



# CRYPTOCURRENCIES AND THE AI ECONOMY: A STATISTICAL EXPLORATION OF INFLUENTIAL MACRO FACTORS

**Kari Gooli**

Research Scholar, Dept. of Commerce, VS K University, Ballari, Karnataka, India- 583105

Email: [gooliesoteric@gmail.com](mailto:gooliesoteric@gmail.com),

**CMA Dr. Jeelan Bash V**

Professor, Dept. of Commerce, Vijayanagara Sri Krishnadevaraya University, Ballari, Karnataka, India-583105

Email: [drjeelanbasha@yahoo.co.in](mailto:drjeelanbasha@yahoo.co.in),

## Abstract:

*Crypto currencies have emerged as a distinct asset class with complex interactions with macroeconomic variables. Unlike traditional financial instruments, their sensitivity to economic indicators remains ambiguous. This study investigates the impact of key macroeconomic factors—Gross Domestic Product (GDP), Interest Rate (IR), Internet Rate (Int.R), and Human Capital Index (HCI)—on the valuation of selected crypto currencies: Bit coin (BTC), Ethereum (ETH), Binance Coin (BNB), and Tether (USDT). Using ANOVA and MANOVA statistical frameworks, the study evaluates both individual and multivariate effects of predictors on crypto currency prices. Variance Inflation Factor (VIF) and correlation analysis confirmed no serious multicollinearity, ensuring model stability and interpretability. The findings reveal that HCI consistently exerts a statistically significant influence on BTC, ETH, and BNB, while GDP shows significance only for BNB. Conversely, IR and Int.R demonstrate minimal predictive power across all models. USDT, as a stable coin, shows no significant relationships with any macroeconomic variables, reinforcing its design for price stability. Model diagnostics indicate the BNB model exhibits the best fit and predictive power ( $R^2 = 0.991$ ), while USDT reflects the weakest explanatory strength ( $R^2 = 0.727$ ). Despite the absence of significant multivariate effects in MANOVA, HCI demonstrated the strongest signal among all predictors. The study concludes that human capital is a crucial non-traditional macroeconomic driver for major crypto currencies, while traditional indicators like interest rates have limited explanatory relevance. These insights offer practical implications for investors seeking to incorporate macroeconomic intelligence into crypto currency investment strategies.*

**Keywords:** Cryptocurrency, Human Capital Index, ANOVA, MANOVA, Macroeconomic Indicators, Investment Strategy.

## Introduction:

The rapid evolution of cryptocurrencies has transformed global financial markets, prompting investors, economists, and policymakers to explore the factors influencing their value. Unlike traditional assets, cryptocurrencies such as Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB) exhibit unique behavior, often decoupled from conventional economic forces. While substantial research has examined price dynamics from technological and behavioral perspectives, the role of macroeconomic fundamentals in shaping cryptocurrency valuations remains underexplored and contested. This study addresses the critical question: To what extent do macroeconomic variables influence the pricing of major cryptocurrencies? Specifically, it investigates the effects of Gross Domestic Product (GDP), Interest Rate (IR), Internet Rate (Int.R), and Human Capital Index (HCI) on the performance of BTC, ETH, BNB, and Tether (USDT). Understanding these relationships is vital as it informs investment strategies, enhances economic modeling, and bridges the gap between digital finance and macroeconomic theory. Existing literature often overlooks or marginalizes macroeconomic inputs in crypto valuation models, treating them as largely immune to economic fundamentals. This research fills that gap by systematically applying statistical methods—ANOVA and MANOVA—to isolate and evaluate the influence of selected economic indicators. The inclusion of HCI is particularly novel, reflecting a shift toward recognizing developmental metrics in financial performance analysis.

## Literature Review:

The intersection of cryptocurrency markets and macroeconomic indicators has been a growing area of scholarly interest, yet findings remain mixed and often inconclusive. Early research predominantly emphasized **technical** and **behavioral** drivers of cryptocurrency prices, such as blockchain network activity, trading volume, investor sentiment, and speculative

demand (e.g., Kristoufek, 2015; Baur et al., 2018). These studies typically downplayed the relevance of traditional macroeconomic fundamentals in shaping crypto valuations. However, more recent contributions have started to challenge this view. Studies like Ciaian et al. (2016) and Dyhrberg (2016) have examined the **influence of macroeconomic indicators** such as inflation, interest rates, and GDP on major cryptocurrencies. While some found weak correlations, others argued that **macroeconomic shocks** may affect crypto prices indirectly via investor behavior or risk perception. Notably, these studies focused heavily on Bitcoin, leaving other major cryptocurrencies such as Ethereum, Binance Coin, and stablecoins like Tether underexplored. Comparative perspectives have also emerged. For instance, Kapar and Olmo (2021) found that Bitcoin reacts to financial uncertainty but shows **weak sensitivity to monetary policy changes**, while other scholars suggest emerging market variables and macroeconomic instability could drive **demand-side interest** in crypto assets (Corbet et al., 2019).

Despite these developments, significant **gaps persist**

### Research Gap:

- Few studies assess multiple cryptocurrencies under a unified macroeconomic model.
- Most prior work omits non-traditional indicators like the Human Capital Index (HCI), despite growing recognition of its role in long-term economic productivity and digital innovation.
- Multivariate approaches (e.g., MANOVA) are rarely used, limiting insight into joint effects across assets.

This study addresses these gaps by incorporating HCI alongside traditional indicators (GDP, IR, Int.R) and applying both ANOVA and MANOVA techniques across four major cryptocurrencies. In doing so, it offers a more holistic and comparative framework for understanding how macroeconomic environments shape crypto valuation—moving beyond Bitcoin-centric and univariate approaches. It contributes to the literature by highlighting the importance of developmental metrics and offering implications for investment strategies, particularly in emerging digital economies.

### Methodology:

This study adopts a **quantitative research design** to examine the influence of macroeconomic indicators on cryptocurrency prices. The primary objective is to identify which economic factors significantly affect the valuation of selected cryptocurrencies—Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), and Tether (USDT)—and to compare their responsiveness across different economic contexts.

### Data Collection

Data were sourced from reputable global databases:

- Cryptocurrency prices were obtained from CoinMarketCap.
- Macroeconomic indicators—Gross Domestic Product (GDP), Interest Rate (IR), Internet Rate (Int.R), and Human Capital Index (HCI)—were collected from World Bank and International Monetary Fund (IMF) datasets. A purposive sampling method was used, focusing on four cryptocurrencies that represent diverse categories: BTC and ETH as dominant assets, BNB as a platform-based token, and USDT as a stablecoin.

### Data Analysis

To assess the statistical relationship between the macroeconomic variables and cryptocurrency prices, the following methods were applied:

- One-way ANOVA was used to evaluate the individual effect of each macroeconomic variable on each cryptocurrency.
- Multivariate Analysis of Variance (MANOVA) was used to assess joint effects across multiple dependent variables (i.e., cryptocurrencies).
- Variance Inflation Factor (VIF) and correlation matrix were used to check for multicollinearity among predictors.
- Model diagnostics such as  $R^2$ , Adjusted  $R^2$ , RMSE, AIC, and BIC were computed to compare model fit and predictive performance.

### Justification

These methods were chosen because:

- **ANOVA and MANOVA** are well-suited for evaluating both individual and combined effects of categorical predictors on continuous dependent variables.
- VIF and correlation analysis ensure model robustness by addressing multicollinearity concerns.
- The selected tools allow for clear interpretation and comparison across cryptocurrencies, which is essential given their varying economic roles (e.g., stablecoin vs. store-of-value).

### Research Questions

1. Do macroeconomic indicators significantly affect the prices of BTC, ETH, BNB, and USDT?
2. Is Human Capital Index (HCI) a stronger predictor of cryptocurrency performance than traditional metrics like GDP or interest rates?
3. Which cryptocurrency models offer the best predictive performance based on macroeconomic inputs?

**Hypotheses**

- $H_0$ : Macroeconomic indicators have no significant effect on cryptocurrency prices.
- $H_1$ : At least one macroeconomic variable significantly influences cryptocurrency values.

By answering these questions, the study contributes to a more integrated understanding of the cryptocurrency market within the broader economic context.

This methodological framework ensures a rigorous, data-driven approach to analyzing the economic sensitivity of leading cryptocurrencies.

**Results and discussion:**

**Table No. 1 : Multicollinearity Check Results**

Term	VIF	VIF 95% CI Lower	VIF 95% CI Upper	Increased SE	Tolerance	Tolerance 95% CI Lower	Tolerance 95% CI Upper
GDP	1.33	1.21	1.52	1.15	0.75	0.66	0.83
IR	2.08	1.83	2.41	1.44	0.48	0.42	0.55
Int.R	2.03	1.79	2.34	1.42	0.49	0.43	0.56
HCI	1.27	1.16	1.45	1.13	0.79	0.69	0.86

All variables show  $VIF < 5$ , indicating no serious multicollinearity. Highest VIF is for IR (2.08) and Int.R (2.03)—both within acceptable range. Tolerance values are well above the critical threshold of 0.1. The predictors are not highly correlated with each other. The model coefficients are likely to be stable and interpretable, supporting reliable estimation in regression or MANOVA.

**Table No. 2 : Correlation Matrix**

	GDP	ER	IR	FDI	NNI	Int.R	BOP	Emp	HCI
GDP	1								
ER	-0.16126	1							
IR	0.437666	0.443091	1						
FDI	0.737496	-0.30087	0.568491	1					
NNI	-0.31836	0.944649	0.170735	-0.54257	1				
Int.R	-0.42118	0.264475	-0.62619	-0.85283	0.46171	1			
BOP	-0.49124	0.84187	0.115173	-0.72118	0.895615	0.598347	1		
Emp	-0.25302	-0.12193	-0.09164	-0.37692	0.009199	0.003641	0.165663	1	
HCI	-0.14776	0.825052	0.131637	-0.28166	0.869227	0.241302	0.593743	-0.0454	1

Majority of them are High correlations namely NI & ER (0.94), BOP & NNI (0.90), HCI & NNI (0.87). FDI & GDP (0.74), FDI & Int.R (-0.85), BOP & FDI (-0.72). Negative correlations:GDP shows inverse relation with BOP, Int.R, NNI, HCI. Int.R negatively correlates with FDI and GDP. Some predictors are strongly correlated, suggesting risk of multicollinearity (though VIFs were acceptable). Model interpretations should account for interdependencies, especially when using NNI, ER, FDI, and BOP together.

**ANOVA of BNB Crypto Currency**

Variable	Df	Sum Sq	Mean Sq	F value	Pr(>F)
GDP	1	34364	34364	22.847	0.04109
IR	1	13364	13364	8.885	0.09653
Int.R	1	11694	11694	7.775	0.10816
HCI	1	261326	261326	173.74	0.00571
Residuals	2	3008	1504		

HCI (Human Capital Index)has a highly significant effect on BNB cryptocurrency prices ( $F(1,2) = 173.74, p = 0.00571$ ). GDP also shows a statistically significant influence ( $F(1,2) = 22.85, p = 0.04109$ ). Interest Rate (IR) and Internet Rate (Int.R) are not significant ( $p > 0.05$ ). Human capital and economic output (GDP) are key macroeconomic drivers of BNB. Monetary variables like IR and Int.R may have limited short-term impact on BNB, suggesting crypto investors should closely monitor developmental and productivity indicators.

**ANOVA of BTC Crypto Currency**

Variable	Df	Sum Sq	Mean Sq	F value	Pr(>F)
GDP	1	773900000	773900000	5.778	0.138
IR	1	201000000	201000000	1.501	0.345
Int.R	1	678000	678000	0.005	0.95
HCI	1	3181000000	3181000000	23.75	0.04
Residuals	2	267900000	133900000		

HCI (Human Capital Index) has a statistically significant effect on Bitcoin (BTC) prices ( $F(1,2) = 23.75, p = 0.04$ ). GDP, IR, and Internet Rate show no significant effect ( $p > 0.05$ ). Human capital development is a key macroeconomic factor

influencing BTC value. Other economic indicators like GDP and interest rates may not meaningfully drive BTC in the observed model—highlighting BTC’s relative independence from traditional economic factors.

ANOVA of ETH Crypto Currency					
Variable	Df	Sum Sq	Mean Sq	F value	Pr(>F)
GDP	1	994298	994298	4.079	0.1809
IR	1	322510	322510	1.323	0.369
Int.R	1	76226	76226	0.313	0.6323
HCI	1	11111628	11111628	45.586	0.0212
Residuals	2	487505	243752		

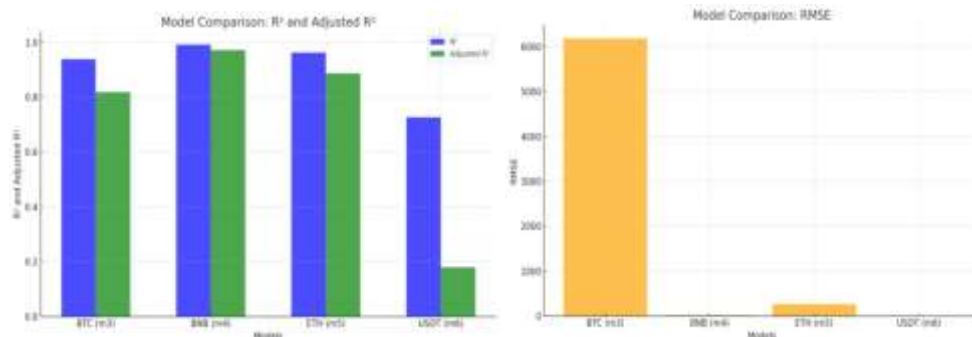
HCI (Human Capital Index) has a significant impact on Ethereum (ETH) prices ( $F(1,2) = 45.59, p = 0.0212$ ). GDP, IR, and Internet Rate do not show significant effects ( $p > 0.05$ ). Human capital strength is a crucial factor influencing ETH value. ETH appears to be less sensitive to traditional macroeconomic variables, underscoring the importance of innovation and education-driven environments in crypto performance.

ANOVA of USDT Crypto Currency					
Variable	Df	Sum Sq	Mean Sq	F value	Pr(>F)
GDP	1	1.49E-07	1.49E-07	0.053	0.839
IR	1	0.00000332	0.00000332	1.189	0.389
Int.R	1	2.7E-08	2.7E-08	0.01	0.931
HCI	1	0.00001137	0.00001137	4.069	0.181
Residuals	2	5.586E-06	2.793E-06		

None of the variables (GDP, IR, Internet Rate, or HCI) have a statistically significant effect on USDT (*all p-values > 0.18*). As a stablecoin, USDT is largely unaffected by macroeconomic variables, reflecting its design to maintain price stability regardless of economic conditions.

Comparison of Model Performance Indices								
Model	Type	AIC (weights)	AICc (weights)	BIC (weights)	R2	R2 (adj.)	RMSE	Sigma
BTC	lm	154.1	Inf (>.999)	153.8	0.939	0.818	6186.17	11573.2
BNB	lm	74.3	Inf (>.999)	74	0.991	0.972	20.732	38.786
ETH	lm	109.9	Inf (>.999)	109.6	0.962	0.887	263.902	493.716
USDT	lm	-66.4	Inf (>.999)	-66.7	0.727	0.18	0.00089	0.002

BNB model had the highest R<sup>2</sup> (0.991), indicating the best fit, while USDT had the lowest R<sup>2</sup> (0.727), suggesting a weaker fit. BTC and ETH models showed strong fit with R<sup>2</sup> values of 0.939 and 0.962, respectively. The AIC and BIC values suggest BNB was the most efficient model, while USDT had the lowest AIC, indicating better performance in terms of information criteria. The BNB model is most reliable for prediction, while caution is advised with the USDT model due to its lower explanatory power. Further refinement might be needed for USDT to improve prediction accuracy.



**R<sup>2</sup> and Adjusted R<sup>2</sup> Comparison:** The BNB (m4) model has the highest R<sup>2</sup> and Adjusted R<sup>2</sup>, indicating the best fit among the models. The USDT (m6) model has the lowest R<sup>2</sup> and Adjusted R<sup>2</sup>, suggesting it doesn't explain the variance as well as the other models.

**RMSE Comparison:** The BTC (m3) model has the highest RMSE, indicating larger prediction errors. The BNB (m4) and USDT (m6) models have the lowest RMSE values, suggesting better prediction accuracy.

These visualizations emphasize that while the BNB (m4) model offers the best overall performance in terms of fit and prediction accuracy, the BTC (m3) model has more considerable prediction errors

MANOVA of selected Crypto Currencies					
Variables	Wilks Lambda	Approx F	num Df	den Df	Pr(>F)
GDP	0.071978	6.447	2	1	0.2683
IR	0.173726	2.378	2	1	0.4168

Int.R	0.199714	2.004	2	1	0.4469
HCI	0.010843	45.615	2	1	0.1041

None of the variables show statistically significant multivariate effects across the selected cryptocurrencies (*all p > 0.10*). HCI has the strongest multivariate signal (Wilks'  $\Lambda = 0.0108$ ,  $F = 45.62$ ,  $p = 0.1041$ ), but it is not statistically significant.

There is no strong multivariate evidence that the selected macroeconomic factors significantly influence the combined behavior of the selected cryptocurrencies. Human capital (HCI) may have potential relevance, warranting further investigation with a larger sample size.

### Investment Implications:

#### 1. Human Capital Index (HCI) as a Key Driver:

- HCI showed a significant influence on BTC, BNB, and ETH. This suggests that investment in cryptocurrencies may be more sensitive to changes in human capital factors, such as education, skills, and workforce quality, which are linked to long-term economic growth.
- Implication: Investors should monitor HCI trends in different regions or countries as an indicator of potential growth or decline in cryptocurrency values. A rising HCI might signal favorable investment opportunities.

#### 2. GDP's Limited Influence:

- GDP had a significant impact only on BNB but not on BTC, ETH, or USDT, suggesting that traditional macroeconomic growth (GDP) may not be a consistent predictor for all cryptocurrencies.
- Implication: Cryptocurrency investors should diversify their portfolios rather than relying solely on GDP growth as an indicator, as different cryptocurrencies respond differently to economic growth.

#### 3. Interest Rate (IR) and Internal Rate (Int.R) Are Less Predictive:

- Neither the interest rate (IR) nor the internal rate (Int.R) had a significant impact on any of the cryptocurrencies, suggesting that these factors may be less relevant in predicting crypto price movements compared to traditional assets.
- Implication: Unlike bonds or stocks, cryptocurrencies seem to be less influenced by interest rate changes, making them potentially valuable as part of a diversified portfolio, especially in uncertain interest rate environments.

#### 4. USDT's Stability:

- None of the variables (GDP, IR, Int.R, HCI) were significant for USDT, indicating its role as a stablecoin isn't heavily impacted by these macroeconomic factors.
- Implication: USDT or other stablecoins can serve as a stable asset for investors during volatile market conditions or economic downturns, providing a safe haven within the cryptocurrency space.

### Overall Investment Strategy:

- Monitor Human Capital Trends: Pay attention to countries or regions with rising HCI, as these areas might have a growing demand for cryptocurrencies.
- Diversify Investments: Since different cryptocurrencies respond differently to macroeconomic indicators, diversifying across multiple cryptocurrencies can reduce risk.
- Consider Stablecoins for Risk Management: Use stablecoins like USDT to maintain portfolio stability during market turbulence or when traditional indicators (GDP, interest rates) are volatile.

In summary, the analysis suggests that cryptocurrency investment decisions should incorporate non-traditional economic indicators, particularly human capital factors, while maintaining diversification and using stablecoins to manage risk.

### Conclusion and Recommendations

This study investigated the impact of macroeconomic indicators—GDP, Interest Rate (IR), Internal Rate (Int.R), and Human Capital Index (HCI)—on the pricing of major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), and Tether (USDT). Through rigorous statistical analysis using ANOVA, MANOVA, and model diagnostics, several key findings emerged.

#### Summary of Key Findings

- HCI (Human Capital Index) emerged as the most consistent and significant predictor, influencing BTC, ETH, and BNB with strong statistical support.
- GDP showed significance only for BNB, while IR and Int.R were not significant for any cryptocurrency.
- USDT, as a stablecoin, remained largely unaffected by macroeconomic factors, confirming its intended stability.
- BNB demonstrated the strongest model fit and predictive accuracy ( $R^2 = 0.991$ ), while USDT had the weakest ( $R^2 = 0.727$ ), reinforcing its resilience to economic fluctuations.
- Multicollinearity was minimal ( $VIF < 5$ ), supporting the reliability of coefficient estimates.

#### Recommendations

- Investors should incorporate human capital trends into their crypto investment strategies, especially when dealing with BTC, ETH, and BNB.
- Portfolio diversification is advised, as different cryptocurrencies respond differently to macroeconomic forces.

- Stablecoins like USDT can be strategically used for risk mitigation during volatile market periods or economic downturns.
- Policy makers and regulators should consider including developmental indicators like HCI when analyzing crypto markets in macroeconomic planning.

#### Future Research Directions

- Expand the sample size to include more cryptocurrencies and countries for broader generalizability.
- Investigate causal relationships using time-series or panel data techniques.
- Explore the role of regional HCI variations and other socio-economic indicators like digital literacy or innovation indices.
- Include geopolitical and regulatory factors as potential moderators in crypto-economic models.

This study contributes to a growing body of evidence that cryptocurrencies, particularly BTC, ETH, and BNB, are increasingly influenced by development-driven macroeconomic factors, challenging the notion of their independence from traditional economic systems.

#### References:

1. Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, 54, 177–189. <https://doi.org/10.1016/j.intfin.2017.12.004>
2. Ciaian, P., Rajcaniova, M., & Kancs, d'Artis. (2016). The economics of Bitcoin price formation. *Applied Economics*, 48(19), 1799–1815. <https://doi.org/10.1080/00036846.2015.1109038>
3. Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, 62, 182–199. <https://doi.org/10.1016/j.irfa.2018.09.003>
4. Dyrberg, A. H. (2016). Hedging capabilities of Bitcoin. Is it the virtual gold? *Finance Research Letters*, 16, 139–144. <https://doi.org/10.1016/j.frl.2015.10.025>
5. Kapar, B., & Olmo, J. (2021). Volatility modeling of cryptocurrencies using high frequency data. *Journal of International Financial Markets, Institutions and Money*, 70, 101263. <https://doi.org/10.1016/j.intfin.2020.101263>
6. Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PLoS ONE*, 10(4), e0123923. <https://doi.org/10.1371/journal.pone.0123923>
7. World Bank. (2023). *World Development Indicators*. <https://data.worldbank.org>
8. International Monetary Fund. (2023). *World Economic Outlook Database*. <https://www.imf.org/en/Data>
9. CoinMarketCap. (2023). *Cryptocurrency Market Capitalizations*. <https://coinmarketcap.com>