero (Sovbetov, 2018). This study argued three points: 1) market beta, volume, and volatility significantly impact cryptocurrency prices, 2) attractiveness of cryptocurrencies only affects pricing in the long-run, and 3) the S&P 500 has a *slight* positive correlation Bitcoin, Ethereum, and Litecoin (Sovbetov, 2018). Another study sought to determine the macroeconomic factors affecting cryptocurrency prices using a time series analysis (Teker et al., 2020). More specifically, Teker et al. (2020) explored the relationship between changes in gold and oil prices changes in various cryptocurrency prices, concluding that the correlation between cryptocurrencies and oil and gold are negligible. One study examined the relationship between macroeconomic news coverage and Bitcoin returns (Corbet et al., 2020). More specifically, the researchers studied how news regarding GDP, unemployment, CPI, and durable goods impact Bitcoin prices, finding that increases in positive news regarding unemployment and durable goods adversely impact Bitcoin's value, increases in negative news regarding unemployment and durable goods positively impact Bitcoin's value, and that any news regarding GDP or CPI do not have an impact on Bitcoin's value (Corbet et al., 2020). Kim (2019) explored the implication that US monetary policy surprises have on cryptocurrency returns, categorizing the digital assets into different groups depending on the technology behind them. Using a panel fixed effect model, the study found that cryptocurrencies with a deep integration of blockchain technology were vulnerable to long-term forward guidance, while cryptocurrencies with top level blockchain were not impacted by any form of monetary policy shocks (Kim, 2019). Finally, Outvorst (2022) investigated how changes in interest rates impact investor preferences for cryptocurrency investments between traditional and cryptocurrency investors. Asking participants a range of portfolio allocation questions with varying interest rates, the study found that changes in interest rates did not change the preferences of investments in traditional assets or cryptocurrencies

(Outvorst, 2022). Research on cryptocurrencies continues to build as more people invest in these digital assets and their popularity grows further. While the current literature is scarce, continuing to build a body of research in this field is necessary for uncovering the factors and determinants which drive cryptocurrency prices.

2.6 Formulation of Predictions

As mentioned in the introduction, one prediction is that Bitcoin returns and prices will have a negative relationship with inflation expectations. The other prediction is that Bitcoin prices and inflation expectations will be cointegrated in the long-run, indicating that both variables have a stable relationship and that they will move together over time. Prior research has indicated that public equities have a negative relationship with interest rates and inflation. This makes sense given that interest rates and inflation are external factors that impact the operations of business, and thus a firm's intrinsic value. Though cryptocurrencies such as Bitcoin do not have intrinsic value in the same way public equities do, there is still reason to believe that they are historically impacted by macroeconomic factors in some capacity. For example, Corbet et al. (2020) found that announcements from the Fed regarding quantitative easing and the FFR can impact digital asset prices. More specifically, Corbet et al. (2020) found that news regarding the FFR has a negative relationship with cryptocurrency prices. Interest rates and inflation can adversely impact investor risk appetite, thus, as the literature indicates, inflation expectations might also have a strong negative impact on Bitcoin. Cryptocurrencies are a historically risky asset class, thus increases in macroeconomic factors such as inflation and interest rates would logically decrease crypto prices. Overall, prior to conducting the analysis, one prediction is that increasing inflation expectations will negatively impact Bitcoin prices and returns. The other prediction is that there is a stable long-term equilibrium relationship between Bitcoin prices and inflation expectations.

III. METHODS & DATA

The data for this analysis will include the following sets: historical Bitcoin prices, historical inflation forecasts from the OECD, the S&P Global Developed Sovereign Bond Index and the S&P Global Developed Sovereign Inflation-Linked Bond Index. The dependent variable will be historical Bitcoin prices and returns, while the independent variables will be the inflation forecast data points mentioned above. Data regarding historical Bitcoin prices is public, and therefore will be pulled from Yahoo Finance for this study. Similar to Eldomiaty et al. (2019), Solnik (1983), and Quayes (2008), this study will examine historical prices in their dollar value form as the dependent variable. Additionally, this study examines historical returns as a dependent variable, similar to Alam et al. (2009), Corbet et al. (2020), and Chaudhary and Marrow (2022). Historical monthly Bitcoin prices and returns will be analyzed with the S&P data. However, for the analyses with the OECD data, historical quarterly Bitcoin prices and returns will be examined, since the OECD dataset on inflation expectations is reported quarterly. Since there are tens of thousands of cryptocurrencies, not all of these digital tokens will be examined. For this research, only Bitcoin prices and returns will be examined. Bitcoin was studied by other researchers such as Tekker et al. (2020), Corbet et al. (2020), and Sovbetov (2018) because it is the most popular and most widely traded cryptocurrency.

Data regarding inflation forecasts are pulled from the OECD and S&P indices. The OECD's data on historical inflation forecasts is a weighted average of inflation expectations for all OECD member countries. As mentioned above, this data is reported quarterly. The difference in yields between the S&P Global Developed Sovereign Inflation-Linked Bond Index and the

S&P Global Developed Sovereign Bond Index is used as a proxy for inflation expectations. This is rooted in the rationale put forth by Kupfer (2018) that inflation-linked bonds are appropriate estimates of inflation expectations. This research uses the S&P Global Developed Sovereign Inflation-Linked Bond Index and the S&P Global Developed Sovereign Bond Index because individuals in developed countries engage in cryptocurrency related transactions and investments more than individuals in emerging countries. This research specifically uses global measurements of inflation forecasts because Bitcoin is a globally accessible asset. For example, inflation expectations in one country can be significantly different than expectations in another country, thus impacting a specific investor's Bitcoin preferences in different ways. More specifically, looking at global inflation expectations in developed nations will better reflect Bitcoin prices and returns than just examining inflation forecasts for some countries since Bitcoin is a globally accessible investment.

This research aims to explore the relationship between historical Bitcoin prices and returns and inflation expectations. Similar to Alam et al. (2009), this research will implement the use of regression analysis. Historical Bitcoin returns and prices will be regressed on both the OECD and global inflation-linked bond data sets. Furthermore, Bitcoin prices and returns will be regressed on *changes* in both the OECD data and the inflation-linked bond data sets. Regressing the data in such a way will better allow for examination into how changes in inflation expectations impact Bitcoin returns and prices. Regression analyses are used to predict values of the Bitcoin returns and prices based on the independent variables of inflation expectations and changes in inflation expectations. In other words, the regression presents an explanation of how the dependent variables impact the independent variable.

Cointegration was another statistical analysis method explored within the literature. Prior to using cointegration, Eldomiaty et al. (2019) specifically used unit root tests to determine the stationarity of data. Like Sovbetov (2018), this study uses the Augmented Dickey-Fuller (ADF) test to determine the stationarity of the relevant time series. From there, cointegration is used to determine the correlation between two or more non-stationary time series. There are multiple methods for calculating cointegration within a data set, however, this study only explores the Johansen cointegration test. The Johansen cointegration method will be implemented within this research to examine the existence of long run equilibrium between Bitcoin returns and prices and inflation expectations, similar to Eldomiaty et al. (2019). In Sovbetov (2018), the researcher also implemented the use of cointegration tests. Cointegration tests check for a long-term equilibrium between multiple times series. Within the Johansen test there are test statistics and eigenvalues. The Johansen test does not rely on the choosing of a dependent variable. If two time series are determined to be cointegrated, then they share a long-term equilibrium and move together in the long-run.

IV. RESULTS & DISCUSSION

4.1 Regression: Monthly Bitcoin Returns vs. Monthly S&P Inflation Spread

The results of this linear regression suggest that there is not a strong linear relationship between monthly Bitcoin returns and the monthly inflation spread derived from the S&P indices. The intercept value is significant, as indicated by a P-value of 0.0379. This suggests that when the inflation spread in this data set is zero, then the expected value of Bitcoin monthly returns is 0.1044. The coefficient for the independent variable (the implied expected inflation rate) is negative and not statistically significant, as evidenced by a P-value of 0.5172. The model fit is very poor as evidenced by a very low R-squared value and a negative adjusted R-squared value.

The results from this regression analysis suggest that the independent variable is not a good predictor of the dependent variable. Table 1 displays the output of this regression analysis.

Table 1

Residuals					
	Min	**1Q**	**Median**	**3Q**	**Max**
	-0.4845	-0.1786	-0.0804	0.0998	4.6145
Coefficients:					
		Estimate	**Std. Error**	**t value**	**P-value**
	(Intercept)	0.1044	0.0497	2.1000	0.0379 *
	Predictor	-1.5302	2.3557	-0.6500	0.5172
Signif. Codes:		*0 '***'*	*0.001 '**'*	*0.01 '*'*	*0.05 '.'*
Residual Standard Error:			0.4847	on 117 degrees of freedom	
Multiple R-Squared:	0.0036	**Adj. Multiple R-Squared:**		-0.0049	
F-Statistic:	0.4219	on 1 and 117	**P-Value:**	0.5172	

4.2 Regression: Monthly Bitcoin Returns vs. Changes in Monthly S&P Inflation Spread

The results of this linear regression suggest that there is not a strong linear relationship between monthly Bitcoin returns and changes in the monthly inflation spread derived from the S&P indices. The coefficient for the independent variable has a P-value of 0.3950, indicating that it is not statistically significant. Furthermore, the dependent variable is statistically significant with a P-value 0.0357, implying that when monthly changes in inflation expectations are zero, Bitcoin will have monthly returns of 0.0952. The overall fit of this model is poor, as evidenced by a very low R-squared value and a negative adjusted R-squared value. The results from this regression analysis suggest that the independent variable is not a good predictor of the dependent variable. Table 2 displays the output of this regression analysis.

Table 2

Residuals					
	Min	**1Q**	**Median**	**3Q**	**Max**
	-0.4714	-0.1827	-0.0675	0.1091	4.6048
Coefficients:					
		Estimate	**Std. Error**	**t value**	**P-value**
	(Intercept)	0.0952	0.0448	2.1250	0.0357 *
	Predictor	-11.4826	13.4490	-0.8540	0.3950
Signif. Codes:		*0 '***'*	*0.001 '**'*	*0.01 '*'*	*0.05 '.'*
Residual Standard Error:			0.4841	on 117 degrees of freedom	
Multiple R-Squared:	0.0062	**Adj. Multiple R-Squared:**		-0.0023	
F-Statistic:	0.7290	on 1 and 117	**P-Value:**	0.3950	

4.3 Regression: Quarterly Bitcoin Returns vs. Quarterly OECD Inflation Forecasts

This regression explores the relationship between quarterly Bitcoin returns and the OECD's quarterly inflation forecasts. The coefficient for the OECD's quarterly inflation forecasts (the independent variable in this regression) is not statistically significant, with a P-value of 0.3697. With a P-value of 0.0591, the coefficient for the intercept is marginally significant. Overall, the fit of the model is not strong, implying that the independent variable is not a good predictor of the dependent variable. This is evidenced by a very low R-squared value (0.0218) and a negative adjusted R-squared value (-0.0046). Table 3 displays the output of this regression analysis.

Table 3

Residuals					
	Min	**1Q**	**Median**	**3Q**	**Max**
	-1.0243	-0.6292	-0.3663	0.0954	7.0448
Coefficients:					
		Estimate	**Std. Error**	**t value**	**P-value**
	(Intercept)	0.6233	0.3201	1.9480	0.0591 .
	Predictor	-7.6943	8.4736	-0.9080	0.3697
Signif. Codes:		*0 '***'*	*0.001 '**'*	*0.01 '*'*	*0.05 '.'*
Residual Standard Error:			1.34	on 37 degrees of freedom	
Multiple R-Squared:	0.0218	**Adj. Multiple R-Squared:**		-0.0046	
F-Statistic:	0.8245	on 1 and 37 I	**P-Value:**	0.3697	

4.4 Regression: Quarterly Bitcoin Returns vs. Changes in Quarterly OECD Inflation Forecasts

This regression explores the relationship between quarterly Bitcoin returns and quarterly changes in the OECD's inflation forecasts. The results of this linear regression suggest that there is not a significant relationship between the independent and dependent variables. For example, the coefficient of the predictor variable is not statistically significant, as it has a P-value of 0.3520. The coefficient of the intercept (0.4587) is somewhat statistically significant, as it has a P-value of 0.045. This implies that when quarterly changes in inflation forecasts are zero, Bitcoin will offer quarterly returns of 0.4587. An R-squared value of 0.0235 and an adjusted R-squared value of -0.0029 suggests that the overall fit of the model is poor and that the model does not explain much of the variation in Bitcoin's quarterly returns. Table 4 displays the output of this regression analysis.

Table 4

Residuals					
	Min	**1Q**	**Median**	**3Q**	**Max**
	-0.9925	-0.5634	-0.3299	0.1136	7.0329
Coefficients:					
		Estimate	**Std. Error**	**t value**	**P-value**
	(Intercept)	0.4587	0.2211	2.0750	0.045 *
	Predictor	-30.2438	32.0586	-0.9430	0.3520
Signif. Codes:		*0 '***'*	*0.001 '**'*	*0.01 '*'*	*0.05 '.'*
Residual Standard Error:			1.339	on 37 degrees of freedom	
Multiple R-Squared:	0.0235		**Adj. Multiple R-Squared:**	-0.0029	
F-Statistic:	0.8900		on 1 and 37 I	**P-Value:**	0.3516

4.5 Regression: Monthly Bitcoin Prices vs. Monthly S&P Inflation Spread

This regression explores the relationship between historical monthly Bitcoin prices and the monthly inflation spread derived from the S&P indices. This regression analysis shows that there is a significant relationship between the independent and dependent variables. The coefficient for the predictor variable and the intercept are statistically significant with P-values of

0.00089 and 1.99e-08. The coefficient estimate for the predictor variable is 243,955, with a standard error of 71,528 and a t-value of 3.411. The intercept has a coefficient estimate of 9,095 with a standard error of 1509 and a t-value of 6.027. The R-squared value for this model is 0.0904, implying that roughly 9.04% of the variance in monthly Bitcoin prices can be explained by the independent variable. Additionally, the adjusted R-squared value is 0.0827. Both these values are relatively low, implying that the model does not fit the data well. The F-statistic is 11.63 and has a P-value of 0.0009. This indicates that there is some statistical significance within the model. Table 5 displays the output of this regression analysis.

Table 5

Residuals					
	Min	**1Q**	**Median**	**3Q**	**Max**
	-11059	-8743	-6044	-522	50180
Coefficients:					
		Estimate	**Std. Error**	**t value**	**P-value**
	(Intercept)	9095	1509	6.0270	1.99e-08 ***
	Predictor	243955	71528	3.4110	0.0009 ***
Signif. Codes:		*0 '***'*	*0.001 '**'*	*0.01 '*'*	*0.05 '.'*
Residual Standard Error:			14720	on 117 degrees of freedom	
Multiple R-Squared:	0.0904		**Adj. Multiple R-Squared:**	0.0827	
F-Statistic:	11.63		on 1 and 117	**P-Value:**	0.0009

4.6 Regression: Monthly Bitcoin Price vs. Changes in Monthly S&P Inflation Spread

This regression explores the relationship between monthly Bitcoin prices and changes in the monthly inflation spread derived from the S&P indices. The coefficient for the predictor variable is 1,275,946 and has a P-value of 0.0025, implying that there is a statistically significant positive relationship between the independent and dependent variables. More specifically, if changes in the inflation expectations increase, then Bitcoin prices would be expected to increase as well. The intercept coefficient is 10,808 and has a P-value of 1.99e-12, indicating that it is statistically significant. The model has a R-squared of 0.0757, implying that 7.57% of the variance in Bitcoin prices is explained by monthly changes in inflation expectations. Additionally, the adjusted R-squared value is 0.0678, suggesting that the model has limited explanatory ability. The F-statistic is 9.582 and has a p-value of 0.0025. This indicates that there is some statistical significance within the model. Table 6 displays the output of this regression analysis.

Table 6

Residuals

	Min	1Q	Median	3Q	Max
	-14872	-9949	-5375	2684	47556

Coefficients:

	Estimate	Std. Error	t value	P-value
(Intercept)	10808	1374	7.8690	1.99e-12 ***
Predictor	1275946	412194	3.0960	0.00246 **
Signif. Codes:	*0 '***'*	*0.001 '**'*	*0.01 '*'*	*0.05 '.'*

Residual Standard Error:	14840	on 117 degrees of freedom

Multiple R-Squared:	0.0757	**Adj. Multiple R-Squared:**	0.0678
F-Statistic:	9.5820 on 1 and 117	**P-Value:**	0.0025

4.7 Regression: Quarterly Bitcoin Prices vs. Quarterly OECD Inflation Forecasts

This regression explores the relationship between quarterly Bitcoin prices and the OECD's quarterly inflation forecasts. The results of this linear regression show that the independent variable has a coefficient of 343,353 and a P-value of 9.26e-05, implying that it is a statistically significant predictor. The intercept has a coefficient of 1,910 and a P-value of 0.522, indicating that it is not statistically significant. The R-squared value of this model is 0.3419, which implies that roughly 34.19% of the variation in the dependent variable can be explained by the independent variable. The adjusted R-squared of this model is 0.3241, implying that OECD's quarterly inflation forecasts may not be a good indicator for the model. The F-statistic is 19.23 and has a P-value of 9.26e-05. This indicates that there is some statistical significance within the model. Table 7 displays the output of this regression analysis.

Table 7

Residuals					
	Min	**1Q**	**Median**	**3Q**	**Max**
	-16911	-6483	-4404	1096	35902
Coefficients:					
		Estimate	**Std. Error**	**t value**	**P-value**
	(Intercept)	1910	2958	0.6460	0.522
	Predictor	343353	78308	4.3850	9.26e-05 ***
Signif. Codes:		*0 '***'*	*0.001 '**'*	*0.01 '*'*	*0.05 '.'*
Residual Standard Error:			12380	on 37 degrees of freedom	
Multiple R-Squared:	0.3419	**Adj. Multiple R-Squared:**		0.3241	
F-Statistic:	19.2300	on 1 and 37 I	**P-Value:**	9.26e-05	

4.8 Regression: Quarterly Bitcoin Prices vs. Changes in Quarterly OECD Inflation Forecasts

This regression explores the relationship between quarterly Bitcoin prices and changes in the OECD's quarterly inflation forecasts. The regression analysis indicates there is a significant positive relationship between quarterly Bitcoin prices and changes in the OECD's quarterly inflation forecasts. The coefficient of the intercept has a value of 9,232 and a P-value of 4.29e-05, implying that it is statistically significant. The coefficient of the predictor variable is 1,364,518 and has a P-value of 3.26e-05, implying that is also statistically significant. The R-squared value of 0.3766 indicates that the independent variable accounts for 37.66% of the variance in quarterly Bitcoin prices. The adjusted R-squared value of 0.3598 implies that the model can explain a decent amount of the variability in the data. The F-statistic of 22.35 and has a p-value of 3.258e-05. This indicates that there is some statistical significance within the model. Table 8 displays the output of this regression analysis.

Table 8

Residuals					
	Min	**1Q**	**Median**	**3Q**	**Max**
	-18870	-7823	-2214	5055	34328
Coefficients:					
		Estimate	**Std. Error**	**t value**	**P-value**
	(Intercept)	9232	1990	4.6380	4.29e-05 ***
	Predictor	1364518	288601	4.7280	3.26e-05 ***
Signif. Codes:		*0 '***'*	*0.001 '**'*	*0.01 '*'*	*0.05 '.'*
Residual Standard Error:			12050	on 37 degrees of freedom	
Multiple R-Squared:	0.3766		**Adj. Multiple R-Squared:**	0.3598	
F-Statistic:	22.35		on 1 and 37 l	**P-Value:**	3.258e-05

4.9 Unit Root Tests

Prior to running cointegration tests, it is necessary to conduct unit root tests in order to determine the stationarity of a time series. In order to conduct unit root tests and cointegration tests, the all eight data sets were converted into time series objects within R studio. Unit root tests were performed using ADF tests. It should be noted that the null hypothesis of an ADF test is that the relevant time series has a unit root, thus indicating the time series is non-stationary. Further, if the reported test-statistic value is greater than the reported critical values, then the null hypothesis cannot be rejected and it is presumed that the time series is non-stationary.

The ADF test for historical monthly Bitcoin prices revealed a test-statistic value of -1.3577. This is greater than the critical values of test statistics at one percent, five percent, and ten percent. The results imply that the null hypothesis cannot be rejected and that the time series is non-stationary.

The ADF test for historical monthly Bitcoin returns revealed a test-statistic value of -7.0053. This is less than the critical values of test statistics at one percent, five percent, and ten percent. The results imply that the null hypothesis can be rejected and that the time series is stationary.

The ADF test for historical monthly inflation expectations from the S&P indices revealed a test-statistic value of -0.9261. This is greater than the critical values of test statistics at one percent, five percent, and ten percent. The results imply that the null hypothesis cannot be rejected and that the time series is non-stationary.

The ADF test for historical changes in monthly inflation expectations from the S&P indices revealed a test-statistic value of -7.221. This is less than the critical values of test statistics at one percent, five percent, and ten percent. The results imply that the null hypothesis can be rejected and that the time series is stationary.

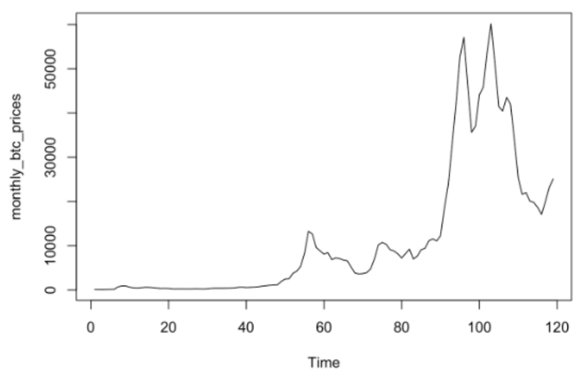
The ADF test for historical quarterly Bitcoin prices revealed a test-statistic value of -0.9825. This is greater than the critical values of test statistics at one percent, five percent, and ten percent. The results imply that the null hypothesis cannot be rejected and that the time series is non-stationary.

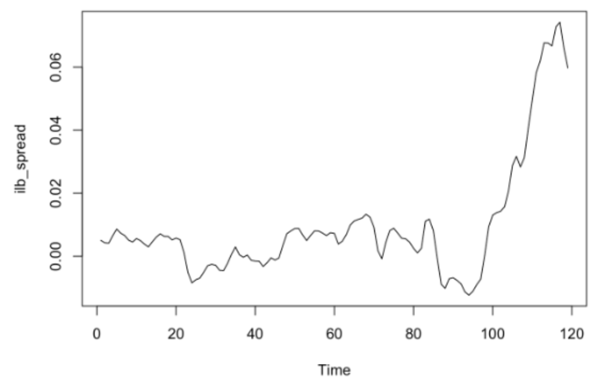
The ADF test for historical quarterly Bitcoin returns revealed a test-statistic value of -8.3548. This is less than the critical values of test statistics at one percent, five percent, and ten percent. The results imply that the null hypothesis can be rejected and that the time series is stationary.

The ADF test for the OECD's historical quarterly inflation forecasts revealed a test-statistic value of -1.3081. This is greater than the critical values of test statistics at one percent, five percent, and ten percent. The results imply that the null hypothesis cannot be rejected and that the time series is non-stationary.

The ADF test for changes in the OECD's historical quarterly inflation expectations revealed a test-statistic value of -2.1835. This is less than the critical values of test statistics at one percent, five percent, and ten percent. The results imply that the null hypothesis can be rejected and that the time series is stationary.

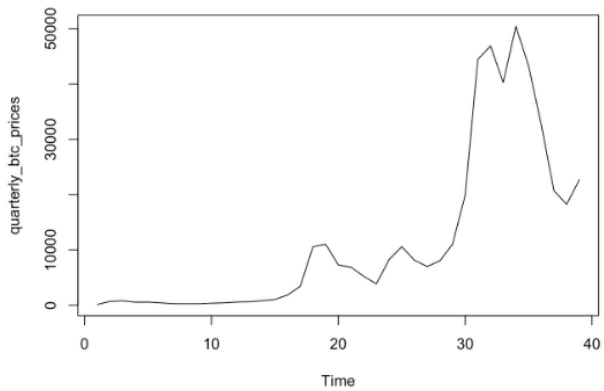
Charts 1 and 2 display the time series for monthly Bitcoin prices and monthly inflation expectations. As mentioned earlier, monthly inflation expectations were measured by taking the difference in yields between the S&P Global Developed Sovereign Inflation-Linked Bond Index and the S&P Global Developed Sovereign Bond Index. Time, which is on the x-axis, refers to months. Months begin in May 2013, hence one is May 2013 and March 2023 is expressed as 119. As the ADF unit root tests have indicated, both these time series are non-stationary.

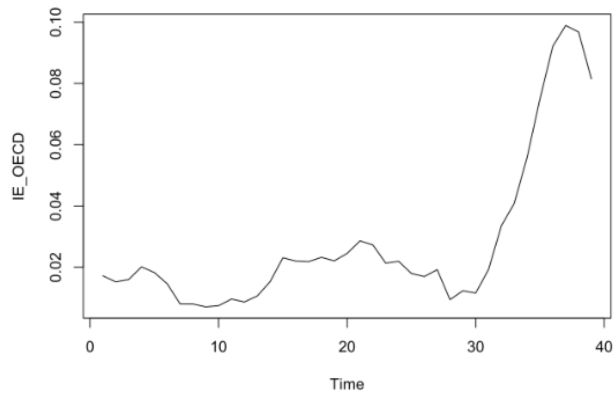




Charts 1 (left) and 2 (right) display the time series plots for monthly Bitcoin prices and monthly inflation expectations dating back to May 2013.

Charts 3 and 4 display the time series for quarterly Bitcoin prices and quarterly inflation expectations. As mentioned earlier, quarterly inflation expectations were sourced from the OECD's historical database. Time, which is on the x-axis, refers to quarters. Quarters begin in Q3-2013, hence one is Q3-2013 and Q1-2023 is expressed as 39. As the ADF unit root tests have indicated, both these time series are non-stationary.





Charts 3 (left) and 4 (right) display the time series plots for quarterly Bitcoin prices and quarterly inflation expectations dating back to Q3-2013.

4.10 Cointegration Tests: Monthly Bitcoin Prices & Monthly S&P Inflation Spread

As mentioned in the prior passage, the ADF unit root tests indicated that the time series for historical Bitcoin prices (monthly and quarterly) and historical inflation expectations (monthly and quarterly) are non-stationary. On the other hand, the time series for Bitcoin returns (monthly and quarterly) and for changes in inflation expectations (monthly and quarterly) are stationary. Cointegration tests can be conducted only on *non-stationary* time series in order to present reliable results.

This Johansen cointegration test examined the relationship between monthly Bitcoin prices and monthly inflation expectations. The value of the test statistic at $r \leq 1$ was 2.20, while the value of the test statistic at $r=0$ was 18.09. The test analyzed these time series at the one percent, five percent, and ten percent significance levels. Increasing from the one percent level to the ten percent level, at $r \leq 1$ the critical values were 11.65, 8.18, and 6.50. Increasing from the one percent level to the ten percent level, at $r=0$ the critical values were 19.19, 14.90, and 12.91. Evidence of cointegration exists because the test statistic for $r=0$ (18.09) was greater than the critical value at the five percent level (14.90). On the other hand, there was no reliable indication of a cointegrated relationship at the one percent significance level. This is evidenced by the fact that the critical value (19.19) was greater than the test statistic (18.09) at the one percent level of significance. It is worth pointing out that at r≤1, the test statistic was 2.20, which was less than all the critical values. This implies that there were no additional cointegrating factors between the time series tested. Simply put: there is indication that a cointegrated relationship between monthly Bitcoin prices and monthly inflation expectations exists at the five percent level of significance.

Examining the eigenvalues put forth by this analysis is one way to understand the strength of the cointegrated relationship. The Johansen test revealed a rather small eigenvalue of 0.1433. From this, it can be deduced that the cointegrated relationship between monthly Bitcoin prices and monthly inflation expectations is relatively weak, given the particularly small size of that eigenvalue (0.1433). Examining the loading matrix also revealed important information about the relationship between the two time series. The weights, as the data within the matrix are referred to, display how each time series responds to deviations away from the long-term equilibrium state. If the coefficients — or weights — are greater in magnitude, then a time series tends to correct in a stronger and quicker fashion. On the other hand, if the weights are smaller, then any corrections or adjustments for a given time series are weaker and slower. This study revealed the following weights: -3.5688e-02 for monthly_btc_prices.d and 6.8753e-08 for ilb_spread.d. These weights are relatively small. Based on the eigenvalues and the loading matrix weights, the strength of the long-term cointegrated relationship appears to be relatively weak. Table 9 displays the output of this cointegration test.

Table 9

Eigenvalues (lambda):

[1]	0.1433	0.0187

Values of Test Statistic and Critical Values of Test:

	test	**10pct**	**5pct**	**1pct**
r <= 1	2.20	6.50	8.18	11.65
r = 0	18.09	12.91	14.90	19.19

Weights W (loading matrix):

	monthly_btc_prices.l2	**ilb_spread.l2**
monthly_btc_prices.d	-3.5688e-02	-7.6934e-03
ilb_spread.d	6.8753e-08	-1.7624e-09

Eigenvectors (normalized to first column):

	monthly_btc_prices.l2	**ilb_spread.l2**
monthly_btc_prices.l2	1.0	1
ilb_spread.l2	-484228.4	2062604

In sum, the Johansen cointegration test revealed that there is a relatively weak cointegrated relationship between monthly Bitcoin prices and monthly inflation expectations. In other words, monthly Bitcoin prices and monthly inflation expectations are able to maintain a long-term equilibrium between each other in a very weak fashion. The test statistics and critical values reveal that a relationship exists. The eigenvalues and the loading matrix weights imply that this long-term relationship between monthly Bitcoin prices and monthly inflation expectations is not strong. If any of these time series were to deviate from the equilibrium in the long-term, then it would take a longer time for corrections to take place. Overall, the Johansen cointegration tests revealed that a weak cointegrated relationship exists between monthly Bitcoin prices and monthly inflation expectations.

4.11 Cointegration Test: Quarterly Bitcoin Prices & Quarterly OECD Inflation Forecasts

The ADF unit root tests conducted earlier revealed the non-stationarity of quarterly Bitcoin prices and quarterly inflation expectations. As a result, a cointegration test can be used between both time series. The value of the test statistic at r≤1 was 0.22, while the value of the test statistic at r=0 was 19.08. The significance levels explored were at one percent, five percent, and ten percent. At r≤1, the critical values were 11.65, 8.18, and 6.50, increasing from the one percent level to the ten percent level. At r=0, the critical values were 19.19, 14.90, and 12.91, increasing from the one percent level to the ten percent level. At r=0, there is evidence that quarterly Bitcoin prices and quarterly inflation expectations share a cointegrated relationship. The evidence is that the test statistic (19.08) was greater than the critical value (14.90) at the five percent level of significance. At r≤1, the test statistic (0.22) was less than the critical values at all levels of significance, implying that there is no further complexity to this cointegrated relationship. Simply put: the test statistics and critical values indicate that there is a long-term cointegrated relationship between quarterly Bitcoin prices and quarterly inflation expectations at the five percent level of significance.

The strength of this cointegration relationship appears to be moderate. This is evidenced by an eigenvalue of 0.4028. This eigenvalue (0.4028) was larger than the eigenvalue from the monthly test (0.1433), implying that at quarterly intervals the long-term relationship between inflation expectations and Bitcoin prices is slightly stronger. However, the eigenvalue of 0.4028 is not particularly large, indicating only a moderate strength for this relationship. Thus, it can be inferred that the strength of the long-term relationship between quarterly Bitcoin prices and quarterly inflation expectations is not consistent in the long-run. In other words, deviations from the long-term equilibrium will readjust and correct in a moderately quick way. Examining the loading matrix also offers important insights. The Johansen test revealed the following weights: 8.7534e-02 for quarterly_btc_prices.d and 3.7838e-07 for IE_OECD.d. These coefficients indicate how strong and fast each time series is able to correct to the equilibrium from any deviations in the long-term. Looking at the results, it is clear that the weights for both time series are rather small. Table 10 displays the output of this cointegration test.

Table 10

Eigenvalues (lambda):

[1]	0.4028	0.0060

Values of Test Statistic and Critical Values of Test:

	test	10pct	5pct	1pct
r <= 1	0.22	6.50	8.18	11.65
r = 0	19.08	12.91	14.90	19.19

Weights W (loading matrix):

	quarterly_btc_prices.l2	IE_OECD.l2
quartery_btc_prices.d	8.7534e-02	1.9280e-02
IE_OECD.d	3.7838e-07	-2.5219e-09

Eigenvectors (normalized to first column):

	quarterly_btc_prices.l2	IE_OECD.l2
quarterly_btc_prices.l2	1	1.0
IE_OECD.l2	-496926	703935.7

Overall, the Johansen test revealed that there is a moderately strong cointegrated relationship between quarterly Bitcoin prices and quarterly inflation expectations. At quarterly intervals, Bitcoin prices and inflation expectations move together in the long-term. The test statistics and critical values reveal that a cointegrated relationship exists. The eigenvalues and the loading matrix weights imply that this long-term relationship between monthly Bitcoin prices and monthly inflation expectations is only moderate. All in all, it appears that there is a moderately strong cointegrated relationship between quarterly Bitcoin prices and quarterly inflation expectations.

V. CONCLUSION

As the results of this study indicate, Bitcoin and inflation expectations have a particularly interesting relationship. More specifically, this study revealed that inflation expectations are a statistically significant predictor of Bitcoin prices, at both monthly and quarterly intervals. On the other hand, regression results indicate that inflation expectations are not a statistically significant predictor of Bitcoin returns, at both monthly and quarterly intervals. Due to Bitcoin's high volatility, returns experience massive fluctuations between negative and positive values. It is very hard to chart a line of best for Bitcoin returns and inflation expectations, as inflation expectations are predominantly positive, while Bitcoin's returns fluctuate wildly between negative and positive values. This is reflected by the higher levels of P-values for regressions run on Bitcoin returns. Prices, on the other hand, are all nonnegative and generally grow over the long-term, while inflation expectations are generally positive too. Although the analyses produced fascinating results, further research is ultimately needed to see how other macroeconomic variables in addition to inflation expectations impact and interact with Bitcoin prices and returns.

Additionally, cointegration tests revealed that Bitcoin prices and inflation expectations are cointegrated, at monthly and quarterly intervals. More specifically, this implies that the times series for Bitcoin prices and inflation expectations share a long-term equilibrium relationship. In other words, both time series tend to move together in the long-term, and any deviation from this equilibrium is usually corrected over time. Though test statistics and critical values indicate that there is at least one cointegrated relationship between these time series — at both the monthly and quarterly intervals — eigenvalues reveal that neither cointegrated relationship is particularly strong. For example, the eigenvalue for the monthly analysis (0.1433) was relatively weak, while the eigenvalue for the quarterly analysis was moderately strong (0.4028). Because unit root tests revealed that the time series of monthly Bitcoin returns, quarterly Bitcoin returns, changes in quarterly inflation expectations, and changes in monthly inflation expectations were stationary, cointegration tests could not be conducted. While the cointegration tests indicate that there is cointegration between Bitcoin prices and inflation expectations, this relationship does not appear to be particularly strong, meaning that corrections from deviations in the long term tend to adjust slowly. Overall, repeating these analyses with other macroeconomic variables would be worthwhile, as it could reveal how inflation expectations, Bitcoin prices, and other factors are cointegrated, if at all.

This study revealed interesting results regarding the relationship between Bitcoin and inflation expectations. At first glance, it appears that there is a statistically relevant relationship between inflation expectations and Bitcoin prices, at both quarterly and monthly intervals. Nonetheless, future research should investigate how other macroeconomic variables impact Bitcoin prices and returns. Moreover, given that Bitcoin is a relatively recent financial product, the present body of data is not robust enough to make conclusive remarks. The data investigated in this study began in 2013, only ten years ago. Additionally, it is worth mentioning that the quarterly measurements of inflation expectations were sourced differently than the monthly measurements of inflation expectations. More specifically, the quarterly inflation forecasts were pulled from the OECD and the monthly inflation expectations were calculated by finding the difference in yields between a global inflation-linked bond index and nominal bond index (both indices from S&P). This could have an impact on the results of the statistical analyses. As mentioned above, however, the point of this study is not to explore the difference between monthly and quarterly intervals. The purpose of this was to test data Bitcoin (both returns and prices) on as many datasets representing inflation expectations as possible. Though the initial indication points to a relationship between inflation expectations and Bitcoin prices, further investigation is necessary in the future due to a relatively small sample of data.

Overall, this research adds to a growing body of cryptocurrency-related literature. As cryptocurrencies continue their meteoric rise in popularity, it has never been more important for regulators and retailers alike to broaden their understandings of how these digital assets function and what variables impact them. Make no mistake: despite the recent fluctuation in the cryptocurrency markets over the past few years, Bitcoin and other digital assets are here to stay. As the body of research grows over time, investors, regulators, and institutions will further uncover the driving factors that influence Bitcoin and cryptocurrency values, and thus make better informed decisions.

WORKS CITED

Alam, Md. Mahmudul, and Md. Gazi Salah Uddin. 2009. "Relationship between Interest Rate and Stock Price: Empirical Evidence from Developed and Developing Countries." *International Journal of Business and Management* 4 (3). https://doi.org/10.5539/ijbm.v4n3p43.

Apergis, Nicholas, and Sophia Eleftheriou. 2002. "Interest Rates, Inflation, and Stock Prices: The Case of the Athens Stock Exchange." *Journal of Policy Modeling* 24 (3): 231–36. https://doi.org/10.1016/s0161-8938(02)00105-9.

Corbet, Shaen, Charles James Larkin, Brian M. Lucey, Andrew Meegan, and Larisa Yarovaya. 2020. "The Impact of Macroeconomic News on Bitcoin Returns." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3550842.

Chaudhary, Manav, and Benjamin Marrow. "Inflation Expectations and Stock Returns." *SSRN Electronic Journal*, November 21, 2022. https://doi.org/10.2139/ssrn.4154564.

Eldomiaty, Tarek, Yasmeen Saeed, Rasha Hammam, and Salma AboulSoud. 2019. "The Associations between Stock Prices, Inflation Rates, Interest Rates Are Still Persistent." *Journal of Economics, Finance and Administrative Science* ahead-of-print (ahead-of-print). https://doi.org/10.1108/jefas-10-2018-0105.

Fama, Eugene F. 1981. "Stock Returns, Real Activity, Inflation, and Money." *The American Economic Review* 71, no. 4: 545–65. http://www.jstor.org/stable/1806180.

Farell, Ryan. 2015. "An Analysis of the Cryptocurrency Industry." *Business Commons Farell*. https://repository.upenn.edu/cgi/viewcontent.cgi?article=1133&context=wharton_research_scholars.

Feldstein, Martin. 1980. "Inflation and the Stock Market." *The American Economic Review* 70, no. 5, 839–47. http://www.jstor.org/stable/1805765.

Hardouvelis, Gikas A. 1987. "Macroeconomic Information and Stock Prices." *Journal of Economics and Business* 39 (2): 131–40. https://doi.org/10.1016/0148-6195(87)90012-9.

Khan, Zohaib, Sangeen Khan and Rukh, Lala. 2012. "IMPACT OF INTEREST RATE, EXCHANGE RATE AND INFLATION ON STOCK RETURNS OF KSE 100 INDEX."

Kim, Jisung. 2019. "The Effect of US Monetary Policy Shocks on Cryptocurrency Returns."

Kupfer, Alexander. 2018. "Estimating Inflation Risk Premia Using Inflation-Linked Bonds: A Review." *Journal of Economic Surveys, 32: 1326-1354*. https://doi.org/10.1111/joes.12265

Lobo, Bento J. 2002. "Interest Rate Surprises and Stock Prices." *The Financial Review* 37 (1): 73–91. https://doi.org/10.1111/1540-6288.00005.

Nakamoto, Satoshi. 2008. “Bitcoin: A Peer-to-Peer Electronic Cash System.” https://bitcoin.org/bitcoin.pdf.

Noam, Eli M. 2019. “The Macro-Economics of Crypto-Currencies: Balancing Entrepreneurialism and Monetary Policy.” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3493333.

Outvorst, Tijn van. 2022. “The Effect of Interest Rates on Traditional and Cryptocurrency Investments.” *Theses.ubn.ru.nl*, July. https://theses.ubn.ru.nl/handle/123456789/12969?locale-attribute=en.

Quayes, Shakil, and A. Jamal. 2008. “Does Inflation Affect Stock Prices?” *Applied Economics Letters* 15 (10): 767–69. https://doi.org/10.1080/13504850600770871.

Sovbetov, Yhlas. 2018. “Factors Influencing Cryptocurrency Prices: Evidence from Bitcoin, Ethereum, Dash, Litecoin, and Monero.” *Journal of Economics and Financial Analysis, 2(2), 1-27*. Available at SSRN: https://ssrn.com/abstract=3125347

Solnik, Bruno. 1983. “The Relation Between Stock Prices and Inflationary Expectations: The International Evidence.” *The Journal of Finance* 38, no. 1: 35–48. https://doi.org/10.2307/2327636.

Teker, Dilek, Suat Teker, and Mustafa Ozyesil. 2020. “Macroeconomic Determinants of Cryptocurrency Volatility: Time Series Analysis.” *Journal of Business & Economic Policy* 7 (1). https://doi.org/10.30845/jbep.v7n1a8.