

Cryptocurrency Returns and the Macro-economy: Evaluating the Predictive Role of Inflation and Financial Conditions

Cheng-Wen Lee¹ and Sephali Bera^{2*}

Abstract

This paper examines how Bitcoin returns interact with macroeconomic and financial drivers—specifically inflation, industrial production, money supply, stock market returns, the wholesale price index, and financial conditions—using monthly data from April 2015 to March 2025. Methodologically, we apply Augmented Dickey-Fuller (ADF) tests, ordinary least squares (OLS) regression, and vector autoregression (VAR) modelling. Because not all variables are stationary at levels, the VAR model is estimated with differencing. The OLS results indicate that traditional macroeconomic factors do not effectively explain Bitcoin returns. However, the VAR analysis reveals that inflation significantly Granger-causes Bitcoin returns, whereas financial conditions and equity markets show negligible predictive power. Impulse response functions confirm that macroeconomic shocks hit Bitcoin only in the short term, and variance decomposition shows that over 84% of Bitcoin's volatility is driven by its own innovations. We conclude that Bitcoin remains a largely decoupled, self-driven asset with minimal integration into traditional macroeconomic fundamentals, despite a modest predictive link to inflation.

JEL classification numbers: G12, E31, E44.

Keywords: Cryptocurrency, macroeconomic, VAR model, ADF test.

¹ Department of International Business, College of Business, Chung Yuan Christian University. Taoyuan City, Taiwan.

^{2*} Ph. D. Program in Business, College of Business, Chung Yuan Christian University. Taoyuan City, Taiwan. *Corresponding author.

1. Introduction

Over the past decade, cryptocurrencies have transformed from a niche technological experiment into a major component of the global financial ecosystem. Initially introduced with Bitcoin in 2009, cryptocurrencies are decentralised digital assets built on blockchain technology that enable peer-to-peer transactions without the need for central authorities such as banks or governments. Over time, the cryptocurrency market has expanded significantly to include a wide range of digital currencies with diverse use cases, consensus mechanisms, and varying levels of adoption. Increasingly, cryptocurrencies are being viewed not only as technological innovations but also as alternative financial assets that may serve purposes such as investment diversification, payment systems, and value storage.

A defining feature of cryptocurrencies is their decentralised structure, which reduces reliance on traditional financial intermediaries. Limited supply, blockchain transparency, high transferability, and global access have driven their popularity among investors (Nakamoto, 2008; OECD, 2022). The development of crypto-related financial products, along with increased participation from institutional investors, has further integrated cryptocurrencies into mainstream financial markets. As a result, there is growing academic and policy interest in understanding what drives their valuation and price volatility.

The importance of cryptocurrencies is especially evident in emerging economies such as India, where rapid digitalisation, expanding internet access, and increasing participation in financial markets have driven significant growth in adoption. India has emerged as one of the largest cryptocurrency markets in terms of user base, despite an evolving regulatory framework that continues to develop. A young population, a rapidly growing fintech ecosystem, and increasing interest in alternative investment opportunities have encouraged many investors to consider cryptocurrencies as instruments for wealth creation, speculation, and portfolio diversification. At the same time, concerns related to financial stability, consumer protection, tax compliance, and monetary sovereignty have led policymakers to closely monitor and regulate this emerging sector.

A key area of debate in academic literature is the set of factors that determine cryptocurrency price movements. One perspective suggests that cryptocurrencies are increasingly influenced by macroeconomic conditions in a manner similar to traditional financial assets. From this viewpoint, variables such as inflation rates, interest rates, exchange rate fluctuations, economic growth, global liquidity, and geopolitical uncertainty play an important role in shaping investor demand and asset valuation. In India specifically, macroeconomic factors such as inflation trends, depreciation or appreciation of the Indian rupee, changes in GDP growth, capital inflows and outflows, and monetary policy actions by the Reserve Bank of India may influence investor behaviour toward cryptocurrencies. During periods of economic uncertainty or currency depreciation, cryptocurrencies are often perceived by some investors as hedging instruments, potentially increasing demand. In contrast, an alternative perspective argues that cryptocurrencies are largely

speculative assets whose prices are driven more by investor sentiment, behavioural biases, and market psychology than by underlying economic fundamentals. The cryptocurrency market is widely recognised for its extreme volatility, rapid price swings, and strong retail investor participation, all of which contribute to short-term speculative trading. In the Indian context, this speculative nature may be further intensified by social media trends, influencer recommendations, online trading platforms, and increased accessibility through digital exchanges. As a result, price movements may often reflect hype cycles, fear and greed dynamics, and momentum trading rather than macroeconomic fundamentals. Empirical research on cryptocurrency price determinants remains mixed and inconclusive. Some studies report statistically significant relationships between cryptocurrency returns and macroeconomic indicators such as inflation, interest rates, exchange rates, stock market performance, and economic policy uncertainty. Other studies, however, find that investor sentiment, trading volume, media attention, and speculative behavior explain a larger share of price variation. In addition, the strength and direction of these relationships often differ across countries, time periods, and market conditions, making it difficult to reach a unified conclusion. This inconsistency highlights an important research gap, particularly in the context of India. While global studies on cryptocurrencies are extensive, relatively few studies focus on how India's unique macroeconomic environment interacts with the cryptocurrency market. Given India's growing role in global digital finance and the rapid expansion of domestic crypto participation, it is essential to understand whether cryptocurrencies behave more like macroeconomically driven financial assets or remain primarily speculative instruments. Therefore, this study aims to examine the relationship between cryptocurrencies and key macroeconomic indicators in the Indian context, while also assessing the relative importance of fundamental economic factors and speculative forces in shaping price dynamics. The findings are expected to provide useful insights for investors, policymakers, and regulators in understanding the evolving role of cryptocurrencies within the financial system.

2. Literature Review

2.1 Cryptocurrency as an Asset

Cryptocurrencies have gained significant attention in financial literature due to their ambiguous classification as either investment assets or speculative instruments. According to Ahmed (2024), Bitcoin liquidity is driven mainly by internal market dynamics rather than external macroeconomic conditions, suggesting that cryptocurrency-specific factors are more robust determinants of liquidity than conventional financial and economic variables. Since the introduction of Bitcoin in 2009, cryptocurrencies have challenged traditional definitions of money and financial assets due to their decentralised structure, blockchain-based technology, and independence from central authorities (Nakamoto, 2008; Yermack, 2015; Baur et al., 2018). A key debate in the literature is whether cryptocurrencies should be considered “digital gold” or speculative assets. The digital gold perspective

suggests that cryptocurrencies, particularly Bitcoin, share characteristics with precious metals such as limited supply, decentralisation, and potential use as a hedge against inflation and economic uncertainty. These features make them attractive for portfolio diversification and long-term value storage.

In contrast, the speculative asset view argues that cryptocurrencies lack intrinsic value and are primarily driven by investor sentiment, speculation, and market psychology. High volatility, rapid price fluctuations, and the absence of cash flows reinforce the argument that cryptocurrencies behave more like speculative instruments than stable financial assets. Overall, the literature remains divided, with cryptocurrencies occupying a hybrid position between alternative investment assets and speculative financial instruments.

2.2 Macroeconomic Determinants in the Indian Market

The relationship between macroeconomic variables and cryptocurrency markets has become an important area of research, especially in emerging economies such as India. Researchers argue that cryptocurrencies may respond to macroeconomic conditions similarly to traditional financial assets (Bouri et al., 2017; Dyhrberg, 2016). Inflation is a key determinant, as rising inflation reduces the purchasing power of fiat currencies and may push investors toward cryptocurrencies as alternative stores of value. Interest rates also influence cryptocurrency demand; lower interest rates increase liquidity and risk-taking behaviour, while higher rates reduce investment in speculative assets. Liquidity conditions, both domestic and global, further affect cryptocurrency markets by shaping investor risk appetite. Expansionary monetary policy tends to increase investment in high-risk assets, including cryptocurrencies.

In India, additional macroeconomic factors such as exchange rate fluctuations of the Indian rupee, GDP growth, capital flows, and monetary policy decisions by the Reserve Bank of India play an important role. Currency depreciation, in particular, may encourage investors to diversify into cryptocurrencies as a hedge against domestic economic instability. However, the extent to which macroeconomic variables influence cryptocurrency prices remains uncertain, especially in emerging economies where behavioural and regulatory factors also play a significant role.

2.3 Empirical Studies

Empirical literature on cryptocurrency price behaviour presents mixed and sometimes contradictory findings. Baur et al., (2018) find that Bitcoin behaves more like a speculative asset than a medium of exchange or stable investment instrument. Dyhrberg (2016) shows that Bitcoin exhibits partial hedge characteristics similar to gold and the US dollar, but also retains strong speculative properties due to its volatility. Ciaian et al., (2016) conclude that Bitcoin prices are mainly driven by market forces such as supply and demand, investor attractiveness, and speculative trading, with limited macroeconomic influence. Klein et al., (2018) challenge the “digital gold” narrative, finding that Bitcoin does not consistently function as a safe-

haven asset. Kurka, (2017) established that the unconditional connectedness between cryptocurrency markets and traditional financial assets is generally weak, providing foundational evidence for the limited transmission of shocks across these asset classes. Recent studies further expand this debate by showing increasing macro-financial linkages in cryptocurrency markets. Inflation expectations have been found to significantly influence cryptocurrency investment behaviour, particularly in emerging economies (Murakami and Viswanath-Natraj, 2025). Macroeconomic shocks are also shown to transmit into cryptocurrency volatility, indicating growing financial integration (Chen, 2025). Wahyuni et al., (2024) find that inflation and interest rates negatively affect Bitcoin returns, while exchange rates and alternative assets significantly influence price movements. Similarly, Lin et al., (2025) show that macroeconomic indicators such as dollar strength, production indices, and treasury yields play an important role in determining cryptocurrency returns.

In addition, recent evidence suggests that both observable macroeconomic factors and latent variables such as investor sentiment jointly influence cryptocurrency behaviour, highlighting the complexity of price formation mechanisms (Brigida, 2026). Overall, contemporary research indicates that cryptocurrency markets are influenced by a combination of macroeconomic forces, financial integration, and behavioural factors.

2.4 Gap in the Literature

Despite extensive global research on cryptocurrencies, several gaps remain in the literature. First, empirical evidence on the impact of macroeconomic variables on cryptocurrency markets remains mixed and inconclusive. Studies often produce differing results regarding whether cryptocurrencies behave like macro-driven assets or speculative instruments. Second, there is a limited number of studies using dynamic econometric approaches such as VAR (Vector Autoregression) models, particularly in the context of emerging economies like India. Such models are important for capturing time-varying relationships and interdependencies between variables. Finally, much of the existing research is based on earlier time periods, with limited focus on post-2015 developments when cryptocurrency markets experienced rapid expansion, increased institutional participation, and greater regulatory attention. This creates a need for updated empirical analysis that reflects current market conditions, especially within the Indian macroeconomic environment.

3. Methodology

3.1 Data and Variables

This study employs monthly time-series data spanning April 2015 to March 2025 to investigate the relationship between cryptocurrency returns and macroeconomic variables in India. Monthly observations provide an appropriate balance between capturing market dynamics and reducing the excessive volatility commonly associated with daily cryptocurrency data.

The analysis incorporates cryptocurrency returns (DLBITC) and six macroeconomic indicators: inflation measured by the Consumer Price Index (DLCPI), industrial production growth (DLIIP), money supply (LM3), stock market returns represented by the BSE index (DLBSE), wholesale price inflation (DLWPI), and the Financial Conditions Index (DLFCI). Variable definitions are presented in Table 1.

Table 1: Define the variables

Variables	Explanation
DLBITC	First difference of log Bitcoin price (proxy for cryptocurrency returns)
DLCPI	Inflation rate proxied by the log difference of the Consumer Price Index
DLIIP	Industrial output growth via log difference of Index of Industrial Production
LM3	Log of money supply (M3), representing liquidity conditions
DLBSE	Stock market return using log difference of the BSE index
DLWPI	Wholesale Price Index inflation (log difference)
DLFCI	Financial Conditions Index (log difference), capturing overall financial stress/liquidity

All variables are transformed into natural logarithms and, where necessary, first-differenced to ensure stationarity. This transformation helps reduce heteroscedasticity, eliminates trends and unit roots, and allows coefficients to be interpreted as approximate percentage changes or elasticities. It also prevents spurious regression, ensuring more robust and credible econometric outcomes. The baseline model is specified as:

$$DLBITC_t = \beta_0 + \beta_1 DLCPI_t + \beta_2 DLIIP_t + \beta_3 LM3_t + \beta_4 DLBSE_t + \beta_5 DLWPI_t + \beta_6 DLFCI_t + \varepsilon_t \quad (1)$$

Where: (DLBITC_t) represents cryptocurrency returns and the explanatory variables capture macroeconomic and financial conditions. The estimated coefficients measure the marginal impact of each macroeconomic variable on cryptocurrency returns.

To account for dynamic interactions and feedback effects among variables, a first-order Vector Autoregression [VAR(1)] model is estimated:

$$Y_t = A_0 + A_1 Y_{t-1} + \varepsilon_t \quad (2)$$

Where: Y_t is the vector of endogenous variables:

[Y_t = DLBITC, DLCPI, DLIIP, LM3, DLBSE, DLWPI, DLFCI]

Unlike conventional regression models, the VAR framework treats all variables as endogenous, allowing each variable to depend on its own lagged values and the lagged values of all other variables in the system. This approach captures dynamic interdependencies, feedback mechanisms, and shock transmission across cryptocurrency and macroeconomic markets. The optimal lag length is selected using the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Hannan–Quinn Criterion (HQ).

3.2 Econometric Procedures

The empirical analysis begins with the Augmented Dickey–Fuller (ADF) unit root test to determine the stationarity properties of each series. The ADF specification is given by:

$$\Delta Y_t = \alpha + \beta_{t+\gamma} Y_{t-1} + \sum \delta_i \Delta Y_{t-i} + \varepsilon_t \quad (3)$$

Where: (Y_t) represents the variable under investigation, (t) denotes the time trend, and (ε_t) is the white-noise error term. The null hypothesis (H_0) states that the series contains a unit root ($(\gamma = 0)$), indicating non-stationarity, while the alternative hypothesis (H_1) suggests that the series is stationary ($\gamma < 0$). The null hypothesis is rejected when the calculated ADF test statistic exceeds the critical value at the 5 percent significance level. Variables found to be non-stationary at levels are transformed through first differencing until stationarity is achieved.

OLS regression is subsequently employed to estimate the short-run relationship between cryptocurrency returns and macroeconomic variables. To ensure model adequacy, diagnostic tests for multicollinearity, heteroscedasticity, and serial correlation are conducted using the Variance Inflation Factor (VIF), White test, and Durbin–Watson statistic, respectively.

Dynamic relationships are then examined using the VAR(1) framework. Model stability is assessed through eigenvalue stability conditions, while residual diagnostics are performed to evaluate serial correlation and normality. To investigate directional relationships among variables, Granger causality tests are conducted within the VAR framework. These tests determine whether past values of a given variable contain predictive information regarding future movements in cryptocurrency returns.

The dynamic effects of macroeconomic shocks are analysed using Impulse Response Functions (IRFs), which trace the response of cryptocurrency returns to a one-standard-deviation innovation in each macroeconomic variable over a forecast horizon of 12–24 months. Finally, Forecast Error Variance Decomposition (FEVD) is employed to quantify the relative contribution of each macroeconomic shock to the variability of cryptocurrency returns, thereby identifying the dominant drivers of cryptocurrency market fluctuations.

4. Empirical Results and Discussion

This section presents the empirical findings concerning the relationship between cryptocurrency returns and selected macroeconomic variables in India. The analysis proceeds in several stages. First, the stationarity properties of the variables are examined using the ADF test. Second, an Ordinary Least Squares (OLS) model is estimated to evaluate the contemporaneous effects of macroeconomic factors on cryptocurrency returns. Third, a Vector Autoregression (VAR) framework is employed to capture dynamic interactions among the variables. The VAR analysis is further extended through Granger causality tests, impulse response functions (IRFs), and forecast error variance decomposition (FEVD) to investigate causality, shock transmission mechanisms, and the relative importance of macroeconomic factors in explaining cryptocurrency market fluctuations.

The stationarity properties of all variables were examined using the ADF unit root test prior to model estimation (Table 2). Establishing stationarity is a prerequisite for reliable time-series analysis because non-stationary variables may generate spurious relationships and misleading statistical inferences.

Table 2: Result of ADF unit root test

Variable	ADF Statistic	p-value	Order of Integration
DLBITC	Significant	0.0000	I (0)
DLCPI	Significant	0.0000	I (0)
DLIIP	Significant	0.0000	I (0)
LM3	Significant	0.0000	I (0)
DLBSE	Significant	0.0000	I (0)
DLWPI	Significant	0.0000	I (0)
DLFCI	Significant	0.0000	I (0)
The null hypothesis of a unit root is rejected at the 1% significance level for all variables. Source: author's own calculation from EViews 8.2			

The results indicate that all variables, namely DLBITC, DLCPI, DLIIP, LM3, DLBSE, DLWPI, and DLFCI, are stationary at levels. The null hypothesis of a unit root is rejected at the 1 percent significance level for all series, with p-values below 0.01. These findings suggest that the variables follow stable stochastic processes and are suitable for subsequent estimation without the need for cointegration analysis or vector error correction modelling. Consequently, the VAR model can be estimated directly in levels.

The baseline OLS model was estimated to assess the direct impact of macroeconomic variables on cryptocurrency returns. The results are shown in the table 3. The estimated model yielded an R^2 value of 0.0579 and an adjusted R^2 value of 0.0070, indicating that the selected macroeconomic variables explain only a small proportion of the variation in cryptocurrency returns. Furthermore, the overall model was statistically insignificant, as indicated by the F-statistic probability value of 0.3455.

Table 3: OLS result with Dependent Variable: DLBITC

Variable	Coefficient	Std. Error	t-Statistic	p-value
Constant	0.098419	0.064183	1.533421	0.128
DLCPI	1.80799	2.868476	0.630296	0.5298
DLIIP	-0.11502	0.180633	-0.63675	0.5256
LM3	-0.00358	0.004093	-0.87353	0.3843
DLBSE	0.544531	0.455387	1.195753	0.2343
DLWPI	0.273153	0.480839	0.568075	0.5711
DLFCI	-2.56018	1.607706	-1.59244	0.1141
$R^2 = 0.0579$				
Adjusted $R^2 = 0.0070$				
F-statistic p-value = 0.3455				
Durbin-Watson stat = 1.838958				

At the individual variable level, none of the explanatory variables were statistically significant at the conventional 5 percent significance level. Financial conditions (DLFCI) exhibited marginal significance at the 10 percent level, suggesting a limited association between broader financial market conditions and cryptocurrency returns. Overall, the OLS findings imply that traditional macroeconomic indicators possess weak explanatory power in predicting cryptocurrency price movements. This result is consistent with the view that cryptocurrency markets are largely influenced by factors beyond conventional macroeconomic fundamentals, including investor sentiment, speculative trading activity, and market-specific developments. To account for dynamic interactions among variables, a VAR model was estimated. Lag selection criteria, including the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Hannan–Quinn Criterion (HQ), consistently identified a first-order VAR specification as the optimal model (Table 4a).

Table 4a: VAR Lag Selection Criteria

Lag	AIC	SC	HQ
0	-16.4386	-16.26679*	-16.3689
1	-16.654	-15.2792	-16.0964
2	-18.65825*	-16.0805	-17.61270*
3	-18.198	-14.4173	-16.6646
Selected Lag Length: VAR(1)			

Table 4b: VAR Stability (AR Roots) Test

Stability Measure	Value
Maximum Inverse Root	0.314
Inside Unit Circle	Yes
Model Stability	Stable
All inverse roots lie within the unit circle, confirming VAR stability	

The stability of the VAR(1) system was subsequently evaluated using the inverse roots of the characteristic polynomial. All roots were found to lie within the unit circle, with the largest modulus equal to 0.314 (Table 4b). This confirms that the estimated VAR model satisfies the stability condition and that any shocks affecting the system gradually dissipate over time. Consequently, the model is suitable for conducting impulse response and variance decomposition analyses.

The Granger causality tests provide evidence regarding the predictive relationships between macroeconomic variables and cryptocurrency returns. The results indicate that inflation, represented by the Consumer Price Index (DLCPI), Granger-causes cryptocurrency returns at the 5 percent significance level (Table 5). This finding suggests that changes in inflation contain useful information for forecasting future cryptocurrency returns.

In addition, stock market returns (DLBSE) and financial conditions (DLFCI) exhibit weak predictive power at the 10 percent significance level. In contrast, industrial production (DLIIP), money supply (LM3), and wholesale price inflation (DLWPI) do not demonstrate statistically significant causal effects on cryptocurrency returns.

Table 5: Granger Causality Test (Dependent Variable: DLBITC)

Variable	Chi-square / F-statistic	p-value	Conclusion
DLCPI	6.249482	0.0439	Significant
DLIIP	0.161498	0.9224	No Causality
LM3	0.18482	0.9117	No Causality
DLBSE	5.534962	0.0628	Weak Significance
DLWPI	0.052087	0.9743	No Causality
DLFCI	5.909976	0.0521	Weak Significance
Significance at 5% indicates Granger causality			
Weak significance refers to the 10% level			

These findings imply that while certain macro-financial variables possess limited predictive content, the overall influence of macroeconomic fundamentals on cryptocurrency markets remains relatively weak. The significance of inflation is particularly noteworthy, as it supports arguments that investors may view cryptocurrencies as a partial hedge against inflationary pressures.

Table 6 the forecast error variance decomposition of Bitcoin returns (DLBITC) over a 10-period horizon, accompanied by a detailed graphical analysis. The results indicate that Bitcoin (DLBITC) is primarily influenced by its own shocks, which account for 84.24% of its forecast error variance over the 10-period horizon. Among the explanatory variables, DLBSE has the highest contribution (6.70%), followed by DLFCI (4.60%) and DLCPI (3.31%). The contributions of DLIIP (0.70%), DLWPI (0.29%), and LM3 (0.13%) are negligible. These findings indicate that Bitcoin is largely self-driven, with only limited influence from macroeconomic and financial variables.

Table 6: Forecast Error Variance Decomposition (10-Period Horizon)

Variable	Contribution (%)
DLBITC	84.24
DLBSE	6.70
DLFCI	4.60
DLCPI	3.31
DLIIP	0.70
DLWPI	0.29
LM3	0.13
Values indicate the percentage contribution of each variable to the forecast error variance of cryptocurrency returns	

Figure 1 is the Graphical illustration of the forecast error variance decomposition (FEVD) of Bitcoin returns, showing the proportion of return variability explained by shocks originating from Bitcoin itself and from other variables in the connectedness framework.

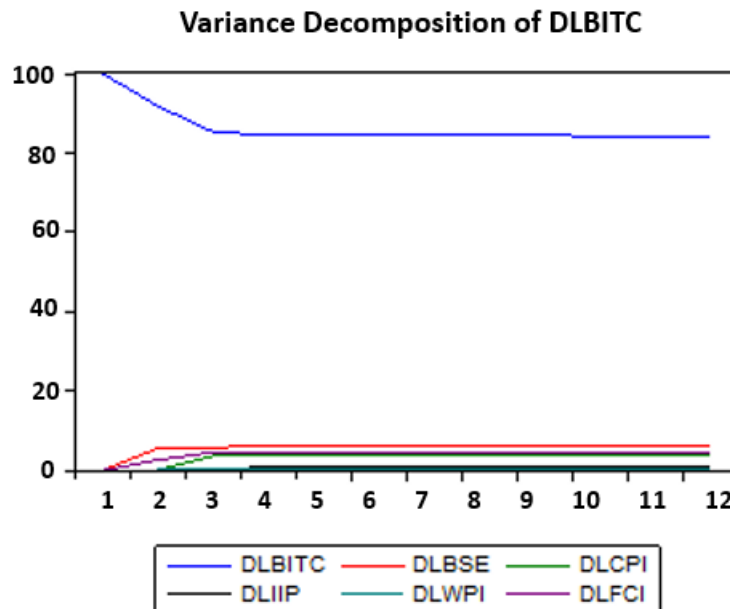


Figure 1: Graphical representation of the variance decomposition framework for Bitcoin returns

Source: Derived from the EViews8 estimation output.

Diagnostic tests confirm the adequacy of the estimated models. Diagnostic test results are shown in the Table 7. No significant serial correlation was detected in the VAR residuals, indicating that the model effectively captures temporal dynamics. While heteroskedasticity and non-normal residuals are present, these findings are typical of financial time-series data and reflect volatility clustering, fat tails, and extreme price movements commonly observed in cryptocurrency markets.

Table 7: Diagnostic Test Result

Diagnostic Test	Result	Conclusion
Serial Correlation	Not Significant	No Autocorrelation
Heteroskedasticity	Present	Common in Financial Data
Normality Test	Rejected	Residuals Non-Normal
Non-normality and heteroskedasticity are common characteristics of Cryptocurrency return series due to high volatility and fat-tailed distributions		

The findings suggest that macroeconomic conditions have a limited influence on cryptocurrency returns in India. While OLS results show weak explanatory power for traditional macroeconomic variables, VAR analyses indicate that inflation, financial conditions, and stock market performance exert only modest predictive effects. Variance decomposition further reveals that most fluctuations in cryptocurrency returns are driven by their own innovations, underscoring the role of investor sentiment, speculation, and cryptocurrency-specific factors. Overall, the results support the view that cryptocurrencies are largely speculative and only weakly connected to traditional macroeconomic fundamentals, functioning as relatively independent financial assets.

5. Conclusion and policy implications

This study investigated the relationship between Bitcoin returns and selected macroeconomic variables using Ordinary Least Squares (OLS) and Vector Autoregression (VAR) techniques. The empirical findings provide several important insights into the extent to which macroeconomic conditions influence cryptocurrency markets.

The results of the unit root tests indicate that all variables are stationary at levels, thereby eliminating the need for cointegration analysis and supporting the application of the selected econometric methods. The OLS estimation reveals that conventional macroeconomic indicators possess limited explanatory power for Bitcoin returns, suggesting that Bitcoin price movements are not strongly driven by traditional economic fundamentals.

The VAR analysis further demonstrates that inflation is the only macroeconomic variable that consistently exhibits a statistically significant influence on Bitcoin returns. Financial conditions and stock market performance display modest predictive effects, whereas money supply, industrial production, and wholesale price inflation do not exert significant influence. These findings imply that Bitcoin's responsiveness to macroeconomic developments is relatively weak and selective.

The impulse response analysis indicates that Bitcoin reacts to macroeconomic shocks primarily in the short run, with the effects dissipating rapidly over time. Furthermore, variance decomposition results reveal that more than 84 percent of the forecast error variance in Bitcoin returns is explained by its own innovations. This finding highlights the dominant role of internal market dynamics, investor sentiment, speculative behavior, and cryptocurrency-specific factors in determining Bitcoin price movements.

Overall, the evidence suggests that Bitcoin functions largely as a speculative and relatively independent financial asset with limited integration into the broader macroeconomic system. While inflation appears to exert some influence, traditional macroeconomic variables generally play a minor role in explaining Bitcoin returns. The findings of this study carry several implications for policymakers, financial regulators, and investors.

First, the limited influence of money supply and industrial production on Bitcoin returns suggests that conventional monetary policy instruments may have little direct impact on cryptocurrency markets. Consequently, central banks should not expect traditional policy measures to significantly affect Bitcoin price dynamics.

Second, the significant causal relationship between inflation and Bitcoin returns indicates that Bitcoin may serve, to some extent, as an alternative store of value during periods of rising inflation. Policymakers should therefore recognize that increasing inflation expectations may stimulate demand for cryptocurrencies as a potential hedge against inflationary pressures.

Third, although Bitcoin is predominantly driven by internal market forces, the observed influence of financial conditions and stock market performance suggests a degree of integration with the broader financial system. This implies that severe disruptions in traditional financial markets may have spillover effects on cryptocurrency markets. Accordingly, regulatory authorities should incorporate cryptocurrency markets into broader financial stability monitoring frameworks.

Fourth, the weak association between Bitcoin returns and macroeconomic fundamentals suggests potential portfolio diversification benefits for investors. Nevertheless, the highly volatile and self-driven nature of Bitcoin markets underscores the importance of effective risk management strategies when incorporating cryptocurrencies into investment portfolios.

Finally, given that Bitcoin valuation is influenced more by market-specific factors than by macroeconomic fundamentals, regulatory efforts should focus on issues such as market transparency, investor protection, speculative trading behavior, liquidity risks, and market integrity rather than attempting to influence cryptocurrency prices through macroeconomic policy interventions.

5.1 Limitations of the Study

Despite providing useful insights, this study is subject to several limitations. First, the analysis is restricted to macroeconomic variables and does not incorporate investor sentiment indicators, blockchain-specific metrics, or market microstructure variables that may influence cryptocurrency returns. Second, the use of monthly data may not fully capture the high-frequency volatility and rapid market adjustments characteristic of cryptocurrency markets. Third, the sample period may encompass structural changes in the cryptocurrency ecosystem, including regulatory developments, technological innovations, and shifts in market participation, which could affect the stability of the estimated relationships.

5.2 Recommendations for Future Research

Future research may extend the present study in several directions. First, incorporating investor sentiment measures, social media indicators, and blockchain network metrics may provide a more comprehensive understanding of cryptocurrency price dynamics. Second, the use of higher-frequency data, such as daily or hourly observations, could offer deeper insights into short-term market

behavior and volatility transmission mechanisms. Third, future studies may employ advanced nonlinear methodologies, including Markov-switching models, regime-dependent frameworks, and machine learning techniques, to capture the complex dynamics of cryptocurrency markets. Finally, comparative analyses involving multiple cryptocurrencies could help determine whether the observed relationships are specific to Bitcoin or represent broader characteristics of the cryptocurrency asset class.

References

- [1] Ahmed, W.M.A. (2024). On the robust drivers of cryptocurrency liquidity: The case of Bitcoin, *Financial Innovation*, 10, 69.
- [2] Baur, D.G, Hong, K. and Lee, A.D. (2018). Bitcoin: Medium of exchange or speculative asset?, *Journal of International Financial Markets, Institutions and Money*, 54, pp. 177–189.
- [3] Bouri, E., Molnár, P., Azzi, G., Roubaud, D. and Hagfors, L.I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?, *Finance Research Letters*, 20, pp. 192–198.
- [4] Brigida, M. (2026). Crypto Pricing with Hidden Factors, Available at SSRN: <https://ssrn.com/abstract=6713065>
- [5] Chen, Z. (2025). From disruption to integration: Cryptocurrency prices, financial fluctuations, and macroeconomy, *Journal of Risk and Financial Management*, 18(7), 360.
- [6] Ciaian, P., Rajcaniova, M. and Kancs, D. (2016). The economics of Bitcoin price formation, *Applied Economics*, 48(19), pp. 1799–1815.
- [7] Dyhrberg, H. (2016). Bitcoin, gold and the dollar—A GARCH volatility analysis. *Finance Research Letters*, 16, pp. 85–92.
- [8] Klein, T., Pham, T. and Walther, T. (2018). Bitcoin is not the new gold – A comparison of volatility, correlation, and portfolio performance, *International Review of Financial Analysis*, 59, pp. 105–116.
- [9] Kurka, J. (2017). Do Cryptocurrencies and Traditional Asset Classes Influence Each Other?, IES Working Paper, No. 29/2017, Charles University in Prague, Institute of Economic Studies (IES), Prague.
- [10] Lin, M., Liu, Y. and Sheng, V.N.K. (2025). Analysis of the impact of macroeconomic factors on cryptocurrency returns - Based on quantile regression study, *International Review of Economics and Finance*, 97, 103757.
- [11] Murakami, D. and Viswanath-Natraj, G. (2025). Cryptocurrencies in emerging markets: A stablecoin solution?. *Journal of International Money and Finance*, 156, 103344.
- [12] Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. www.bitcoin.org
- [13] OECD (Organisation for Economic Co-operation and Development) (2022). Crypto-assets and decentralized finance: Risks, regulation, and policy implications. <http://dx.doi.org/10.2139/ssrn.3440802>

- [14] Wahyuni, M.T., Ridwan, E. and Salim, D.F. (2024). US macroeconomic determinants of Bitcoin, *Investment Management and Financial Innovations*, 21(2), pp. 240–252.
- [15] Yermack, D. (2015). Is Bitcoin a Real Currency? An Economic Appraisal, In *Handbook of Digital Currency*, Elsevier.