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Reassessing Bitcoin's Market Behavior: The Impact of Macroeconomic Indicators and Investor Sentiment on Cryptocurrency Price Dynamics (2014 –2024)

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Abstract

This study investigates the key macroeconomic, behavioral, and cryptocurrency-specific determinants of monthly Bitcoin price fluctuations over the period January 2014 to December 2024. It aims to provide empirical insights into Bitcoin's evolving role within global financial markets, considering both traditional market indicators and investor sentiment. Using a time-series econometric approach, the study employs an Ordinary Least Squares (OLS) regression model on a balanced monthly dataset comprising Bitcoin price, trading volume, Google Trends, the S&P 500 index, and the EUR/USD exchange rate. Stationarity and diagnostic tests are conducted to ensure model robustness. Interaction terms and lag structures are included to capture delayed or compounding effects. The results reveal that Bitcoin prices exhibit a strong and statistically significant co-movement with the S&P 500 index, suggesting a growing alignment with equity markets. Google Trends—a proxy for public interest—shows a marginally significant influence, indicating the relevance of retail investor sentiment. Conversely, Bitcoin trading volume and the EUR/USD exchange rate do not significantly affect price movements within the sample period. The findings highlight Bitcoin's sensitivity to macro-financial conditions and investor psychology rather than conventional liquidity or currency dynamics. The study is limited to monthly data, which may overlook short-term shocks and intramonth volatility. Proxy variables such as Google Trends offer only partial insight into complex behavioral phenomena. Future research should explore high-frequency data and incorporate more granular sentiment and policy metrics. The demonstrated relationship between Bitcoin and the S&P 500 suggests that Bitcoin may not serve as an effective hedge during equity market downturns. Investors and portfolio managers should account for its risk-on behavior in asset allocation. Regulators and policymakers should consider Bitcoin's increasing integration with traditional markets when designing oversight frameworks. This study offers a novel, interdisciplinary analysis of Bitcoin price dynamics by simultaneously accounting for macroeconomic, behavioral, and market-specific variables. It contributes to both academic understanding and practical decision-making regarding the financialization and regulation of digital assets.

Keywords: Bitcoin, Cryptocurrency markets, Google Trends, Investor sentiment, Macroeconomic indicators, Market behavior. Risk assets.

1. Introduction

Cryptocurrencies, as decentralized digital assets, have emerged as a transformative force in contemporary finance, challenging conventional paradigms of monetary theory, asset valuation, and institutional intermediation. Since Bitcoin's inception through Nakamoto's (2008) groundbreaking white paper, the digital asset ecosystem has expanded exponentially, giving rise to a multitude of alternative cryptocurrencies (altcoins), each with unique technological structures, governance models, and intended use cases (Antonopoulos, 2014; Schilling & Uhlig, 2019).

This explosive growth has been enabled by broader macro-structural developments, notably the global rise in internet accessibility and digital literacy (Corbet, Lucey, & Yarovaya, 2019), and heightened investor appetite for non-traditional assets following the 2008 global financial crisis (Baur, Hong, & Lee, 2018). Consequently, cryptocurrencies have garnered attention across diverse audiences—from speculative retail traders to sophisticated institutional investors seeking inflation hedges, portfolio diversification, and exposure to blockchain-driven innovations (Dyhrberg, 2016; Weber, 2016).

Beyond speculative appeal, cryptocurrencies represent a fundamental reconfiguration of financial architecture. Their decentralized, protocol-based governance challenges the central authority of traditional financial institutions, raising the prospect of democratized finance, disintermediated transactions, and transparent, low-cost global payments (Yermack, 2015). The underlying blockchain infrastructure is now being applied across sectors, from supply chain management and digital identity to decentralized finance (DeFi), which enables automated lending and asset exchange via smart contracts (Schilling & Uhlig, 2019).

However, the evolution of this sector is fraught with volatility, uncertainty, and controversy. While advocates highlight decentralization and financial inclusion, critics raise concerns about extreme market instability, speculative bubbles, security vulnerabilities, and insufficient regulatory clarity (Auer & Claessens, 2018; FSB, 2021). These opposing views underscore the need for rigorous empirical research that transcends anecdotal narratives and systematically investigates the underlying factors driving cryptocurrency prices and market behavior.

Despite a growing body of literature, existing studies often suffer from data limitations, theoretical fragmentation, and the challenges posed by cryptocurrencies' relatively short and volatile market history. Attempts to model price behavior have drawn on both classical financial theories—such as the Efficient Market Hypothesis—and alternative perspectives emphasizing network externalities, innovation diffusion, and socio-political adoption dynamics (Cheah & Fry, 2015; Ciaian, Rajcaniova, & Kancs, 2016). The task is further complicated by the hyper-reactivity of cryptocurrency markets to external signals—such as social media trends, regulatory announcements, or macroeconomic news—which often trigger disproportionate price responses and amplify behavioral biases like herding or irrational exuberance (Auer & Claessens, 2018; Gurdgiev & O'Loughlin, 2020).

Given this context, the present study addresses a critical research gap by offering a robust, data-driven analysis of the key economic, technological, and regulatory factors that influence cryptocurrency valuation, with a primary focus on Bitcoin. Utilizing ordinary least squares (OLS) regression techniques on a comprehensive dataset, this research empirically tests how macroeconomic indicators—such as interest rates, inflation, and equity index performance—interact with cryptocurrency-specific metrics (e.g., trading volume, mining difficulty, network usage) and exogenous policy announcements to shape market outcomes.

The central objectives of the study are threefold: (1) to map the relationships between macroeconomic conditions and cryptocurrency returns; (2) to assess the influence of blockchain-specific metrics on price volatility; and (3) to evaluate the effects of regulatory and institutional announcements on market sentiment and price formation. These aims are operationalized through a structured set of research questions exploring correlations, causal links, and interactive effects across time horizons.

The originality of this study lies in its interdisciplinary integration of economic, technological, and regulatory variables within a single empirical framework. By bridging theoretical insights from finance, behavioral economics, and innovation studies with practical concerns around market regulation and technological design, the research generates actionable knowledge for multiple stakeholder groups.

The implications are multifaceted. For academia, the study contributes to the refinement of financial theories under conditions of digital innovation, offering insights into whether cryptocurrencies conform to or deviate from classical market behavior (Yermack, 2015; Böhme et al., 2015). For investors and financial institutions, understanding the determinants of price volatility can enhance trading strategies, improve risk management, and inform portfolio diversification decisions (Baur & Dimpfl, 2021). Policymakers and regulators may use the findings to calibrate policy tools that balance innovation with systemic stability—crafting proportionate responses to market behavior without curtailing the benefits of decentralization (ECB, 2019; FSB, 2021). Finally, technology developers can better align their offerings with market dynamics and user expectations, increasing the adoption and impact of blockchain-based services.

In conclusion, this research seeks not only to fill a theoretical and empirical gap but also to influence real-world practice across finance, regulation, and technology development. Through robust analysis and interdisciplinary scope, it underscores the social, economic, and policy relevance of understanding digital asset markets in an increasingly digitized financial world.

2. Literature Review

2.1. Introduction

The academic exploration of cryptocurrency markets encompasses a wide range of theoretical frameworks, reflecting the interdisciplinary nature of these digital assets. Traditional financial theories such as the Efficient Market Hypothesis (EMH) and Modern Portfolio Theory (MPT) have been employed to examine whether cryptocurrencies—primarily Bitcoin—respond to new information in a manner consistent with efficient markets (Urquhart, 2016; Yermack, 2015). According to the EMH framework, the prices of tradable assets should fully reflect all available information, with any new developments prompting immediate market adjustments (Fama, 1970). Several scholars have sought to determine whether the pronounced price deviations and volatility patterns in Bitcoin and other cryptocurrencies align with—or contradict—the notion of market efficiency, producing evidence to support both sides of the debate (Nadarajah & Chu, 2017; Bariviera, 2017).

Another prominent strand of theoretical inquiry investigates the conceptualization of digital currencies as a new form of money or store of value. Early works drew comparisons between Bitcoin and commodities like gold, portraying both as scarce assets that may function as inflation hedges (Dyhrberg, 2016; Baur, Hong, & Lee, 2018). Others have questioned whether cryptocurrencies fulfill the classical roles of money—medium of exchange, unit of account, and store of value (Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014; Weber, 2016). These debates often center around practical considerations such as transaction costs, network scalability, and user adoption rates, alongside theoretical interpretations of monetary legitimacy (Weber, 2016; Yermack, 2015). The decentralized and algorithmic nature of cryptocurrencies, however, challenges conventional models predicated on centralized monetary authorities, calling for adjustments or entirely new theoretical constructs to account for phenomena such as cryptographic security, consensus mechanisms, and token minting (Nakamoto, 2008; Antonopoulos, 2018).

Behavioral finance theories have also gained traction in the context of cryptocurrency research, particularly due to the significant role of speculation, sentiment, and herd behavior in these markets (Gurdgiev & O'Loughlin, 2020). In contrast to the strictly rational assumptions of neoclassical theory, behavioral approaches posit that cognitive biases, social dynamics, and psychological factors can generate inefficiencies and pricing anomalies (Cheah & Fry, 2015; Akerlof & Shiller, 2010). Frequent boom-and-bust cycles in Bitcoin and altcoin prices have been interpreted through the lens of behavioral patterns such as extrapolative expectations and groupthink (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018; Wheatley, Sornette, Huber, & Reppen, 2019). As such, scholars continue to explore how these elements intersect with more traditional economic forces in shaping cryptocurrency valuation.

2.2. Macroeconomic and Market Factors

The interaction between cryptocurrency markets and the global macroeconomic environment is a critical area of inquiry, as digital assets do not operate in an economic vacuum. Contrary to earlier perceptions that Bitcoin and other cryptocurrencies are entirely decoupled from traditional financial dynamics, a growing body of research suggests that cryptocurrencies are indeed responsive—often acutely—to shifts in global liquidity, investor sentiment, monetary policy, and other macro-level indicators (Baur et al., 2018; Dyhrberg, 2016). Periods of expansionary monetary policy, characterized by low interest rates and ample liquidity, may provide fertile ground for investors seeking higher-risk or more speculative assets, thereby increasing demand for cryptocurrencies (ECB, 2019; Corbet, Lucey, & Yarovaya, 2019). Conversely, tightening monetary conditions or surges in geopolitical uncertainty have also coincided with increased interest in Bitcoin, fueling debate over whether cryptocurrencies can serve as "safe haven" assets akin to gold or other traditional hedges (Baur & Lucey, 2010). Similar diversification dynamics have been observed in traditional investment environments as well; for example, Golfinopoulos, Lois, and Repousis (2024) found that during the pre-COVID period in Greece, gold was the most efficient asset, real estate the most stable, and housing prices positively correlated with equities and deposit rates. These findings underline the enduring appeal of certain asset classes during periods of macroeconomic stress and offer a comparative lens through which the behavior of digital assets can be evaluated.

Empirical studies have attempted to isolate the effects of various macroeconomic variables on cryptocurrency prices. Katsiampa (2017) and Baur and Dimpfl (2021) noted that extreme Bitcoin price movements occasionally trigger concurrent turbulence in stock markets, suggesting partial integration with broader financial systems. At the same time, alternative research trajectories argue that certain cryptocurrencies exhibit low or even negative correlations with conventional asset classes under specific conditions, rendering them attractive tools for portfolio diversification (Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017). Nevertheless, drawing definitive conclusions remains challenging due to the fluid nature of both cryptocurrency markets and macroeconomic conditions, compounded by data limitations that hinder long-horizon or cross-cycle analyses (Cheah & Fry, 2015; Kliber, Marszałek, Musiałkowska, & Świerczynski, 2019).

Beyond conventional macro indicators such as interest rates and inflation, investor sentiment and media coverage have emerged as influential drivers of cryptocurrency market activity. The proliferation of social media platforms, online forums, and dedicated crypto news outlets has accelerated the speed at which information—and misinformation—spreads among traders (Gurdgiev & O'Loughlin, 2020). Sharp price increases or collapses are often associated with high volumes of online discourse, underscoring the role of collective psychology in amplifying both bullish and bearish momentum (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018). Similarly, policy announcements—whether favorable, restrictive, or ambiguous—frequently spark heightened volatility in crypto markets. Auer and Claessens (2018) demonstrate that news of regulatory crackdowns in certain jurisdictions can prompt sharp downward price adjustments, while signals of institutional endorsement—such as the launch of cryptocurrency futures or exchange-traded funds—can foster investor optimism, occasionally fueling rapid price surges.

Moreover, the growing presence of institutional entities and large corporate actors in the crypto landscape implies that global liquidity conditions, corporate treasury strategies, and broader capital flows may significantly influence digital asset valuations (Böhme et al., 2015; FSB, 2021). When major firms announce Bitcoin purchases or integrate cryptocurrencies into their business models, these events can trigger surges in buying pressure, reflecting shifting market perceptions of crypto assets as a legitimate asset class or strategic reserve. However, the lasting impact of such announcements remains uncertain, as short-term euphoria may subside if market fundamentals fail to support elevated valuations (Corbet et al., 2019). Thus, the interplay of macroeconomic forces, regulatory frameworks, and evolving investor psychology creates a highly dynamic environment in which cryptocurrency prices may undergo abrupt transitions from bullish exuberance to bearish retreat—and vice versa—often within compressed time horizons.

2.3. Volatility, Price Formation, and Market Efficiency

One of the most persistent and defining characteristics of cryptocurrency markets is their pronounced volatility—a tendency for rapid and significant price fluctuations that can occur within hours or even minutes. Compared to established asset classes such as equities, bonds, or commodities, digital currencies like Bitcoin exhibit considerably higher volatility levels, making them attractive to speculators seeking outsized returns while raising concerns among risk-averse investors and regulators interested in market stability (Cheah & Fry, 2015; Bariviera, 2017). A robust body of academic research has sought to understand and model this volatility through econometric approaches, including GARCH-family models, stochastic volatility frameworks, and regime-switching models (Katsiampa, 2017; Chan, 2017). These methodologies aim to capture volatility clustering, asymmetries, and the propensity for shocks—be they technological, economic, or regulatory—to exert lasting impacts on future price behavior.

Volatility, of course, does not exist in a vacuum but is intricately tied to price formation mechanisms and the broader issue of market efficiency. Price discovery in cryptocurrency markets—shaped by 24/7 global trading across multiple exchanges with varying liquidity levels and regulatory oversight—is often influenced by arbitrage dynamics, network congestion effects, and the influx of new participants (Gandal, Hamrick, Moore, & Oberman, 2018). Transaction delays or disparities in trade execution quality can result in price discrepancies that agile traders may exploit, sometimes smoothing inefficiencies over time, but also potentially introducing frictions or amplifying speculative bubbles. The intangible nature of most cryptocurrencies, lacking conventional financial statements or intrinsic yields, further blurs the line between fundamental valuation and speculative fervor (Ciaian et al., 2016; Wheatley et al., 2019).

Scholars have debated whether cryptocurrencies conform to the Efficient Market Hypothesis (EMH), which posits that asset prices reflect all available information and follow a random walk, rendering them theoretically unpredictable beyond random noise (Fama, 1970). Empirical findings have been mixed: some studies point to fleeting or partial inefficiencies—manifested in serial correlation, predictable price patterns, or exploitable anomalies—particularly during the early years of Bitcoin trading (Urquhart, 2016; Bariviera, 2017). Others suggest that as trading volumes scale, institutional participation increases, and arbitrage channels become more efficient, cryptocurrency markets may gravitate toward greater efficiency, reducing the scope for persistent abnormal returns (Nadarajah & Chu, 2017).

Nevertheless, the prevalence of behavioral factors, hype-driven cycles, and exogenous shocks (e.g., regulatory interventions, celebrity endorsements, or technological upgrades) continues to challenge assumptions of informational efficiency. The role of irrational exuberance, fear of missing out (FOMO), and sudden fear-induced sell-offs (panic selling) is more prominent in the cryptocurrency space than in most traditional markets, amplifying price swings and reducing the predictive power of conventional financial models. Recent studies also emphasize the influence of algorithmic trading and high-frequency trading (HFT), which can magnify short-term inefficiencies while potentially stabilizing markets in the longer term (Schilling & Uhlig, 2019; Gandal et al., 2018).

The heterogeneity of market efficiency across different cryptocurrencies and time horizons adds another layer of complexity. While Bitcoin enjoys relatively higher liquidity and robust infrastructure, smaller altcoins often exhibit thin order books, making them more susceptible to price manipulation, pump-and-dump schemes, and sharp volatility spikes. This segmentation highlights the need to view the "cryptocurrency market" not as a monolithic entity but as a constellation of sub-markets that differ significantly in maturity, trading activity, developer engagement, and real-world application (Schilling & Uhlig, 2019).

Indeed, ongoing technological innovation—such as the implementation of layer-two scaling solutions, decentralized finance (DeFi) protocols, and cross-chain interoperability—further complicates the assessment of market dynamics. These developments can enhance liquidity, reduce transaction costs, and improve market depth, potentially fostering greater efficiency, but also introduce new vectors of systemic risk and speculative behavior (Antonopoulos, 2018; FSB, 2021).

2.4. Synthesis and Alignment with Research Objectives

This literature review demonstrates a comprehensive understanding of existing academic discourse across three core dimensions—financial theory, macroeconomic linkages, and market microstructure. The theoretical diversity captured herein provides the necessary foundation for the empirical investigation undertaken in this study, which seeks to analyze how macroeconomic conditions, cryptocurrency-specific indicators, and regulatory events influence digital asset prices, with a particular focus on Bitcoin.

By building on established findings and addressing unresolved tensions—such as the conditional efficiency of crypto markets, the evolving relationship with macroeconomic indicators, and the behavioral underpinnings of investor sentiment—this research aligns closely with its stated objectives. The selected literature not only contextualizes the research questions but also informs the methodological approach, ensuring continuity between theory, data analysis, and interpretation of results. In doing so, the study contributes meaningfully to the ongoing academic effort to integrate cryptocurrencies into mainstream financial and economic scholarship, while offering practical insights for investors, policymakers, and technologists.

3. Research Methodology

3.1. Introduction

This study employs a quantitative time-series methodology to investigate the determinants of Bitcoin price movements over the monthly period from January 2014 to December 2024. The analytical framework integrates five key variables: Bitcoin Price, Bitcoin Trading Volume, Google Trends (serving as a proxy for public attention or investor sentiment), the S&P 500 Index (reflecting equity market trends), and the EUR/USD exchange rate (capturing foreign exchange market dynamics). The primary objective is to identify and interpret the relationships shaping Bitcoin's performance within a broader macro-financial and economic context.

The selection of monthly frequency data is deliberate to capture relatively stable patterns while mitigating the influence of intraday noise and extreme volatility typical of cryptocurrency markets. The theoretical rationale underpinning this approach is rooted in established time-series analysis, which allows for examination of variable evolution over consistent chronological intervals—an essential consideration when studying the dynamic and often sentiment-driven Bitcoin market. Unlike cross-sectional methodologies, which treat observations as temporally independent, time-series models explicitly account for serial dependence and lagged effects, which are critical when analyzing volatile assets subject to delayed market reactions.

Monthly intervals strike a balance by capturing medium-term trends and cyclical variations without succumbing to the distortions of daily or hourly noise. Conversely, longer intervals, such as annual data, would obscure important month-to-month fluctuations in investor sentiment, equity market performance, and currency volatility—factors previously demonstrated to influence Bitcoin prices.

Given the nature of financial and economic time series, the methodology incorporates rigorous diagnostic testing to ensure the validity of econometric modeling. Stationarity of variables is assessed using standard tests such as the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Many macroeconomic indicators, including exchange rates and equity indices, often exhibit trends or unit roots that can invalidate ordinary least squares (OLS) regressions if unaddressed. Non-stationary series are transformed through differencing, logarithmic returns, or growth rates to stabilize variance and avoid spurious inference.

Furthermore, the model explores potential lag structures, recognizing that Bitcoin price responses may not be instantaneous. For example, heightened Google search activity in one month may precede price effects in subsequent months. Similarly, shifts in the S&P 500 or EUR/USD exchange rate might influence Bitcoin markets with temporal delays due to portfolio rebalancing or risk hedging processes.

Bitcoin trading volume is incorporated to capture liquidity and market depth—dimensions critical for understanding volatility in an evolving asset class. Volume fluctuations may signal periods of market exuberance or stress, distinguishing tranquil price moves from turbulent phases.

The use of Google Trends data is especially salient, as it operationalizes behavioral finance theory by providing a measurable proxy for investor sentiment and media-driven attention. This variable complements traditional financial indicators, acknowledging the psychological and social dynamics that affect asset pricing in emerging technological markets.

The inclusion of the S&P 500 Index facilitates evaluation of Bitcoin's integration with traditional equity markets, testing hypotheses regarding Bitcoin's role as a risk-on asset or a potential hedge. Similarly, the EUR/USD exchange rate situates Bitcoin within global currency markets, enabling analysis of fiat currency volatility's spillover effects on digital asset valuations.

To ensure robustness, the methodology implements diagnostic checks for residual autocorrelation, heteroskedasticity, and multicollinearity, safeguarding the statistical validity of conclusions. It also accounts for structural breaks and regime shifts across the 2014–2024 period, reflecting regulatory changes, market maturation, and macroeconomic shocks.

Data collection harmonizes multiple sources into a coherent monthly time series, balancing cryptocurrency-specific variables with traditional market indicators. This comprehensive design aspires to yield empirically grounded insights into the multifaceted drivers of Bitcoin pricing dynamics.

3.2. Research Design and Methodological Approach

The research adopts a quantitative time-series design focused on examining how selected macroeconomic indicators and sentiment-related variables interact with monthly Bitcoin price dynamics from January 2014 through December 2024. The study's dataset comprises five principal variables: Bitcoin Price, Bitcoin Trading Volume, Google Trends, the S&P 500 Index, and the EUR/USD exchange rate. Monthly data frequency is selected to balance temporal granularity with the need to smooth extreme intraday cryptocurrency volatility. Additionally, this frequency aligns with the reporting cycles of key macroeconomic indicators, facilitating consistent and interpretable comparisons between Bitcoin and broader market trends.

The theoretical underpinning posits that despite Bitcoin's technological novelty, its price behavior is amenable to rigorous financial and macroeconomic time-series analysis. By organizing data chronologically and applying formal econometric procedures, the study assesses contemporaneous relationships (e.g., between Bitcoin price and investor attention) and dynamic effects over time, which are particularly relevant given Bitcoin's sensitivity to momentum, global risk sentiment shifts, and changes in public interest.

Recognizing the unique statistical properties of financial time series, the methodology addresses challenges such as non-stationarity, structural trends, and serial correlation—features that, if neglected, can result in spurious conclusions. Tests such as the Augmented Dickey-Fuller (ADF) guide necessary data transformations (e.g., differencing, logarithmic scaling) to achieve stationarity and valid inference.

The extended sample period encompasses multiple cryptocurrency market cycles and regulatory environments, from early high-uncertainty years to phases of institutional adoption and market integration. The study incorporates structural break tests and dummy variables representing known policy announcements and macroeconomic shocks. Sub-sample analyses further explore whether relationships remain stable across different market regimes.

Each variable contributes unique insights: Bitcoin trading volume proxies liquidity and market activity; Google Trends reflects retail investor sentiment; the S&P 500 captures U.S. equity market performance, indicating whether Bitcoin acts as a risk asset or hedge; and the EUR/USD exchange rate contextualizes Bitcoin within global foreign exchange dynamics.

The methodological design facilitates a multidimensional inquiry into the interplay of macroeconomic factors, market conditions, and behavioral elements shaping Bitcoin's price trajectory. Robustness checks, including outlier exclusion and alternative sentiment proxies, are planned to ensure result validity.

In summary, the design provides a comprehensive, theoretically grounded, and methodologically rigorous framework to elucidate the determinants of Bitcoin price behavior in a rapidly evolving financial landscape.

3.3. Data Collection and Sources

This study utilizes a balanced monthly dataset spanning from January 2014 to December 2024, designed to capture the medium-term dynamics of Bitcoin price movements in relation to both cryptocurrency-specific variables and broader macro-financial indicators. The dataset comprises five core variables: Bitcoin price, Bitcoin trading volume, Google Trends search interest, the S&P 500 Index, and the EUR/USD exchange rate. The monthly frequency was selected to smooth out high-frequency noise common in daily cryptocurrency data while preserving economically meaningful variations.

Bitcoin Price and Trading Volume: Daily data on Bitcoin's price and trading volume were obtained from *Investing.com*, a reputable aggregator of historical cryptocurrency market data. These values were aggregated to monthly frequency using end-of-month prices and total monthly volume. This ensures consistency with macroeconomic indicators and enhances temporal alignment across variables.

Google Trends (Investor Sentiment Proxy): Data on public interest in Bitcoin were collected via *Google Trends*, based on global search frequency for the keyword "Bitcoin." These search indices were aggregated to monthly values and scaled between 0 and 100. The variable serves as a proxy for retail investor sentiment and public attention.

S&P 500 Index: The S&P 500, a benchmark for U.S. equity markets and a proxy for investor risk appetite, was sourced from *Investing.com.* Monthly closing values were used to align with other macroeconomic indicators and capture broader market sentiment.

EUR/USD Exchange Rate: The EUR/USD exchange rate, a widely observed currency pair in global financial markets, was included to reflect macro-financial developments potentially influencing investor preferences toward fiat currencies versus alternative assets like Bitcoin. Monthly data were sourced from *Investing.com.*

To ensure coherence and comparability, all variables were aligned on a monthly basis, cross-validated against alternative macroeconomic sources (e.g., the World Bank), and checked for completeness, temporal consistency, and outlier sensitivity. This comprehensive data harmonization process provides a robust empirical foundation for the econometric modeling that follows.

3.4. Variable Definitions and Transformations

Each variable was selected for its theoretical and empirical relevance to Bitcoin market behavior. Table 1 summarizes the key characteristics, definitions, and transformations applied to each variable.

3.4.1. Bitcoin Price

- Definition: End-of-month closing price of Bitcoin (USD).
- Source: *Investing.com*, with data aggregated from multiple cryptocurrency exchanges.
- Role: Dependent variable in all model specifications, reflecting monthly valuation.
- Transformation: Logarithmic returns to address non-stationarity and heteroskedasticity.

3.4.2. Bitcoin Trading Volume

- Definition: Monthly total trading volume of Bitcoin, expressed in USD.
- Source: *Investing.com.*
- Role: Proxy for market liquidity and trading intensity.
- Transformation: Natural logarithm [ln (Volume)] to stabilize variance and normalize the distribution.

3.4.3. Google Trends (Investor Attention)

- Definition: Normalized index (0–100) of monthly global search interest for "Bitcoin."
- Source: *Google Trends.*
- Role: Behavioral proxy for investor sentiment and media-driven attention.
- Transformation: Applied as-is or log-transformed where appropriate, depending on distributional characteristics.

3.4.4. S&P 500 Index

- Definition: End-of-month closing level of the S&P 500 Index.
- Source: *Investing.com.*
- Role: Indicator of macroeconomic sentiment and equity market trends.
- Transformation: Monthly log returns, conditional on stationarity tests.

3.4.5. EUR/USD Exchange Rate

- Definition: End-of-month exchange rate of the euro against the U.S. dollar.
- Source: *Investing.com* (FX market data).
- Role: Proxy for global currency market fluctuations affecting investor portfolio allocations.
- Transformation: First differences or log differences, depending on results of unit root tests (ADF).

3.5. Data Validation and Quality Control

Each time series was subjected to rigorous data quality checks, including:

- Identification and treatment of missing values.
- Detection of structural breaks or anomalous spikes.
- Retention of genuine market-related outliers to preserve informational content.

Where appropriate, robustness checks were performed by excluding potential outliers to assess their influence on model estimates. The use of multiple, reputable data sources—complemented by consistency checks with macroeconomic datasets—ensures high data integrity and transparency.

3.6. Econometric Model Specification

The empirical analysis adopts a multivariate time-series regression framework to examine the impact of market activity, investor sentiment, and macroeconomic conditions on Bitcoin's monthly return dynamics. The model is designed to address key econometric challenges typical of financial time series, including non-stationarity, autocorrelation, and potential endogeneity among regressors.

3.6.1. Dependent Variable Selection

To ensure stationarity and mitigate the risk of spurious regression associated with non-stationary price levels, the dependent variable is defined as the monthly logarithmic return of Bitcoin:

$$\text{BTC\_RETt}=\ln\left(\frac{Price_t}{Price_{t-1}}\right)$$

This transformation stabilizes variance and captures meaningful percentage changes in value, suitable for return-based financial modeling.

3.6.2. Independent Variables and Transformations

The model incorporates four explanatory variables, each transformed as necessary to achieve stationarity and improve interpretability:

- Bitcoin Trading Volume (VOL_t): Log-transformed to reduce skewness, and heteroskedasticity. It captures market liquidity and trading intensity.
- Google Trends (GTRENDS_t): Used as a normalized index of investor attention. Differencing or logarithmic transformation is applied based on results from unit root tests, accounting for behavioral shifts in public interest.
- S&P 500 Index (SP500_t): Incorporated as monthly logarithmic returns to represent U.S. equity market performance and general macroeconomic sentiment..
- EUR/USD Exchange Rate (EUR_USD_t): Modeled using first or log differences to address non-stationarity. Reflects foreign exchange market dynamics and potential substitution effects between fiat and crypto assets.

The primary specification employs an Ordinary Least Squares (OLS) model:

$$\text{BTC\_RET}_t = \alpha + \beta_1 \ln(\text{VOL}_t) + \beta_2 \text{GTRENDS}_t + \beta_3 \ln\left(\frac{\text{SP500}_t}{\text{SP500}_{t-1}}\right) + \beta_4 \Delta \ln(\text{EUR\_USD}_t) + \varepsilon_t,$$

Where:

- α is the intercept,
- ε_t is the stochastic error term,
- β_i are the estimated coefficients quantifying the marginal effect of each independent variable.

3.6.3. Model Extensions and Refinements

To enhance the model's explanatory power and robustness, the following extensions are considered:

- Lagged Regressors: Inclusion of lagged values (e.g., GTRENDSt−1) captures delayed effects of sentiment or market conditions on returns.
- Autoregressive Component: An AR(1) term, BTC_RETt−1, is included to account for return persistence and momentum effects, common in financial return series.
- Interaction Terms: Interaction between sentiment (GTRENDSt) and volume, or between equity (SP500) and currency (EUR/USD), investigates compound effects and cross-market spillovers.

3.6.4. Diagnostic Testing and Model Evaluation

Comprehensive diagnostic procedures ensure model reliability:

- Stationarity Testing: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests verify the stationarity of all variables. Appropriate transformations (e.g., differencing, logarithmic) are applied where required.
- Multicollinearity Assessment: Variance Inflation Factors (VIF) and correlation matrices detect collinearity. If necessary, Principal Component Analysis (PCA) is employed to reduce dimensionality.
- Residual Diagnostics: Tests for autocorrelation (Durbin-Watson, Ljung-Box) and heteroskedasticity guide corrective measures such as Newey-West standard errors or the use of GARCH-type models to capture volatility clustering.
- Model Selection Criteria: The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and adjusted R^2 are used to determine optimal model structure and lag order, balancing explanatory power and parsimony.

3.6.5. Interpretation of Coefficients

The estimated coefficients (β_i) offer insights into the economic significance of each factor:

- $\beta_1 > 0$: Higher trading volume is associated with increased returns, reflecting greater market engagement or speculative inflows.
- $\beta_2 \neq 0$: Public interest, proxied by Google Trends, significantly influences return dynamics, capturing the behavioral aspect of the crypto market.
- β_3: A positive or negative value indicates the nature of Bitcoin's co-movement with traditional equity markets, informing its classification as a risk asset or diversification hedge.
- β_4: Reflects sensitivity to currency market fluctuations and the potential macroeconomic repositioning between fiat and crypto assets.

This modeling framework facilitates a nuanced understanding of Bitcoin's return behavior by integrating liquidity measures, sentiment indicators, and macroeconomic variables within a statistically rigorous structure. By addressing common time-series challenges and incorporating interaction dynamics, the model enhances our ability to capture the evolving financial profile of Bitcoin within the global asset ecosystem.

3.7. Ethical Considerations and Study Limitations

This time-series study adheres to strict ethical standards by exclusively utilizing publicly accessible, aggregate data from reputable sources such as Investing.com and Google Trends. This approach ensures no personal or proprietary data breaches, aligning with principles of data confidentiality and reproducibility.

Nevertheless, several ethical and methodological caveats must be acknowledged. Cryptocurrency markets are inherently volatile and prone to speculative behavior, including possible manipulation. While this study does not aim to detect manipulation, it remains vigilant against interpreting anomalies that may reflect artificial market distortions. Findings are presented cautiously, emphasizing probabilistic associations rather than deterministic predictions, to avoid misguiding less-experienced investors or encouraging speculative excess.

Methodologically, the study is constrained by its chosen monthly frequency, which smooths over intramonth volatility and event-driven price shocks, potentially omitting important short-term dynamics. The sample period (2014–2024) spans multiple distinct market regimes, including rapid technological innovation and evolving regulatory landscapes. Structural breaks within this period may limit the temporal stability and generalizability of results, despite robustness checks such as sample-splitting and sensitivity analyses.

Proxy variables such as Google Trends and the S&P 500 index provide valuable but imperfect measures of investor sentiment and market conditions. Google Trends does not differentiate informed from superficial attention, while the S&P 500 may inadequately represent global risk dynamics. Data quality, especially in Bitcoin's early years, can be inconsistent, posing potential measurement error risks.

Finally, the risk of spurious correlations is inherent in multi-variable time-series analyses, particularly in emerging, volatile asset classes. Although rigorous diagnostic tests mitigate these concerns, causal inference remains tentative. The study stresses cautious interpretation, recognizing that correlation does not imply causation.

In sum, this research contributes to the scientific understanding of medium-term Bitcoin price drivers through ethically sound and methodologically robust empirical analysis, while transparently addressing inherent limitations. It provides a foundation for future investigations employing higher-frequency data, more complex models, or expanded contextual variables to deepen insights into Bitcoin's role within the evolving global financial system.

4. Results

4.1. Introduction

The results are derived using *EViews*, a widely accepted econometric software package, which enables rigorous time series and regression analysis.

Employing advanced diagnostic and estimation tools within *EViews*, the study aims to quantify both the direction and magnitude of the influence that each explanatory variable exerts on the monthly fluctuations of Bitcoin prices.

Before reporting the model estimates, it is essential to outline the preliminary steps undertaken. Stationarity tests—including the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests—were conducted to examine the presence of unit roots in the variables. Non-stationary series were transformed via logarithmic conversion or differencing to ensure stationarity, thereby safeguarding the validity of subsequent ordinary least squares (OLS) regressions.

In addition, multicollinearity was assessed using correlation matrices and Variance Inflation Factor (VIF) diagnostics available in *EViews*. This guided the inclusion or exclusion of lagged variables and highly correlated regressors to avoid redundancy and inflated standard errors.

The core analytical framework consists of an OLS model estimating the impact of monthly changes in Bitcoin transaction volume, public interest (proxied by Google Trends), broader market movements (via the S&P 500), and foreign exchange fluctuations (EUR/USD) on Bitcoin returns. Complementary models investigate lagged effects and alternative specifications to assess the predictive power of explanatory variables over time.

Robustness tests, including the White heteroskedasticity test and the Breusch-Godfrey LM test for serial correlation, were also performed to confirm the reliability and efficiency of the estimates by verifying key OLS assumptions.

The following sections sequentially present descriptive statistics, correlation analyses, and regression findings. Descriptive statistics provide an overview of central tendencies and variability, while correlation analyses offer preliminary insights into relationships among variables. Regression results then provide quantitative evidence of statistically and economically significant drivers of Bitcoin's monthly price dynamics.

Throughout the analysis, attention is given to both statistical significance (p-values, t-statistics) and economic relevance (magnitude of coefficients). Collectively, these findings contribute to understanding the interplay between market liquidity, retail investor interest, macroeconomic indicators, and digital asset valuation, shedding light on Bitcoin's evolving role within the global financial system.

4.2. Descriptive Statistics

The next step involves analyzing the descriptive statistics of the five key variables in this study: Bitcoin Price, Bitcoin Transaction Volume (BTC_VOL), EUR/USD exchange rate, Google Trends index, and the S&P 500 index. The dataset consists of 132 monthly observations spanning from January 2014 to December 2024.

These summary statistics provide initial insights into the distributional properties of each variable, highlighting potential issues such as skewness, kurtosis, and outliers that may influence subsequent econometric analyses (Table 1).

Table 1. Descriptive Statistics.

Variable	Mean	Median	Standard Deviation	Skewness	Kurtosis
Bitcoin Price	151.0351	34.8380	230.3446	1.769095	5.337703
Bitcoin Volume	190,611.3	4.0950	1,040,427	7.415928	59.18235
EUR/USD	11,216.01	11,184.50	1,592.396	-5.1210	38.20597
Google Trends	18.34091	14.0000	15.72271	1.841150	8.098613
S&P 500	3,235.86	2,919.50	1,120.951	0.618619	2.314317

Bitcoin Price shows a mean value of approximately $151, while the median is significantly lower at $34.84. This large gap suggests a strong right-skewed distribution, indicating that a small number of exceptionally high prices raise the average. The high standard deviation (230.34) reflects significant price volatility throughout the sample period.

Bitcoin Transaction Volume exhibits an even more pronounced disparity between the mean (190,611.3) and median (4.10), accompanied by an extremely large standard deviation (over one million). This pattern indicates heavy skewness with occasional months of extraordinarily high trading activity dominating the volume distribution.

EUR/USD Exchange Rate appears in large numeric terms due to scaling (e.g., multiplied by 1,000). The mean (11,216.01) and median (11,184.50) are close, indicating a relatively symmetric distribution. However, significant negative skewness (-5.12) and a high kurtosis value (38.21) reveal the presence of extreme movements or "fat tails" in the exchange rate.

Google Trends data for the term "Bitcoin" ranges from 0 to 100, with a mean value of 18.34 and median of 14.00. The positive skewness (1.84) and the peak value of 100 suggest episodic spikes in public interest, likely corresponding to major events or speculative surges.

S&P 500 index displays a mean of 3,235.86 and median of 2,919.50, with moderate skewness (0.62). The index's range reflects significant growth and volatility over the examined period, though less extreme than the Bitcoin variables.

Also, correlation coefficients reveal several statistically significant relationships ($p < 0.01$ unless stated otherwise) in Table 2. Table 2 presents the pairwise covariance, correlation, and probability values between key financial and search trend variables: Bitcoin Price, Bitcoin Volatility, EUR/USD exchange rate, Google Trends, and the S&P 500 index. The results reveal both the strength and direction of the relationships among these variables.

Table 2. Covariance, Correlation and Probability Matrix.

Variable Pair	Covariance	Correlation	Probability
Bitcoin Price - Bitcoin Volume	84,746,171	0.3563	0.0000
Bitcoin Price - EUR/USD	72,552.93	0.1993	0.0220
Bitcoin Price - Google Trends	1,345.88	0.3745	0.0000
Bitcoin Price - S&P 500	-133,906.20	-0.5226	0.0000
Bitcoin Volume - EUR/USD	1.19E+08	0.0726	0.4083
Bitcoin Volume - Google Trends	1,792,701	0.1104	0.2075
Bitcoin Volume - S&P 500	-2.21E+08	-0.1910	0.0282
EUR/USD - Google Trends	7,883.85	0.3173	0.0002
EUR/USD - S&P 500	-414,457.20	-0.2340	0.0069
Google Trends - S&P 500	-9,897.98	-0.5659	0.0000

Results from the analysis of Covariance and Correlation show that:

- Bitcoin Price and Bitcoin Volume show a moderate positive correlation (0.3563), indicating that higher prices tend to coincide with increased transaction volumes, consistent with heightened market activity during price rallies.
- Bitcoin Price and EUR/USD exhibit a weaker but still significant positive correlation (0.1993, p=0.022), hinting at a modest relationship between currency exchange fluctuations and Bitcoin valuation.
- Bitcoin Price and Google Trends also display a moderate positive correlation (0.3745), suggesting that surges in public interest align with upward price movements.
- Bitcoin Price and S&P 500 are negatively correlated (-0.5226), implying that Bitcoin prices tend to move inversely to the U.S. stock market within the sample timeframe.
- Bitcoin Volume and S&P 500 also have a significant negative correlation (-0.1910), though weaker than price-volume relationships.
- Google Trends and S&P 500 show a strong negative correlation (-0.5659), indicating that public interest in Bitcoin increases during stock market downturns or reduced performance.
- Other correlations, such as between EUR/USD and Google Trends (0.3173), suggest interconnectedness between macroeconomic factors and investor attention.

The analysis highlights a notable negative covariance between the S&P 500 and Bitcoin-related variables, suggesting a possible inverse relationship during the sample period (2014–2024). Additionally, Google Trends appears moderately correlated with both Bitcoin Price and the EUR/USD rate, indicating the potential influence of public interest and macroeconomic factors on cryptocurrency markets.

Bitcoin price shows moderate positive correlations with Google Trends and trading volume, and a strong negative correlation with the S&P 500, suggesting its potential as a hedge against traditional markets (Figure 1).

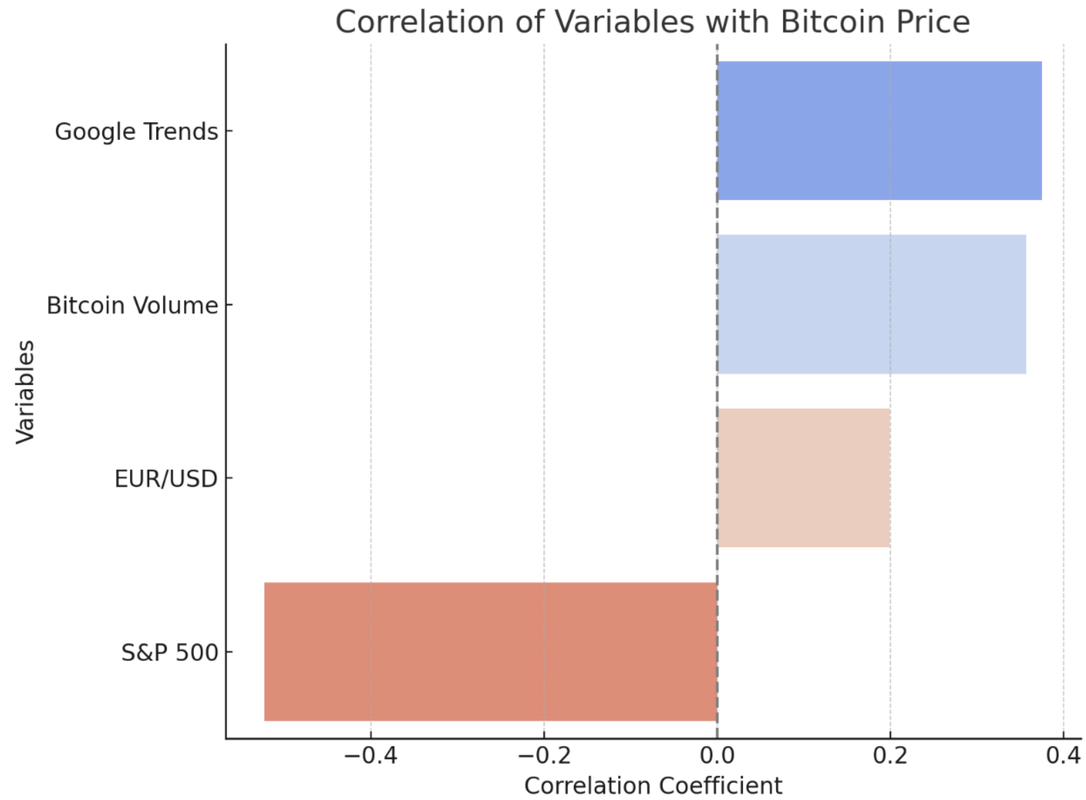

Figure 1. Correlation of Variables with Bitcoin Price.

4.3. Stationarity

The results from the Augmented Dickey-Fuller (ADF) tests, summarized in Table 3, confirm that all the variables included in the model—namely LN_BITCOIN_PRICE, LN_BITCOIN_VOL, LN_EUR_USD, LN_S_P500, and GOOGLE_TRENDS—are stationary in their level forms. In all cases, the ADF test statistics are significantly lower than the 1%, 5%, and 10% critical values, and the associated p-values are well below the 0.01 threshold, allowing for confident rejection of the null hypothesis of a unit root. Thus, these series do not exhibit stochastic trends, and mean-reverting properties are present.

Table 3. ADF Test Statistics and Stationarity Decision.

Variable	ADF Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value	Stationary at Level?
LN_BITCOIN_PRICE	-9.534362	-3.500	-2.891	-2.582	0.0000	Yes
LN_BITCOIN_VOL	-12.21276	-3.500	-2.891	-2.582	0.0000	Yes
LN_EUR_USD	-11.40171	-3.500	-2.891	-2.582	0.0000	Yes
LN_S_P500	-13.42599	-3.500	-2.891	-2.582	0.0000	Yes
GOOGLE_TRENDS	-4.386357	-3.500	-2.891	-2.582	0.0005	Yes

The diagnostic results of the ADF regression models, presented in Table 4, further reinforce this conclusion. All five variables exhibit large and significantly negative coefficients on their lagged levels, indicating strong corrective forces against deviations from the mean. For instance, the coefficient for LN_S_P500 is -1.169809 with a highly significant t-statistic (-13.42599), suggesting that deviations in the log S&P series quickly revert to equilibrium. R-squared values range from 0.25 (GOOGLE_TRENDS) to 0.58 (LN_S_P500), reflecting varying levels of explanatory power, yet collectively offering robust support for stationarity..

Notably, Durbin-Watson (DW) statistics for all regressions are near 2.0, indicating minimal autocorrelation in the residuals and strengthening the reliability of these results.

Regarding the constant term, only LN_BITCOIN_PRICE and LN_S_P500 show statistically significant intercepts, potentially pointing to mild deterministic trends in those series. The other variables' constants are not statistically significant, implying the absence of deterministic drift.

Figure 2 illustrates the ADF test statistics for the variables. All values are significantly lower than the 1% critical threshold (−3.5), shown as a red dashed line, which confirms that each series is stationary at level form. Among them, LN_S_P500 exhibits the strongest stationarity, followed closely by LN_BITCOIN_VOL and LN_EUR_USD, suggesting stable and mean-reverting behavior. Although GOOGLE_TRENDS has the least negative ADF statistic, it still clearly meets the stationarity condition. These findings validate the use of all variables in further time series modeling without the need for differencing.

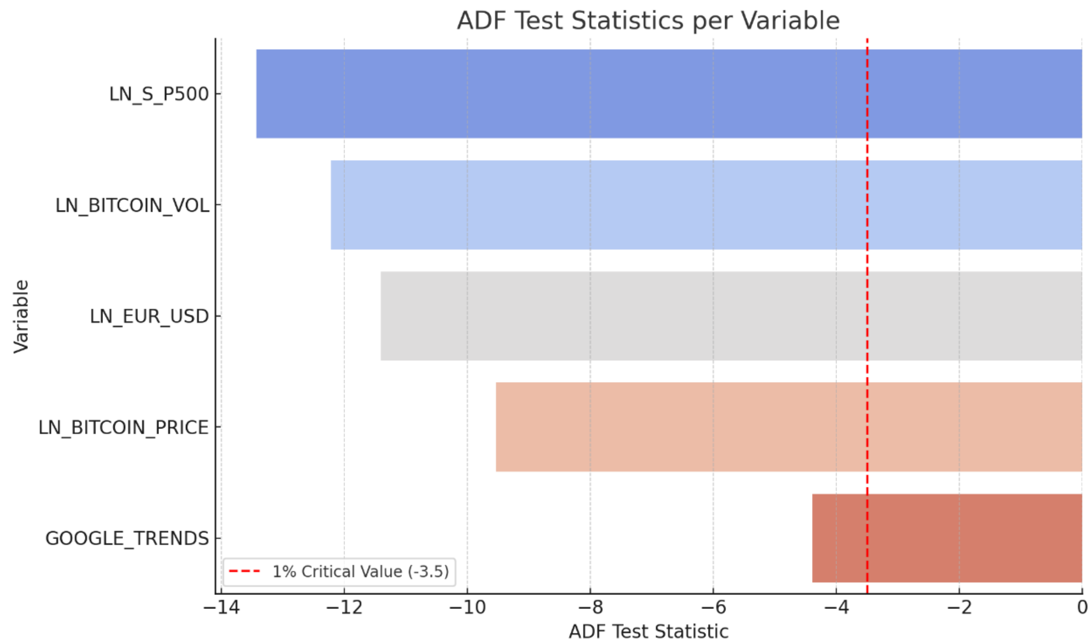

Figure 2. ADF Test Statistics per Variable.

The comprehensive ADF testing framework applied in this study confirms that all five time series are stationary in levels (Table 4), thereby obviating the need for differencing. This result carries important econometric implications: it mitigates the risk of spurious regression typically associated with non-stationary data when applying time series techniques such as ordinary least squares (OLS) or cointegration analysis. The stationarity of the log-transformed Bitcoin price, transaction volume, macro-financial indicators, and Google Trends index justifies their use in level-form models without further transformation. Consequently, this finding lays a robust foundation for subsequent dynamic econometric modeling and inference.

Table 4. ADF Regression Diagnostics.

Variable	Lagged Term Coefficient	t-Statistic	R-squared	DW Statistic	Constant Significant? ($p < 0.05$)
LN_BITCOIN_PRICE	-0.817478	-9.534362	0.415269	1.986869	Yes ($p = 0.0409$)
LN_BITCOIN_VOL	-1.073754	-12.21276	0.538159	2.004335	No ($p = 0.0687$)
LN_EUR_USD	-1.007749	-11.40171	0.503874	2.000121	No ($p = 0.3192$)
LN_S_P500	-1.169809	-13.42599	0.584762	2.052380	Yes ($p = 0.0030$)
GOOGLE_TRENDS	- 0.504421	-4.386357	0.248016	1.986631	No ($p \approx 0.3192$)

In Figure 3 are presented the lagged level coefficients from the ADF regressions. These coefficients capture the strength of mean reversion, with more negative values indicating faster return to equilibrium. The LN_S_P500 again stands out with the most negative coefficient (−1.17), indicating the most robust corrective force against deviations from the mean.

GOOGLE_TRENDS, while still exhibiting stationarity, shows a relatively weaker mean-reversion dynamic. These results align with the ADF test statistics and support the conclusion that all series exhibit suitable time series properties for regression analysis.

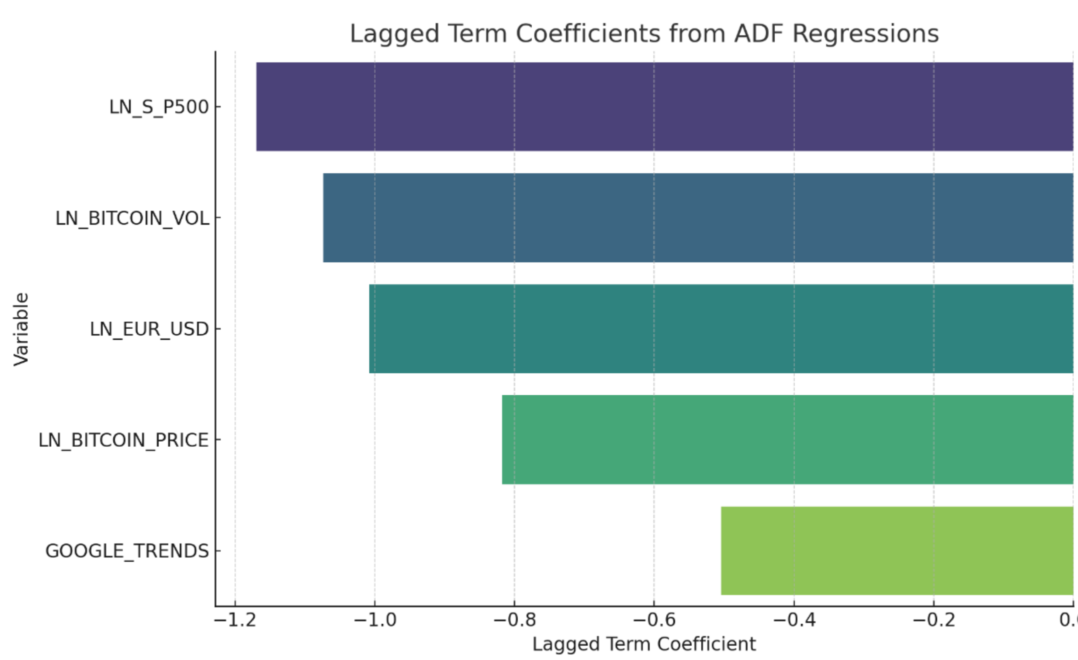

Figure 3. Lagged Term Coefficients from ADF Regressions.

4.4. OLS Regression Analysis

This section presents the results of an ordinary least squares (OLS) regression examining the determinants of monthly log changes in Bitcoin's price. The model includes explanatory variables that capture investor sentiment and broader macro-financial conditions.

Among the variables considered, the logarithm of the S&P 500 index (LN_S&P500) emerges as both statistically significant and economically meaningful (coefficient = 1.4963, $p = 0.0018$), indicating a strong positive co-movement between Bitcoin and U.S. equity markets. This supports the view of Bitcoin as a partially risk-sensitive asset, responsive to shifts in traditional financial markets.

The GOOGLE_TRENDS variable also exhibits a positive effect, marginally significant at the 10% level (coefficient = 0.0024, $p = 0.0597$). This suggests that increased public interest—likely reflecting heightened retail investor attention—may exert upward pressure on Bitcoin prices, consistent with existing findings in the cryptocurrency literature.

By contrast, LN_BITCOIN_VOL and LN_EUR_USD are not statistically significant ($p = 0.5787$ and $p = 0.2923$, respectively), suggesting that neither trading volume nor the EUR/USD exchange rate meaningfully influence monthly Bitcoin price fluctuations in this model. This may reflect Bitcoin's global, decentralized structure, where conventional volume and exchange rate indicators have limited explanatory power.

The constant term is also statistically insignificant, indicating no systematic trend in Bitcoin prices after controlling for the included variables.

The model accounts for approximately 11.3% of the variation in monthly Bitcoin returns ($R^2 = 0.113$; Adjusted $R^2 = 0.085$). While modest, this level of explanatory power is not uncommon for financial time series characterized by high volatility. Importantly, the overall model is statistically significant, as indicated by the F-statistic ($F = 4.01$, $p = 0.0043$), and the Durbin–Watson statistic (1.68) suggests no major concerns with autocorrelation in the residuals.

Table 5. OLS Regression Results.

Variable	Coefficient	Std. Error	t-Statistic	p-value
GOOGLE_TRENDS	0.0024	0.0013	1.90	0.0597
LN_BITCOIN_VOL	−0.0048	0.0087	−0.56	0.5787
LN_EUR_USD	−0.00002	0.00002	−1.06	0.2923
LN_S&P500	1.4963	0.4686	3.19	0.0018
Constant	−0.0073	0.0309	−0.24	0.8126
R-squared	0.113			
Adj. R-squared	0.085			
F-statistic (p)	4.01 (0.0043)			
Durbin-Watson	1.68			

Table 5 reports the estimated coefficients, standard errors, t-statistics, and p-values for all model variables. Standard errors are heteroskedasticity-consistent. Statistical significance is assessed at the 10%, 5%, and 1% levels.

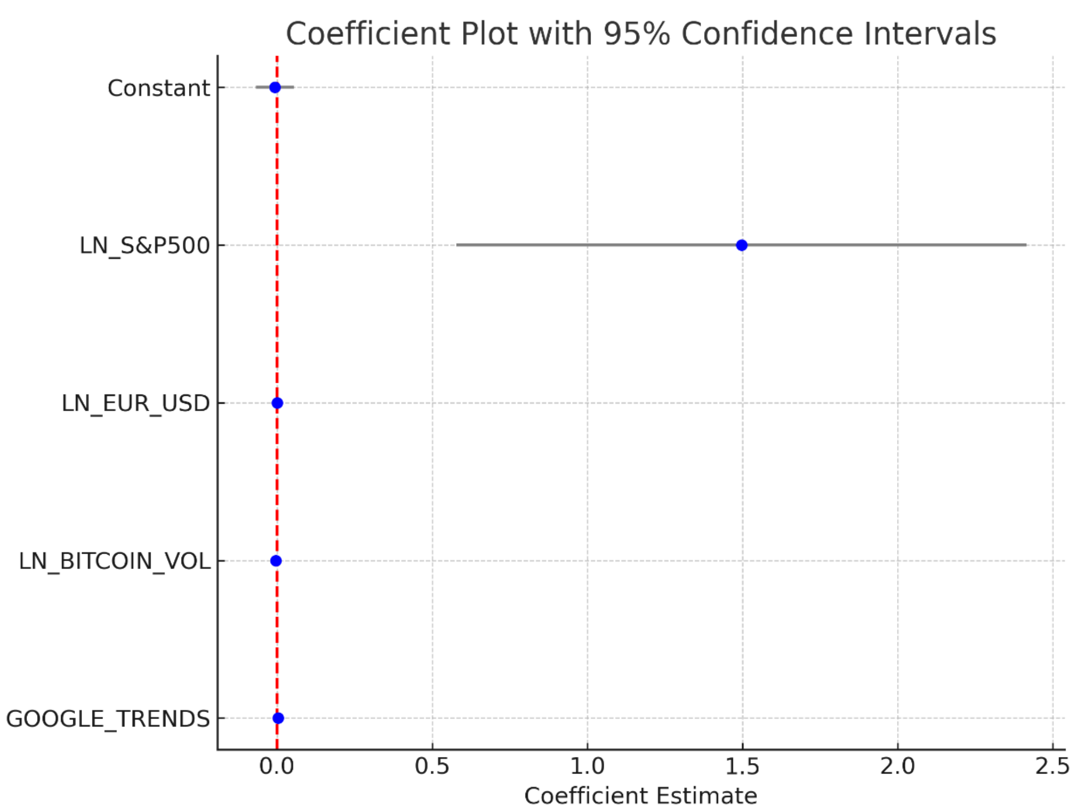

Figure 4. Coefficient Plot with 95% Confidence Intervals

Figure 4 Presents the estimated coefficients alongside 95% confidence intervals. LN_S&P500 clearly stands out as the only statistically robust predictor. The positive, marginally significant coefficient for GOOGLE_TRENDS further suggests a potential role of investor sentiment. For all other variables, confidence intervals span zero, indicating a lack of significant association with Bitcoin price changes.

5. Conclusion and Policy Implications

This study investigates the primary determinants of monthly Bitcoin price fluctuations over the period January 2014 to December 2024, integrating both cryptocurrency-specific factors—namely, Bitcoin trading volume and Google Trends—and broader macroeconomic indicators such as the EUR/USD exchange rate and the S&P 500 index. Preliminary statistical tests confirmed the stationarity and appropriateness of the log-transformed variables for time series regression analysis. Descriptive and correlation statistics revealed notable distributional asymmetries: Bitcoin price and volume were characterized by substantial volatility and skewness, while Google Trends and the S&P 500 index demonstrated lower dispersion, yet significant deviations from normality. These findings justified the use of robust econometric techniques to prevent spurious inference.

Utilizing an Ordinary Least Squares (OLS) regression framework, the results reveal that the S&P 500 index is the only consistently significant predictor, exhibiting a strong and positive association with Bitcoin prices. This suggests that Bitcoin, often portrayed as an alternative or uncorrelated asset, increasingly responds to broader macro-financial conditions, reflecting a partial integration with traditional financial markets. The Google Trends variable displayed marginal significance, underscoring the potential role of retail investor sentiment in influencing price dynamics. In contrast, neither Bitcoin trading volume nor the EUR/USD exchange rate had a statistically meaningful impact on monthly price variation. Although the model explains a limited portion of Bitcoin's price volatility, the findings highlight the influence of systemic economic factors and investor attention in shaping the cryptocurrency's market behavior.

5.1. Implications For Research

This study contributes to the growing literature on cryptocurrency price dynamics by empirically linking Bitcoin to conventional financial market indicators. It challenges the simplistic classification of Bitcoin as an isolated or purely speculative asset, offering evidence that its valuation is increasingly shaped by macroeconomic conditions. These findings suggest fruitful directions for future research, including the application of advanced methodologies—such as Vector Autoregression (VAR), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and natural language processing (NLP) for sentiment analysis—to better capture the complex and dynamic drivers of digital asset prices. Researchers are also encouraged to explore higher-frequency datasets and include regulatory, geopolitical, and media-related variables to enhance explanatory power and temporal granularity.

5.2. Implications For Practice and Policy

For market participants, the positive and significant relationship between Bitcoin and the S&P 500 index calls for a reassessment of Bitcoin's role in portfolio diversification. Rather than acting as a hedge or safe haven, Bitcoin may amplify exposure to equity market movements. The influence of public interest, as proxied by Google search activity, further underscores the relevance of investor sentiment monitoring in risk management practices.

From a regulatory standpoint, the increasing entanglement of crypto and traditional financial markets suggests the need for more coordinated and adaptive oversight frameworks. The apparent irrelevance of the EUR/USD exchange rate also reinforces the transnational nature of Bitcoin markets, implying that regulatory approaches should consider cross-jurisdictional implications and systemic interconnectedness.

5.3. Societal Impact

By identifying the macroeconomic and behavioral factors that influence Bitcoin prices, this research informs public discourse on the financial significance and risks associated with cryptocurrencies. Understanding that Bitcoin reacts not only to speculative dynamics but also to broader economic indicators may lead to more informed decision-making, enhance financial literacy, and promote responsible adoption of digital assets. As cryptocurrencies increasingly intersect with household wealth and financial system stability, such insights are essential for shaping inclusive, transparent, and resilient digital financial environments.

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