Proceedings of the 8th International Conference on Economic Management and Green Development
DOI: 10.54254/2754-1169/2024.MUR17833

The Impact of US Macroeconomic Factors on Bitcoin Prices: A Vector Auto-Regression (VAR) Model Analysis

Zizhao Wang[1,a,*]

[1]*School of Computer Science, Fudan University, Shanghai, China*
a. 21307130036@m.fudan.edu.cn
**corresponding author*

Abstract: Having emerged as a significant asset in the global financial landscape, particularly in the past decade, Bitcoin not only offers a decentralized alternative to financial traditions, but also potential for speculating and value storing. As Bitcoin matures, its impact on financial markets also grows rapidly, making it a critical subject for study. This paper focuses on the impact of seven selected key U.S. macroeconomic factors on Bitcoin prices by running a Vector Auto-Regression (VAR) model and performing Impulse Response Function (IRF) analyses. The indicators aim to stand for macroeconomic aspects including monetary policies, economic and market performance, inflation, commodity prices, and currency value. After obtaining quarterly time series from 2010 to 2024, a VAR model was utilized, attempting to capture dynamic relationships and lagged effects between the variables. The findings are expected to offer insights into Bitcoin's dynamic interactions with macroeconomic conditions and prospects, especially for investors considering Bitcoin as a potential hedge in their portfolio and researcher interested in related topics.

Keywords: Bitcoin, Macroeconomic Factors, Vector Auto-Regression, Cryptocurrency.

1. Introduction

In recent decades, the financial market has witnessed rapid transformations with the emergence, increasing popularity and potential future dominance of digital assets like Bitcoin, which is expected to play an important role in e-commerce and beyond in the future [1]. Thus, Bitcoin has not only attracted considerable attention from investors seeking its potential as a hedge against uncertainty and a store of value, but also become a research focus especially on cryptocurrency. Invented in 2009 as an obscure digital experiment, Bitcoin has gradually evolved into an outstanding and prominent asset class. The cryptocurrency's dynamic pricing can be influenced by various factors, including macroeconomic conditions and prospects of inflation, monetary policy, and economic growth.

Bitcoin's price formation is such a dynamically complex economic process, even making it a formidable challenge to theorists. Many previous research has explored how Bitcoin's pricing is potentially related with macroeconomic conditions, expectations and news [2,3]. These researches aim to improve our understanding of the determinants of Bitcoin's price formation, while consequently, enhancing expected investment returns of portfolios with Bitcoin. Thus, this paper builds on past research, attempting to analyze the impact of key US macroeconomic factors on Bitcoin prices. The study is expected to offer insights and potential implications for investors, researchers and policymakers.

© 2025 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2754-1169/2024.MUR17833

2. Literature Review

Many studies have examined the relationship between Bitcoin prices and macroeconomic variables, with several studies exploring Bitcoin's interaction with these factors using various methodologies to capture its unique dynamics in the macroeconomic system. Das and Kannadhasan, for instance, focused on how global economic factors, especially economic policy uncertainty (EPU) and crude oil prices, affect Bitcoin prices by employing a wavelet-based approach [4]. Their results indicate that though Bitcoin remains relatively insulated from these factors in the short term, they exhibit significant co-movement relationship with EPU and crude oil in the medium to long term. This dynamic suggests that Bitcoin's response to macroeconomic shock shifts over time, emphasizing on the potential benefit of dynamic research approaches like Vector Auto-Regression (VAR).

On the other hand, Vaddepalli and Antoney mainly analyzed the impact of inflation, financial openness, and internet penetration on Bitcoin transactions across select economies, finding no statistically significant relationship between these indicators and Bitcoin transaction volumes [5]. This highlights that Bitcoin may operate outside the traditional drivers of economic activity, suggesting its idiosyncratic nature as a digital asset. However, Deniz and Teker provide a different perspective by showing that Bitcoin's price movements are predominantly driven by its own dynamics, with external factors like gold and oil having minimal impact [6]. These findings underscore Bitcoin's distinctive price behavior, which contrasts with traditional commodities and currencies.

While these studies contribute valuable insights, they are often limited by short time frames, narrow geographic scopes, or the exclusion of critical macroeconomic variables. For example, Wang et al. applied shrinkage methods to predict Bitcoin volatility, focusing on technical indicators and macroeconomic factors but only within a specific economic period of less than a decade [7]. Therefore, this study, by leveraging a broader dataset from 2010 to 2024 and incorporating seven key U.S. macroeconomic indicators representing the overall macroeconomic landscape, aims to address these limitations. Vector Auto-Regression (VAR) model is a strong macroeconomic forecasting tool due to its flexibility, empirical nature, and ability to capture interdependencies among variables [8], and the use of a VAR model in this paper is expected to capture the dynamic, lagged effects between Bitcoin prices and macroeconomic factors, thus offering a more comprehensive view of Bitcoin's behavior in the context of broader economic trends.

3. Data and Methodology

3.1. Data and Variables

In this study, quarterly time series of several carefully chosen US macroeconomic factors are utilized as independent factors, along with a time series of Bitcoin prices as the dependent variable. The seven selected US macroeconomic indicators—consisting of the Federal Funds Rate (IR), Quarterly Growth Rate of Real Gross Domestic Product (GDP), Bloomberg Commodity Index (BCM), S&P 500 Index (SPX), US Dollar Index (USD), M2 Money Supply (M2), and Consumer Price Index for All Urban Consumers (CPI)—are intended to comprehensively represent US macroeconomic, including aspects such as monetary policies, economic and market performance, inflation, commodity prices, and currency value. The quarterly time series data covers the period from 2010 Q1 through 2024 Q2, primarily because the first recorded commercial transaction involving Bitcoin took place in 2010. Additionally, since the macroeconomic indicator with the lowest reporting frequency is the quarterly reported US GDP, all the time series are transformed into a quarterly format. The data for this study were obtained from several reliable online sources, including the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org) and WSJ Markets which is provided by the Wall Street Journal

DOI: 10.54254/2754-1169/2024.MUR17833

(https://www.wsj.com/market-data). Although the dataset is not very large, it is expected that this will not significantly undermine the analysis and conclusions.

3.2. Model Construction

Due to the dynamic interrelationships and lagged effects of macroeconomic factors, where changes in one variable often impact others over time, it is suggested that the Vector Auto-Regression (VAR) model may effectively handle the endogeneity and feedback mechanisms among these variables, allowing for the analysis of lead-lag relationships and joint forecasting. Therefore, the VAR model for this study is expressed as equation (1):

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + C + u_t \tag{1}$$

Where Y_t stands for:

$$Y_t = \left(BTC_t\ IR_t\ GDP_t\ BCM_t\ SPX_t\ USD_t\ M2_t\ CPI_t\right)^T \tag{2}$$

Additionally, in equation (1), A_i, p, C and u_t respectively represent the coefficient matrices, the number of lags, the constant vector and the stochastic error term vector.

More explicitly, the time series of Bitcoin prices (BTC_t) can be extended and expressed in the following equation (3):

$$\begin{aligned} BTC_t = {} & \alpha_{1,1,1} BTC_{t-1} + \alpha_{1,2,1} IR_{t-1} + \alpha_{1,3,1} GDP_{t-1} + \alpha_{1,4,1} BCM_{t-1} \\ & + \alpha_{1,5,1} SPX_{t-1} + \alpha_{1,6,1} USD_{t-1} + \alpha_{1,7,1} M2_{t-1} + \alpha_{1,8,1} CPI_{t-1} + \cdots \\ & + \alpha_{1,1,p} BTC_{t-p} + \cdots + \alpha_{1,8,p} CPI_{t-p} + c_{BTC} + u_{BTC,t} \end{aligned} \tag{3}$$

Where $\alpha_{1,j,k}$ represents the coefficients of lagged variable j in the equation for variable 1, namely BTC, at lag k, while c_{BTC} and $u_{BTC,t}$ are the intercept term and error term in equation (3).

4. Results and Discussion

4.1. The ADF Test

Econometric studies have suggested financial and macroeconomic time series variables usually lack stationarity, which could lead to spurious [9]. Therefore, before analyzing the results of the VAR econometric model, it is suggested that conducting the Augmented Dickey-Fuller (ADF) test will allow for an accurate examination of the dynamic relationships between BTC and the macroeconomic indicators. The results of the ADF test are summarized in Table 1, indicating that most of the variables achieve stationarity at the 1% or 5% level of significance after being integrated of order one, while BTC and GDP are already stationary at zero order of integration. Thus, it can be concluded that BTC and all the macroeconomic indicators are difference stationary processes, and the stationarity condition for the Engel and Granger approach is satisfied [9].

Table 1: Results of ADF Unit Root Test

Variables	BTC	BCM	SPX	CPI	IR	GDP	M2	USD
ADF Test Statistics	-2.94	-7.26	-9.24	-2.93	-6.33	-7.06	-3.53	-7.74
Order of Integration	I(0)	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)
Stationary Level	5%	1%	1%	5%	1%	1%	5%	1%

4.2. VAR Order Selection

After ensuring stationarity through the ADF test, the next indispensable step is to determine the

DOI: 10.54254/2754-1169/2024.MUR17833

optimal lag length for the VAR model using various criteria [10]. As shown in Table 2, the Akaike Information Criterion (AIC), Final Prediction Error (FPE), and Hannan-Quinn Information Criterion (HQIC) all favor a lag length of 4. Prior study has indicated that for VAR models with quarterly time series, HQIC appears to be the most accurate criterion [10]. Thus, despite the Bayesian Information Criterion (BIC) suggesting a shorter lag, choosing 4 lags generally allows the model to capture the full dynamics of the variables while maintaining stability.

Table 2: VAR Order Selection Test (* highlights the minimum values)

Lag Length	AIC	BIC	FPE	HQIC
0	37.02	37.33	1.196e+16	37.14
1	32.45	35.2*	1.272e+14	33.49
2	31.96	37.16	9.471e+13	33.94
3	31.77	39.42	1.378e+14	34.68
4	28.71*	38.8	2.454e+13*	32.55*

4.3. Multicollinearity Analysis

Before running the VAR model, checking for multicollinearity among predictors to ensure reliable coefficient estimates and accurate interpretation is necessary. Otherwise, multicollinearity might cause inflated standard errors, leading to some independent variables being statistically insignificant when they should be significant, thus distorting the regression results [11]. The Variance Inflation Factor (VIF) helps assess multicollinearity by quantifying how much a variable's variance is inflated due to its correlation with other variables. The results presented in Table 3 indicate that multicollinearity is generally moderate, with all variables showing VIF values below 5. The highest VIF values are for CPI and IR, indicating some level of correlation with other predictors, but overall, the results are acceptable.

Table 3: Results of the Variance Inflation Factor Test

Variable	const	BTC	BCM	SPX	CPI	IR	GDP	M2	USD
VIF	4.043	2.267	1.849	2.013	3.289	3.160	2.063	2.273	1.176

4.4. The VAR Model Regression Results

VAR regression was performed using the VAR Model in equations (1) and (3), and the results are shown in the table 4 and table 5. Based on the coefficients and p-values shown in Table 5, a preliminary conclusion can be reached. BTC itself has consistent impact at the first three lags, indicating that Bitcoin Prices are greatly influenced by its own past values, with a strong autocorrelation that diminishes at higher lags. GDP shows increasingly significant negative effects across all lags, while BCM is significant only at the first lag. Additionally, at certain lags, USD and CPI show borderline significance. By contrast, other variables, such as IR, SPX and M2 do not suggest consistent pattern of impacts on Bitcoin prices at most of the lags observed.

Table 4: Summary of VAR Regression Results

Description	Value	Description	Value
Model	VAR	HQIC	32.5508
Method	OLS	Log likelihood	-1021.23
BIC	38.8019	FPE	2.45419e+13
Nobs	50.0000	AIC	28.7064

DOI: 10.54254/2754-1169/2024.MUR17833

Table 5: Regression Results for BTC Equation (3)

Variable	Lag1		Lag2		Lag3		Lag4	
	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
BTC	1.53	0	0.95	0	-1.06	0	-0.23	0.18
IR	-471.1	0.92	4336.62	0.42	113.5	0.98	-6402.37	0.36
GDP	-2E+05	0.07	-302263	0.08	-506184	0.01	-639136	0
BCM	334.42	0.03	26.47	0.84	-68.11	0.57	27.26	0.81
SPX	-4.19	0.48	-0.32	0.96	9.9	0.19	8.32	0.21
USD	344.96	0.20	558.57	0.05	240.68	0.40	232.06	0.35
M2	-11.72	0.22	-3.12	0.72	-5.84	0.44	1.49	0.83
CPI	-1831	0.08	-545.55	0.56	-109.69	0.90	548.4	0.48

4.5. Analysis of Impulse Response Function

After preliminarily analyzing the implications of the regression coefficients, it is believed that Impulse Response Function (IRF) analyses could enhance our understanding of the dynamic relationships between variables over time. Specifically, this means examining how each variable impacts Bitcoin prices dynamically over time.

As shown in figure 1, the response of BTC to BCM increases significantly over time, rising from 334.42 in period 2 to 1713.51 in period 11. This suggests that shocks to BCM have a growing positive effect on BTC, supporting the typical idea of BTC as a hedge against inflation and proving other researchers' findings that bitcoin may be used as a safe haven by the financial market [12]. In contrast, the response of BTC to CPI is highly negative, indicating that shocks to CPI initially have a strong adverse impact on BTC. Although both BCM and CPI are considered typical inflation indicators, this discrepancy might be due to BCM's association with "hard assets" and major commodities in the market that preserve purchasing power, while rising CPI could lead to tighter monetary policies and lower consumer spending, thus weakening BTC.

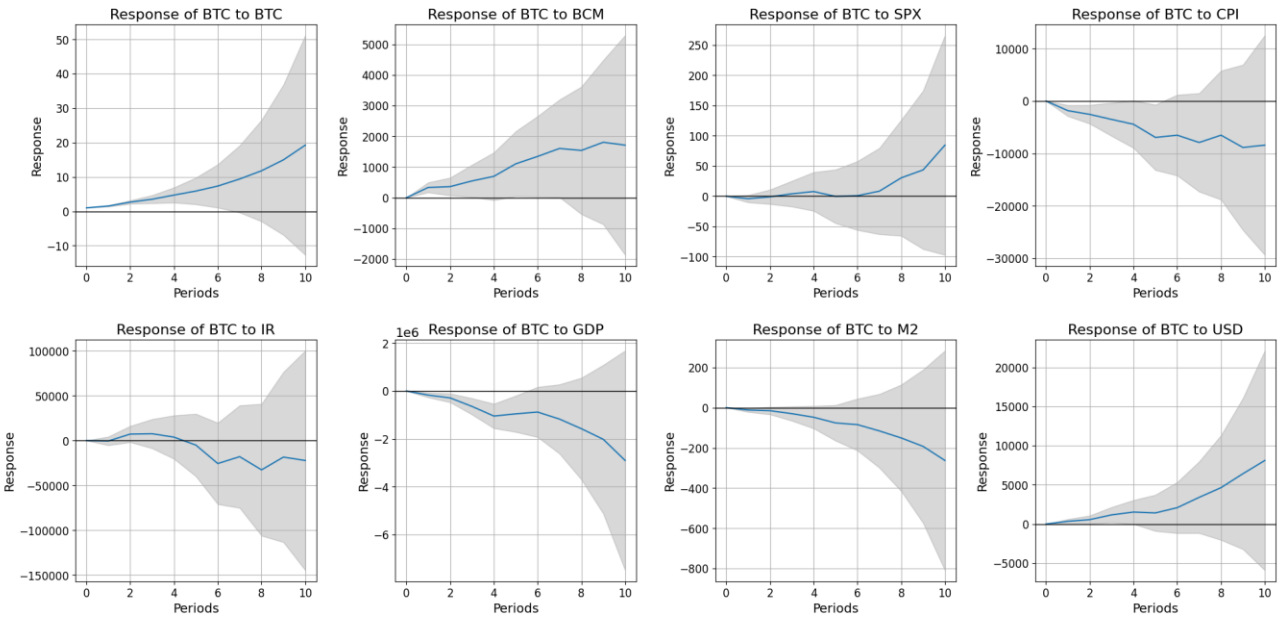

Figure 1: Results of the Impulse Response Function Test

The response of BTC to SPX fluctuates, showing both positive and negative values, implying an inconsistent correlation between BTC and the broader stock market, which supports findings that global macro-financial developments do not significantly affect Bitcoin price in the long run [13]. Similarly, BTC's response to IR starts negative but varies over time, reflecting a complex interaction. Initially, BTC may be viewed as an inflation hedge in a high-IR environment, but as IR rises, the negative impact on BTC could stem from reduced liquidity and decreased investor risk appetite.

BTC's response to GDP starts very negative and worsens, possibly due to stronger confidence in traditional assets during economic growth periods, which diminishes BTC's appeal. The consistently negative response of BTC to M2 suggests that increased liquidity may reduce BTC's value, indicating it may not serve as a hedge against rising money supply. Conversely, BTC's response to USD shows a positive trend, suggesting that BTC benefits from a strong USD as a store of value and an attractive asset for diversifying away from traditional currencies.

5. Conclusion

The findings of this paper offer insights into Bitcoin's dynamic interactions with economic variables and highlight its evolving role in the financial landscape. In summary, the results reveal that Bitcoin prices exhibit significant autocorrelation, particularly at lags 1 and 2, suggesting that past prices are strong predictors of future values. Bitcoin's interactions with macroeconomic factors emphasize its role as a dynamic asset with varying responses to inflation indicators, monetary policy, and economic conditions. The increasing positive impact of the Bloomberg Commodity Index supports its potential function as an inflation hedge, while negative reactions to the Consumer Price Index and the M2 Money Supply reflect challenges during periods of rising prices and liquidity. Fluctuating responses to the S&P 500 Index and the Federal Funds Rate suggest a complex relationship with broader market conditions, and a positive response to the US Dollar Index underscores Bitcoin's appeal as a store of value amidst currency fluctuations.

These findings underscore Bitcoin's potential as an inflation hedge and its sensitivity to economic growth indicators. The positive relationship with BCM reinforces Bitcoin's role in preserving value during inflationary periods, while the negative association with GDP suggests decreased appeal during economic expansions. The mixed responses to SPX and IR reveal that Bitcoin's interactions with broader financial conditions are intricate and variable. Additionally, the consistently negative impact of M2 highlights challenges in times of increased liquidity.

Despite the insights, several limitations remain, such as the exclusion of certain important macroeconomic factors that might significantly influence Bitcoin prices. Further study could be improved by incorporating a wider range of macroeconomic indicators. Additionally, employing a higher number of lags in the VAR model might reveal a more detailed pattern and deeper relationships. The study relied on relatively lower-frequency data such GDP growth rate, which may overlook the short-term dynamics and immediate responses. Given the 24/7 nature of cryptocurrency markets, higher-frequency data may be necessary to capture Bitcoin's rapid response to economic events. Furthermore, the gap between the release of official macroeconomic indicators and the actual, real-time impact on Bitcoin prices leaves room for improvement in future researchers. This gap may suggest potential application of sentiment analysis and real-time economic data.

References

[1] Polasik, M., Piotrowska, A. I., Wisniewski, T. P., Kotkowski, R., & Lightfoot, G. (2015). Price Fluctuations and the Use of Bitcoin: An Empirical Inquiry. International Journal of Electronic Commerce, 20(1), 9–49.

[2] Bakas, D., Magkonis, G., & Oh, E. Y. (2022). What drives volatility in the Bitcoin market? Finance Research Letters, 50, 103237.

DOI: 10.54254/2754-1169/2024.MUR17833

[3] Corbet, S., Larkin, C., Lucey, B. M., Meegan, A., & Yarovaya, L. (2020). The impact of macroeconomic news on Bitcoin returns. The European Journal of Finance, 26(14), 1396–1416.
[4] Das, D., & Kannadhasan, M.S. (2018). Do global factors impact bitcoin prices?: evidence from wavelet approach. Journal of economic research, 23, 227-264.
[5] Vaddepalli, S., & Antoney, L. (2017). Are economic factors driving Bitcoin transactions? An analysis of select economies. Journal of Emerging Issues in Economics, Finance and Banking (JEIEFB), 6(2), 2215-2227.
[6] Deniz, E., & Teker, D. (2019). DETERMINANTS OF BITCOIN PRICES. PressAcademia Procedia, 10(1), 17-21.
[7] Wang, J., Ma, F., Bouri, E., & Guo, Y. (2023). Which factors drive Bitcoin volatility: Macroeconomic, technical, or both? Journal of Forecasting, 42(4), 970-988.
[8] Lupoletti, W. M., & Webb, R. H. (1986). Defining and Improving the Accuracy of Macroeconomic Forecasts: Contributions from a VAR Model. The Journal of Business, 59(2), 263–285.
[9] Engle, R.F., & Granger, C.W. (1987). Co-integration and error correction: representation, estimation and testing. Econometrica, 55, 251-276.
[10] Ivanov, V. & Kilian, L. (2005). A Practitioner's Guide to Lag Order Selection For VAR Impulse Response Analysis. Studies in Nonlinear Dynamics & Econometrics, 9(1).
[11] Daoud, J. I. (2017). Multicollinearity and regression analysis. Journal of Physics: Conference Series, 949(1), 012009.
[12] Neves, R. d. (2020). Bitcoin pricing: impact of attractiveness variables. Financial Innovation, 6(1), 21.
[13] Ciaian, P., Rajcaniova, M., & Kancs, d'Artis. (2015). The economics of BitCoin price formation. Applied Economics, 48(19), 1799–1815.