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The Relationship Between Macroeconomic Indicators and Cryptocurrency Prices

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Introduction

The relationship between macroeconomic indicators and cryptocurrency prices, particularly Bitcoin, has become a subject of increasing interest in the field of financial economics. This study aims to analyze how key macroeconomic indicators such as inflation, unemployment, and GDP growth affect cryptocurrency prices, with a focus on Bitcoin. The significance of this research lies in its potential to provide insights into the evolving role of cryptocurrencies in the global financial system. Knowing better how this instrument works, would allow also relevant financial institutions to implement it as an additional instrument of payment.

Literature Review

Several studies have examined the impact of macroeconomic variables, particularly inflation, unemployment, and GDP growth, on Bitcoin prices.

Hartono and Suyanto (2023) [1] analyzed nine key determinants of Bitcoin price using a Vector Error Correction Model (VECM). They found that GDP, both from Indonesia and the US, had a strong positive effect on Bitcoin price in both the short and long term. This suggests a significant income effect on Bitcoin demand.

Regarding inflation, Bhattacharya and Nguyen (2022) [2]found a strong positive correlation between inflation and Bitcoin prices. They suggest that Bitcoin is used for transaction purposes despite soaring prices of goods and services, indicating that it might not be an effective hedge against inflation.

While specific research on unemployment's direct impact on Bitcoin price is less prevalent in these search results, Kapar and Olmo's study[3] [3] found that factors such as the S&P 500 index and Google searches had positive effects on Bitcoin price, while a fear index (proxied by the FED Financial Stress Index) had a negative effect2. This suggests that broader economic sentiment, which can be influenced by unemployment rates, may play a role in Bitcoin price dynamics.

These studies collectively indicate that macroeconomic variables, particularly GDP growth and inflation, have significant impacts on Bitcoin prices, so through our analysis we would expect a similar or comparable result.

Methodology Approach and Data

This study will utilize a dataset covering the period from 2015 to 2024, incorporating yearly data on Bitcoin prices, inflation rates, unemployment figures, and GDP growth rates globally. The analysis will employ a combination of tests, including:

- Autocorrelation Test (Breusch-Godfrey): to check for serial correlation in the panel data.
- Test (Breusch-Pagan): to detect variability in the error terms across observations.
- Cross-Sectional Dependence Test: to account for interdependencies between cross-sectional units
- Collinearity Analysis: to ensure no collinearity in the model.

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[1] "Major determinants of Bitcoin price: Application of a vector error correction model", Hartono and Suyanto (2023)

[2] "Macro-Financial Parameters Influencing Bitcoin Prices: Evidence from Symmetric and Asymmetric ARDL Models", Bhattacharya and Nguyen (2022)

[3] "Analysis of Bitcoin prices using market and sentiment variables", Kapar and Olmo (2020)

Hypotheses:

H0: Macroeconomic indicators (inflation, unemployment, and GDP growth) have no significant impact on Bitcoin prices.

H1: Macroeconomic indicators (inflation, unemployment, and GDP growth) have a significant impact on Bitcoin prices.

By examining these relationships, this study aims to contribute to the growing body of literature on the interplay between traditional economic factors and the emerging cryptocurrency market, providing valuable insights for investors, policymakers, and researchers in the field of financial economics.

Exploratory Data Analysis

Data sources and Sample

For this analysis were considered three major macroeconomic indicators -inflation, unemployment, and GDP growth- to understand their influence on cryptocurrency prices, specifically. Bitcoin will be used as the proxy for the cryptocurrency market, as it is the largest and most widely recognized. The dataset runs from Q1 2015 through Q4 2024, counting a total of 40 observations for each variable. Quarterly frequency is chosen because not all the key variables, like global liquidity or M2 money supply, were available on a monthly basis, and it is important that all data points be consistently comparable.

The variables analysed are:

- Gold Price: a traditional safe haven asset. A comparison with Bitcoin, considered by some a digital version of gold, can highlight a change in role of crypto
- Inflation (CPI): measured as a year-over-year one-month percentage change in the Consumer Price Index. With higher inflation, investors seek so-called safe-haven assets or higher-yielding assets.
- GDP per Capita (OECD area) : A means of judging economic growth. Booms are associated with bullish markets, while recessions are associated with bearish trends.
- VIX: The so-called "fear index", showing volatility. Due to their speculative nature, virtual currencies are more vulnerable to uncertainty.
- World Money Supply (WM2): A broad money supply measure, and with higher liquidity, investment in riskier assets increases, such as crypto.

The macroeconomics data were sourced from the World Bank and from the Federal Reserve Bank of St. Louis FRED. The latter source data from quality institutions including the Federal Reserve System, the U.S. Bureau of Economic Analysis and BEA, among others, and as such, remains one of the most popular choices for academic and professional researchers.

Bitcoin prices, gold prices and the Volatility Index, were sourced from Yahoo Finance. Its data is sourced from exchanges and financial institutions, ensuring accuracy and reliability. The data covers a date range from 2015 to 2024, as there is no available valuation regarding Bitcoin before this period. Prices are reported daily, so to suit the frequency level for the macroeconomic dataset each daily closing price obtained within the dataset has been averaged for a quarterly average.

By combining price data from Yahoo Finance with macroeconomics data from FRED and the World Bank, this analysis integrates two robust and complementary data sources.

Overall summary statistics

After transforming data, descriptive statistics were conducted on GDP per capita, Bitcoin Price, Gold Price, inflation, global liquidity and volatility index. The variables give an indication of the central tendency by using the median and mean values. For instance, the mean (10,831.39) and median (4,102.30) for Bitcoin_Price, show the presence of outliers since some of the observations are far away from the typical measure. Standard deviation values show the variability of each variable. Bitcoin_Price and Gold_Price have high values for standard deviation, which reflects high volatility in financial markets.

For some variables, the range (the difference between the smallest and highest values) is significantly high. VIX, for example, varies between 9.510 and 53.540. These are immense variations in market uncertainty, as noted.

A skewed mean and median value is indicated by variables like OECD_GDP_Change and Bitcoin_Price. In addition, Bitcoin_Price is most likely right-skewed because the mean value is highly larger compared to the median. There are no missing values, which simplifies the data analysis process.

Table 1: Descriptive statistics for numeric variables in dataset

	OECD_GDP_Change	Bitcoin_Price	Gold_Price	OECD_CPI	WM2NS	VIX
Min.	-10.094	4.90	1060.300	0.637	9882.300	9.510
1st Qu..25%	0.363	401.95	1244.000	1.514	11879.050	13.830
Median	0.533	4102.30	1326.500	2.073	13941.900	16.310
Mean	0.491	10831.39	1481.217	2.952	14988.936	18.253
3rd Qu..75%	0.722	15193.90	1763.050	2.745	18898.000	19.685
Max.	9.437	58763.70	1969.000	10.395	21852.500	53.540
Std Dev	2.097	15116.49	277.439	2.593	3966.014	7.312
NA's	0.000	0.00	0.000	0.000	0.000	0.000

The histograms in Appendix 1 demonstrate considerable variability and deviation from normality across the macro-financial variables. There is skewness in OECD_GDP_Change and CPI. Bitcoin_Price has high volatility, represented by numerous outliers, and is heavily right skewed. Gold_Price has a slight right-skew with non-normality, and WM2NS depicts a bimodal pattern. The patterns indicated here signal some kind of transformation that could level off the skewness and dispersion for proper modeling.

The analysis, spanning Appendices 1 to 5, reveals key insights into the dataset. Appendix 1 (histograms) highlights non-normal distributions, particularly for Bitcoin_Price, while Appendix 2 (box plots) confirms significant variability and outliers, especially in Bitcoin_Price and VIX. Appendix 3 (time series) shows heightened volatility across variables, with sharp spikes around 2020 linked to global economic shocks. Bitcoin_Price exhibits the most erratic behavior compared to other variables.

Scatterplots in Appendix 4 reveal a positive relationship between Bitcoin_Price and Gold_Price, but weaker, inconsistent trends with other variables like OECD_CPI and OECD_GDP_Change, suggesting Bitcoin's unique dynamics. Appendix 5 (correlation matrix) highlights strong links among traditional economic indicators but moderate correlations between Bitcoin_Price, Gold_Price, and WM2NS, reflecting partial alignment with monetary trends while VIX remains largely independent. Together, the findings emphasize variable interconnections, Bitcoin's distinct behavior, and the need for careful contextual analysis.

Methods

Relationship between variables

To examine the impact of gold prices, GDP per capita, inflation, unemployment, global liquidity and volatility on Bitcoin prices this study employed a time series analysis. Multiple linear regressions and dynamic models were used to explore this relationship.

Estimation equation and approach

Due to the time series nature of gathered data, both linear regressions and dynamic models with lagged variables were examined. Estimated equation for this study's regression is as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + u$$

y - dependent variable

x_k - explanatory variables

β_0 - intercept

β_k - corresponding coefficients

u - error term

Assumptions

Multi Linear Regression base assumptions consist of linear relationship, independence of errors, homoscedasticity, no perfect collinearity and strict exogeneity. Dynamic models assume linearity, time dependence, stationarity, lagged effects, independence of errors and strict exogeneity.

Limitations of approach

Low number of observations limits the statistical capabilities of this study - some data are collected monthly or quarterly and since Bitcoin was created in 2010, the size of the dataset is significantly low. This issue influences predictive value of models and presents a real problem when assessing relationships between variables. Results of this study should be confronted with further studies involving bigger datasets in order to confirm or reject its findings.

Issues and biases

Tests and transformations

Bitcoin Prices, Gold Prices and WM2NS were changed to logarithms after examination of their time plots. To assess homoscedasticity and serial correlation, Breusch - Pagan test for homoscedasticity and Breush - Godfrey test were conducted. To check potential collinearity within the model, Variation Inflation Factor was calculated for each variable. After examination, following steps were taken to improve the model: transformation of variables to first differences, introduction of seasonal dummies, introduction of time trend, introducing dynamic nature of model with lagged explained variable.

Autocorrelation and Time

Main issue during assessing the correct form of the model was the process of determining the best method of including time properties of data. Value of Breusch - Godfrey test for serial correlation was 18.701 with 1 degree of freedom and p-value = 1.529e-05, therefore we reject the null hypothesis, that there is no serial correlation, for the alternative hypothesis, that serial correlation exists in the model. First possible solution to this problem was to introduce seasonal quarterly variables, but this was not sufficient. Two further solutions were tested: introduction of time trend and change in nature of the model to dynamic (introduction of lags).

Collinearity

Variation Inflation Factor shows values significantly higher than 10 for trend and log(WM2NS) in model with time trend. This shows high collinearity with global liquidity (log(WM2NS)), which implies that much of the time trend is already included in liquidity. Analysis of the time plot of global liquidity supports this conclusion. Therefore trend is not to be included and another method to include time trend is to be used.

Homoscedasticity

Value of Breush - Pagan test equalled 10.633 with 4 degrees of freedom and p-value = 0.03102, therefore we reject the null hypothesis, that homoscedasticity is present, for the alternative hypothesis, that heteroscedasticity is present. This problem might stem from low count of observations. This issue was resolved by introducing Heteroscedasticity- and autocorrelation-consistent (HAC) estimators of the variance-covariance matrix.

Interpretation of findings

Final two models were those with different natures: Multiple Linear Regression Model and dynamic first differences model with lagged Bitcoin Prices. The second model was particularly problematic because of R-squared equal to 1, showing near perfect fit - clear overfitting problem. This problem might have occurred for a few reasons: quarterly data does not reflect well the volatility of Bitcoin prices, low number of observations or other problems connected with data sample.

Results

Interpretation of estimated parameters

Table 1: Regression Results

	Dependent variable:			
	log(Bitcoin_Price)		diff_log_Bitcoin_Price	log(Bitcoin_Price)
	OLS		*dynamic linear*	*OLS*
	(1)	(2)	(3)	(4)
lag(log(Bitcoin_Price), 1)		1.000***		
		(0.000)		
log(Gold_Price)	−4.077***	0.000		−3.168***
	(0.828)	(0.000)		(0.855)
OECD_CPI	−0.166***	0.000		−0.167***
	(0.061)	(0.000)		(0.058)
log(WM2NS)	12.451***	−0.000		6.640***
	(0.682)	(0.000)		(2.359)
VIX	−0.040**	−0.000		−0.036**
	(0.017)	(0.000)		(0.016)
L(diff_log_Bitcoin_Price, 1)			1.000***	
			(0.000)	
diff_log_Gold_Price			0.000	
			(0.000)	
trend				0.409**
				(0.160)
Constant	−80.811***	−0.000	−0.000*	−857.063***
	(6.789)	(0.000)	(0.000)	(303.400)
Observations	47	47	46	47
R^2	0.919	1.000	1.000	0.930
Adjusted R^2	0.911	1.000	1.000	0.922
Residual Std. Error	0.750 (df = 42)	0.000 (df = 41)	0.000 (df = 40)	0.705 (df = 41)
F Statistic	1.19e+02*** (df = 4; 42)	1.85e+36*** (df = 5; 41)	3.74e+38*** (df = 5; 40)	1.09e+02*** (df = 5; 41)
Note:				*p<0.1; **p<0.05; ***p<0.01

The coefficient for the logarithm of Gold Price equals to -4.077 and is statistically significant at a level below 0.01 (p-value = 1.37e-05, ***), indicating a strong inverse relationship between gold prices and the dependent variable. Specifically, a 1% increase in the price of gold is associated with an average of 4.077% decrease in the dependent variable. This result aligns with the notion that gold often acts as a safe-haven asset, with increased demand for gold potentially reducing the attractiveness of alternative, more risky assets such as Bitcoin.

The OECD Consumer Price Index (CPI) exhibits a statistically significant negative coefficient of -0.166 at the same high level of significance (p-value = 0.00955, ***). Rise of 1 unit in this variable causes averagely 0.166% drop in target variable. This finding suggests that rising inflation, as measured by the OECD CPI, tends to reduce the dependent variable. The negative relationship may reflect a broader economic context in which inflation erodes the purchasing power of assets or shifts investment preferences.

The logarithm of the WM2NS variable, representing money supply, shows a pronounced positive effect on the dependent variable, with a coefficient of 12.451, also significant at the 0.01 level (p-value = < 2e-16, ***). A 1% increase in money supply corresponds to an average of 12.451% increase in the dependent variable. This result highlights the potential for expansive monetary policy to fuel demand for speculative or alternative assets, such as Bitcoin.

Market volatility, measured by the VIX index, has a modest but statistically significant (p-value = 0.02022, *) negative effect on the dependent variable, with a coefficient of -0.040. Increase in market volatility by 1 unit of measure in VIX index results in an average of 0.04% fall of Bitcoin price. This indicates that greater market uncertainty and volatility are associated with a slight decline in the dependent variable. The finding may reflect a shift in investor sentiment during periods of heightened uncertainty, where safer or more stable assets become preferable.

The constant, at -80.811, is highly statistically significant (p-value = 4.82e-15, ***). It represents the baseline level of the dependent variable when all independent variables are equal to zero, adjusted for any logarithmic transformations in the data. While the magnitude of this value is large, its role is primarily interpretive in the context of the transformed variables.

The overall fit of the model is notably strong. The R^2 value of 0.919 indicates that 91.9% of the variation in the dependent variable is explained by the independent variables. The adjusted R^2 of 0.911 further corroborates this, accounting for the complexity of the model and the number of predictors. F-statistic of 119.0 confirms the joint significance of the explanatory variables, highlighting the robustness of the model.

Taken together, the results suggest a complex interplay of economic and financial indicators in explaining the variation in the dependent variable. Gold prices, inflation, money supply, and market volatility all emerge as significant factors, with their respective directions of influence offering valuable insights into asset dynamics. While most coefficients align with theoretical expectations, issues mentioned in the previous chapter encourage exploring relationships between variables with other types of data (daily, weekly).

Conclusion

This paper investigated the relationship between key macroeconomic indicators and Bitcoin prices to assess how traditional economic factors influence the valuation of cryptocurrencies. The reason that moved us to conduct this research, was due to the growing prominence of Bitcoin in financial markets and to understand the interrelation with broader trends within the economy.

Our findings indicate that macroeconomic variables do indeed play a significant role in influencing Bitcoin prices. Specifically, we found that GDP per capita and global liquidity had a positive impact on Bitcoin prices, which means that during periods of economic growth and high liquidity, investors would be more likely to allocate capital to riskier assets such as cryptocurrencies. The inflation and gold price had a weaker but significant relationship with Bitcoin, which indicated that Bitcoin might be a store of value like gold but much more volatile. VIX, the proxy for market uncertainty, negatively influenced the prices of Bitcoin, which again assured that cryptocurrencies were more appealing to investors during stable rather than unstable economic conditions. Overall, the regression models explained over 90% of the variation in Bitcoin prices, indicating a strong model fit.

Despite the robustness of our results, this analysis also underlined some limitations in the present research. Since Bitcoin prices are highly volatile and include outliers, drawing any definite conclusion from the linear econometric model is quite difficult. Apart from this, the constraint of the dataset – given by the lack of daily macroeconomic data- limited our ability to explore more granular or real-time effects. Future research could address these limitations by incorporating more sophisticated models that account for non-linear relationships and by utilizing higher-frequency data to capture more immediate market reactions.

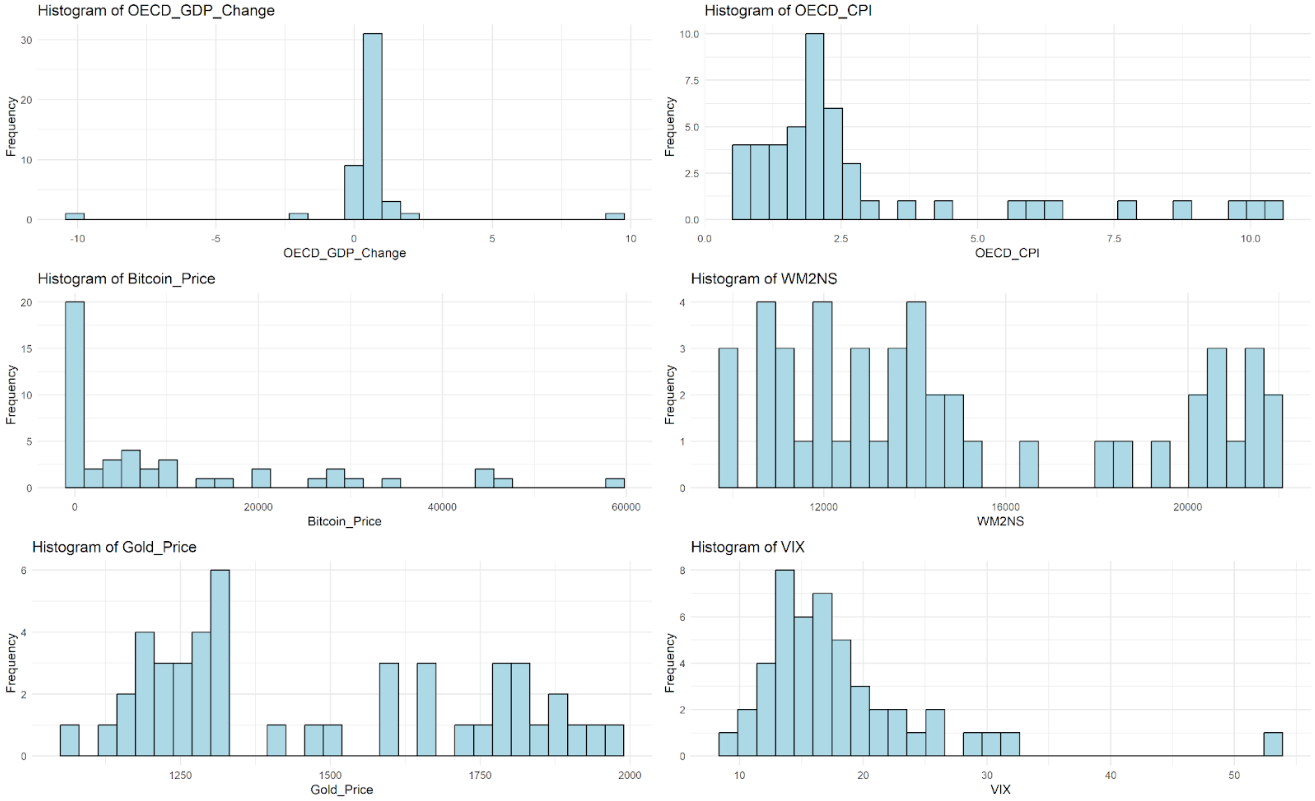
From our study, we learned that while Bitcoin responds to traditional macroeconomic factors, but with deviations from conventional assets given its speculative nature and the effect of market sentiments. This distinction underscores the relevance of considering both economic fundamentals and behavioural factors when analysing cryptocurrencies.

Future empirical research in this field can be complemented by a few refinements. For example, other variables could be considered, such as central bank policies, geopolitical events, or regulatory changes; these might have a great impact on the price of Bitcoin. Second, machine learning techniques may help in identifying complex patterns and interactions that are difficult to be captured by traditional econometric models. This research can be expanded by including a number of cryptocurrencies other than Bitcoin to throw light on more features of the overall crypto market.

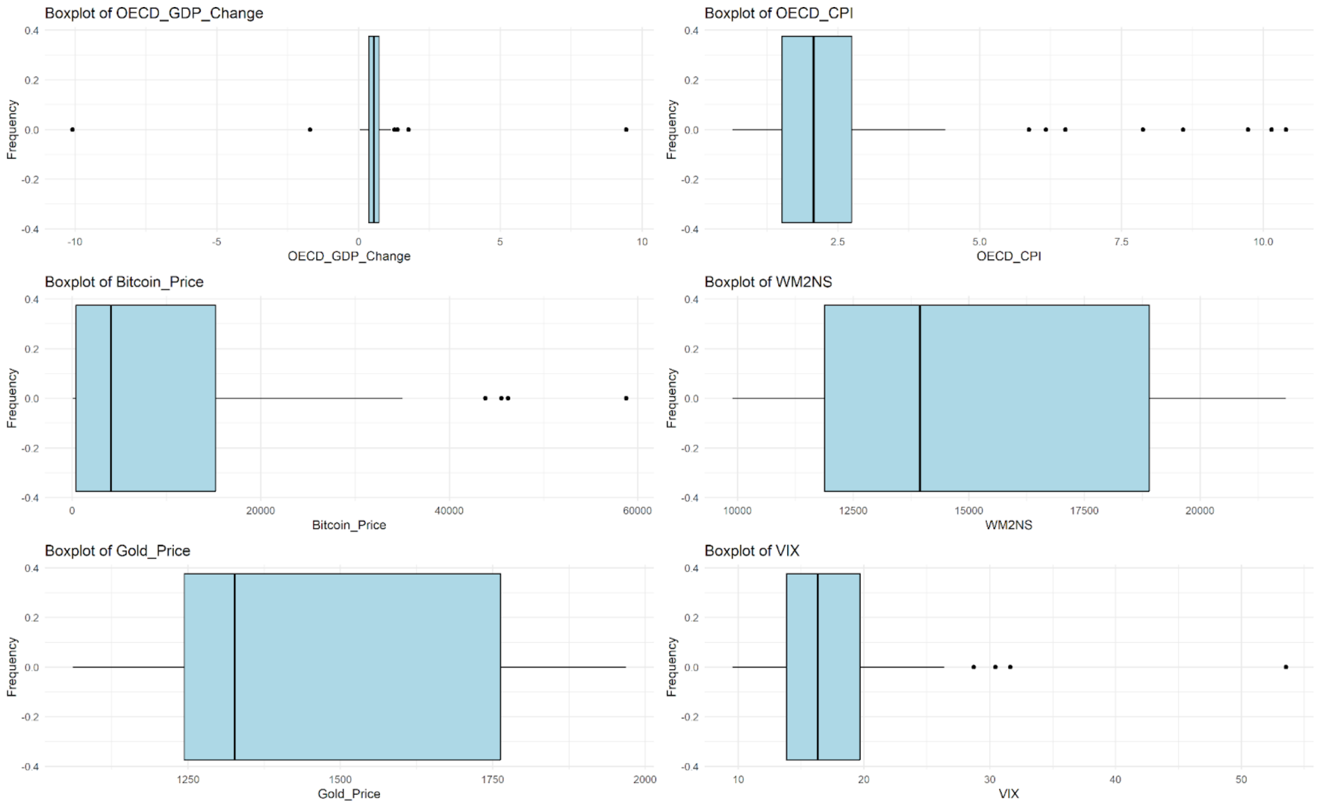
In conclusion, our contribution is threefold to add to the growing literature on the intersection of macroeconomics and cryptocurrency markets. We do find evidence that Bitcoin prices are impacted by macroeconomic indicators; however, more work is needed to properly understand the dynamics and to be able to make more actionable conclusions for both investors and policymakers navigating this emerging asset class.

Appendices

Appendix 1: Histograms

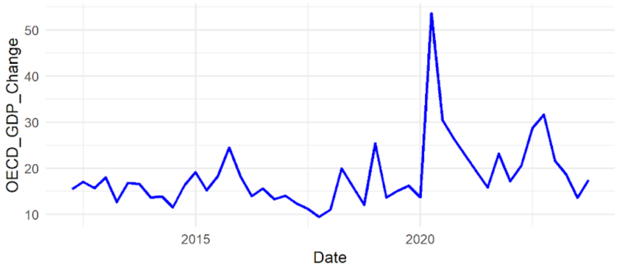


Appendix 2: Boxplots

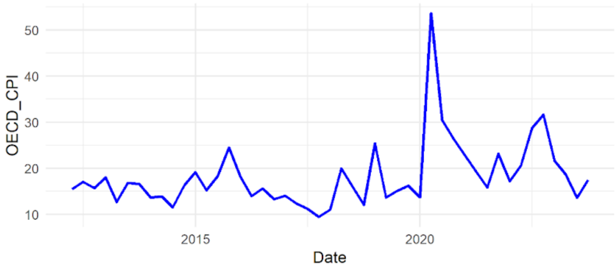


Appendix 3: Time plots

Time plot of OECD_GDP_Change



Time plot of OECD_CPI



Time plot of Bitcoin_Price

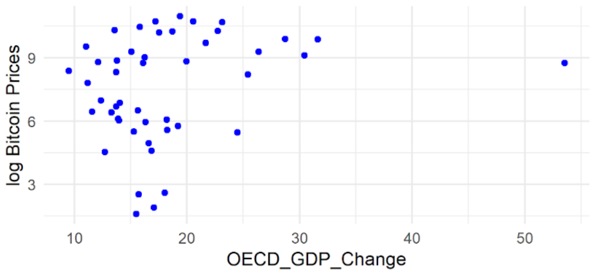
Time plot of WM2NS

Time plot of Gold_Price

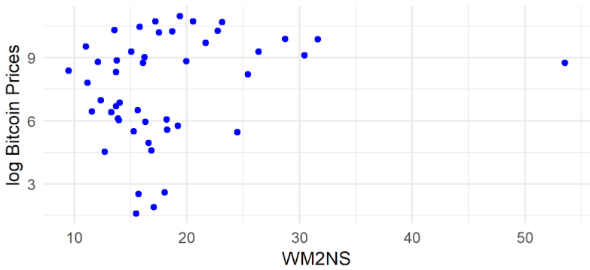
Time plot of VIX

Appendix 4: Scatterplots

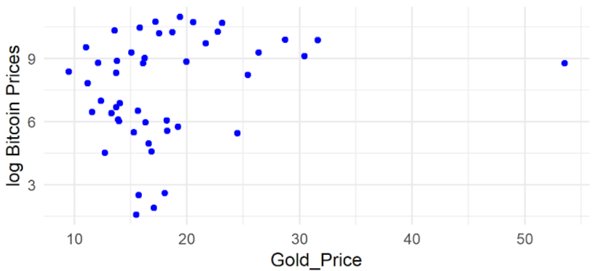
Scatterplot of log_Bitcoin_Price vs OECD_GDP_Change



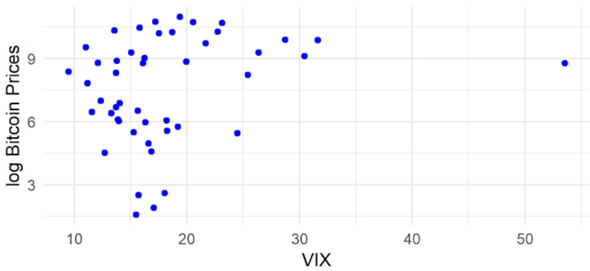
Scatterplot of log_Bitcoin_Price vs WM2NS



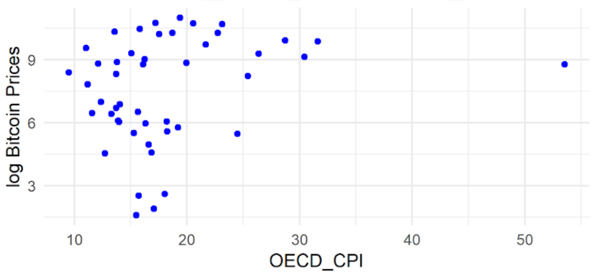
Scatterplot of log_Bitcoin_Price vs Gold_Price



Scatterplot of log_Bitcoin_Price vs VIX



Scatterplot of log_Bitcoin_Price vs OECD_CPI



Appendix 5: Correlation matrix