

Bitcoin's short- and long-run interactions with equity markets, oil prices and US macroeconomics: a global perspective

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Abstract

Purpose – This study investigates the dynamic relationships between Bitcoin returns, global oil prices and equity markets, with a particular focus on the USA (S&P 500) and Saudi Arabia (Tadawul All Share Index – TASI). This study also aims to assess how macro-financial conditions, both domestic and international, influence cryptocurrency performance in the short- and long run.

Design/methodology/approach – Using monthly data from August 2010 to June 2025, the study applies vector autoregression and vector error-correction models to capture short-term spillovers and long-term equilibrium relationships between Bitcoin, oil prices, equity indices, inflation, US federal funds rate and GDP growth. Dummy variables are included to control for structural breaks and extreme market events.

Findings – Bitcoin exhibits strong persistence and significant short-run sensitivity to US equity and monetary policy shocks, while TASI impacts are more delayed. Oil prices consistently affect Bitcoin, highlighting the role of global commodities. Long-term equilibria reveal that Bitcoin adjusts to deviations from macro-financial fundamentals, with stronger influence from US than Saudi markets.

Originality/value – This study integrates both developed and emerging market financial factors, offering new insights into Bitcoin's cross-market linkages and return dynamics.

Keywords Bitcoin, Oil prices, Equity markets, VAR, VECM, Saudi Arabia, US macroeconomic conditions

Paper type Research paper

1. Introduction

Over the past decade, Bitcoin has emerged as the most prominent and widely traded cryptocurrency, attracting attention from individual investors, institutional participants and policymakers alike. Its rapid price fluctuations and apparent detachment from traditional financial assets have sparked widespread research into the factors driving its returns and risk behavior. Among these, global oil prices, major equity markets and key macroeconomic indicators have been identified as particularly influential. Understanding these relationships is critical for investors seeking portfolio diversification, for risk managers optimizing asset allocation and for policymakers assessing systemic risks in financial markets.

While prior studies have largely focused on Bitcoin's interactions with US financial markets, the growing integration of emerging markets into the global financial system calls



JEL classification – C32, E44, G10, G12

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for a broader perspective. The Saudi Arabian equity market, represented by the Tadawul All Share Index (TASI), is particularly noteworthy given Saudi Arabia's central role in global oil production and its expanding financial connectivity. Investigating the dynamic interplay between Bitcoin, TASI and global oil prices – while controlling for US macro-financial conditions, offers a novel lens to understand how both domestic and international factors shape cryptocurrency behavior. Saudi Arabia's macroeconomic structure – characterized by high energy dependence, emerging technological integration and evolving environmental economic dynamics – further motivates its inclusion in examining regional spillovers (Abid, 2025a).

This study makes several key contributions in a concise, unified framework. First, it uses a vector autoregression (VAR) and vector error-correction model (VECM) to analyze short-run spillovers and long-run equilibrium relationships among Bitcoin returns, oil prices and major equity indices in both developed (US) and emerging (Saudi) markets. Second, it integrates US macro-financial indicators – including inflation, the federal funds rate and GDP growth – to capture cross-market linkages. Third, by combining developed and emerging market perspectives in a single framework, the study provides a clear contribution to understanding Bitcoin's global and regional interdependence without repeating prior claims.

The study addresses the following research questions (RQs):

- RQ1.* Do Bitcoin returns exhibit short-run and lagged responses to global and regional market factors such as oil prices, the S&P 500 and TASI?
- RQ2.* Do long-run equilibrium relationships exist between Bitcoin returns and macro-financial fundamentals across developed and emerging markets?
- RQ3.* How do these relationships inform investors and policymakers regarding Bitcoin's role as an integrated or independent financial asset?

By focusing on lagged spillovers and equilibrium linkages, this analysis examines how shocks originating in US and Saudi markets propagate over time to influence Bitcoin return dynamics. The VAR–VECM methodology is particularly suitable for capturing interdependencies among multiple financial variables and identifying both immediate and delayed effects. This approach provides critical insights into the temporal behavior of Bitcoin returns and highlights the interconnectedness between cryptocurrency markets, traditional equity markets and global commodity markets.

Building on theoretical and empirical insights, the following hypotheses guide this study:

- H1.* Bitcoin returns are significantly influenced by global and regional financial variables, including oil prices and major equity markets (S&P 500 and TASI).
- H2.* The impact of US macro-financial factors (monetary policy, inflation and equity performance) on Bitcoin returns is stronger and more immediate than that of Saudi market variables, reflecting differences in financial integration and market depth.
- H3.* Bitcoin exhibits both short-run spillovers and long-run equilibrium linkages with traditional financial and commodity markets, indicating partial integration rather than complete independence.

These hypotheses provide a theoretical foundation for the subsequent VAR and VECM analyses and help interpret how global and regional forces jointly shape Bitcoin's return dynamics.

The remainder of the paper is structured as follows: Section 2 reviews the theoretical and empirical literature on Bitcoin, equity markets, oil prices and US macro-financial variables; Section 3 describes the data used in the analysis; Section 4 outlines the empirical methodology, including VAR and VECM techniques; Section 5 presents the empirical results along with a detailed discussion of Bitcoin's dynamic interactions with financial and macroeconomic variables; and Section 6 concludes with policy implications, study limitations and suggestions for future research.

2. Literature review

The evolving landscape of financial markets has witnessed the emergence of Bitcoin as a significant asset class, prompting extensive research into its interactions with traditional financial markets, commodities and macroeconomic indicators (Baur *et al.*, 2018; Ullah, 2024). Recent work emphasizes that Bitcoin's role extends beyond speculation, it responds systematically to both global and regional macro-financial conditions, with implications for diversification, hedging and systemic risk. The following review critically synthesizes prior evidence on Bitcoin's linkages with traditional markets, oil prices and macroeconomic variables, highlighting methodological approaches, key limitations and empirical gaps that motivate this study's hypotheses.

2.1 Bitcoin and traditional financial markets

Bitcoin's interaction with traditional financial markets has been widely examined, with studies assessing whether it functions as a hedge, haven or diversifier relative to equities and bonds. Research generally shows that Bitcoin's correlations with traditional assets are unstable and often regime dependent. For example, Tzeng and Su (2024) find that Bitcoin responds strongly to US macro-financial shocks – including interest rates and inflation, indicating that its behavior is sensitive to broader market cycles. Benigno and Rosa (2023) similarly show that Bitcoin's reactions to macroeconomic news mirror shifts in overall investor sentiment rather than reflecting isolation from traditional markets. Evidence from European markets (Aliu *et al.*, 2021a, 2021b) further highlights short-term diversification benefits, although these studies rely on static portfolio frameworks that understate volatility clustering and tail dependence. Bouri *et al.* (2017) demonstrate that correlations between Bitcoin and equities intensify during periods of financial stress, implying that any hedging potential is conditional rather than universal. Collectively, the literature suggests that Bitcoin may offer diversification benefits in normal periods, but these advantages weaken during episodes of heightened uncertainty, justifying the need for dynamic models capable of capturing evolving spillovers and market regimes.

Recent evidence also highlights the significant role of monetary policy uncertainty and inflation shocks in shaping financial market dynamics (Abid *et al.*, 2024a; Abid, 2025b), reinforcing the sensitivity of Bitcoin to shifts in liquidity and policy expectations.

Overall, prior studies provide descriptive rather than causal insights. Few addresses endogeneity between macro-shocks and Bitcoin returns, and most assume constant parameters despite evidence of volatility clustering. This motivates our use of VAR–VECM methods with structural dummies to capture both short-run spillovers and long-run equilibria.

2.2 Bitcoin and oil prices

The relationship between Bitcoin and oil prices has garnered attention due to the pivotal role of oil in global economics. Alokley *et al.* (2024) used copula models and machine learning techniques to explore the interdependencies between Bitcoin, oil prices and the Saudi equity

market, finding significant linkages that underscore the interconnectedness of these markets. Other studies (Ciner *et al.*, 2013; Shahzad *et al.*, 2019) have found that oil price shocks can transmit through global liquidity channels to cryptocurrency markets, influencing Bitcoin returns and volatility. This line of research contributes to understanding how commodity price fluctuations, particularly in oil-exporting regions, can affect Bitcoin dynamics.

Oil, as a key macroeconomic barometer, transmits global liquidity and inflation shocks that may influence cryptocurrencies. Alokley *et al.* (2024) used copula models and machine-learning algorithms to assess dependence between Bitcoin, oil prices and the Saudi equity market, finding significant nonlinear linkages. Other work (Ciner *et al.*, 2013; Shahzad *et al.*, 2019) confirmed that oil shocks propagate through financial channels to affect crypto-asset volatility. Aliu *et al.* (2021a, 2021b) expanded this literature by analyzing return spillovers among the top 15 cryptocurrencies during COVID-19 and the Russia–Ukraine war, demonstrating that connectedness intensifies under stress, implying diversification collapses when most needed.

Energy-related indicators are closely tied to macro-financial movements in oil-intensive economies (Abid, 2025c), further supporting the integration of Brent oil prices into models examining regional and global spillovers.

These findings suggest that Bitcoin's correlation with commodities like oil is time-varying and crisis-dependent, reinforcing the need to model structural breaks and nonlinear effects explicitly, as done in our dummy-augmented VAR framework.

2.3 Bitcoin and the Saudi equity market (TASI)

The Saudi market offers a relevant emerging-economy context due to its oil dependence and growing financial openness. Alokley *et al.* (2024) documented positive correlations between Bitcoin and TASI returns, consistent with regional spillovers. However, such studies often overlook structural integration mechanisms and rely on contemporaneous correlations without testing for cointegration or causality. Haider Ali *et al.* (2025) noted that increased cross-border capital flows amplify transmission between TASI and global markets, suggesting that ignoring emerging-market linkages underestimates Bitcoin's regional interdependence.

Studies examining GCC economies confirm the central role of energy markets, macroeconomic fundamentals and structural factors in shaping regional financial behavior (Abid *et al.*, 2024b; Chaabouni and Abid, 2025), which supports the relevance of incorporating TASI and oil prices in our empirical framework.

By incorporating TASI alongside US variables in a unified VAR–VECM, the present study directly addresses this omission, linking to *H1* (Bitcoin's sensitivity to global and regional variables) and *H3* (its mixed short- and long-run relationships).

2.4 US macroeconomic indicators and Bitcoin

US macro-financial variables shape worldwide liquidity and investor behavior. Tzeng and Su (2024) confirmed that inflation and interest-rate innovations predict cryptocurrency volatility. Mahmoudi (2023) used a Markov-switching VAR to show that monetary-policy uncertainty depresses Bitcoin returns across low- and high-volatility regimes, with stronger effects in turbulent periods. Yet, the method's limitations are notable: regime classification depends on prior assumptions, and monthly data may blur intramonth policy shocks, causing structural events (e.g. ETF approvals or halvings) to be mis-identified as regime shifts. Nuhui *et al.* (2023) further observed that diversification gains from crypto assets shrink as volatility rises, emphasizing the need for models that accommodate state-dependent relationships.

Collectively, these studies align with *H2*, implying that US macro-financial channels exert stronger and faster influence on Bitcoin than regional markets, but they also justify refining identification through explicit event dummies and cointegration analysis.

2.5 Synthesis and research gap

Across the reviewed literature, three patterns emerge. First, diversification results are period-specific and vanish during crises, indicating conditional integration. Second, most prior studies adopt linear or static designs that cannot capture evolving spillovers or equilibrium linkages. Third, few examine both developed and emerging-market drivers jointly. Consequently, a unified model combining global (USA) and regional (Saudi + oil) factors within a VAR–VECM system can bridge this gap by distinguishing short-run contagion from long-run adjustment paths.

This analytical choice directly operationalizes our hypotheses: *H1* (global + regional determinants), *H2* (US dominance and transmission speed) and *H3* (coexistence of short-run spillovers and long-run equilibria). A detailed comparative summary of the key studies discussed above, including their methodologies, findings, limitations and relevance to the present hypotheses (*H1–H3*), is provided in Appendix.

3. Methodology

In the methodological design, we proceed step by step to capture both baseline dynamics and the role of structural shocks. We begin with the baseline VAR specification that models the dynamic interactions between Bitcoin, the S&P 500, US macroeconomic variables and oil prices, without accounting for discrete event shocks. To assess regional market effects, we next estimate the baseline VAR using the Saudi stock market index (TASI) instead of the S&P 500, alongside the same set of US macroeconomic variables and oil prices.

The general form of the baseline VAR model with *p* lags can be expressed as:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \quad (1)$$

where:

Y_t = ($k \times 1$) vector of endogenous variables;

A_i = coefficient matrices; and

ε_t = vector of white-noise error terms.

This specification captures short-run interdependencies and lagged spillovers between the variables.

The optimal lag length (*p*) was selected using the Akaike information criterion (AIC) and the Schwarz Bayesian information criterion (SBIC), ensuring parsimonious yet well-specified models. The lag order minimizing both AIC and SBIC was used for all subsequent estimations.

Building on these benchmarks, we then extend the S&P 500 model by introducing event dummies for Bitcoin halving events, ETF announcements and FOMC policy meetings, to capture the impact of major structural shocks on Bitcoin's return dynamics. Finally, we apply the dummy-augmented VAR framework to the TASI-based system, allowing us to test whether regional market linkages interact with global event-driven shocks in influencing Bitcoin.

The dummy-augmented VAR specification is defined as:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + D_t \gamma + \varepsilon_t \quad (2)$$

where D_t is a vector of dummy variables representing structural events (Bitcoin halving, ETF announcements, FOMC meetings), and γ is the associated coefficient vector.

Each dummy variable is coded as $D_t = 1$ for the month in which the event occurs, and $D_t = 0$, otherwise. This operationalization isolates the effects of specific shocks. The dummies are treated as strictly exogenous, implying they are determined outside the system and uncorrelated with the residual vector ε_t .

This sequential approach ensures that the analysis moves from general baseline interactions to more refined models that account for both global financial dynamics and event-specific shocks.

Since the variables are often non-stationary but may be cointegrated, we further extend the analysis using a VECM. The VECM combines short-run adjustments with long-run equilibrium constraints. Its general form is expressed as:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t \quad (3)$$

where $\Pi = \alpha\beta'$ contains the cointegration vectors (β) and adjustment coefficients (α). The error correction term $\beta' Y_{t-1}$ represents deviations from long-run equilibrium, and α indicates the speed of adjustment.

Impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) are derived to assess dynamic relationships and shock propagation. The IRF at horizon h is given by:

$$IRF_{jk}(h) = e_j' \Psi_h P e_k \quad (4)$$

where e_j and e_k are selection vectors, P is the Cholesky factorization matrix and Ψ_h are moving-average coefficient matrices. The FEVD, measuring the proportion of variable j 's forecast variance explained by shocks to variable k , is defined as:

$$\theta_{jk}(h) = \frac{\sum_{i=0}^{h-1} (e_j' \Psi_i P e_k)^2}{\sum_{i=0}^{h-1} (e_j' \Psi_i P P' \Psi_i' e_j)} \quad (5)$$

These procedures enable tracing of both short- and long-term shock transmission across markets and macroeconomic variables.

Estimation follows three steps: unit root testing (ADF), Johansen cointegration testing to identify the number of long-run relationships and estimation of the VECM using maximum likelihood methods (Johansen, 1991; Lütkepohl, 2005).

The overall estimation process proceeds sequentially as follows:

- Data transformation and stationarity testing (ADF tests).
- Lag length determination via AIC and SBIC.
- Baseline VAR estimation.
- Inclusion of dummy variables for structural events.
- Johansen cointegration tests.
- Estimation of the VECM for cointegrated systems.
- Computation of impulse responses and variance decompositions.

A schematic flowchart of the procedure is provided in [Figure 1](#).

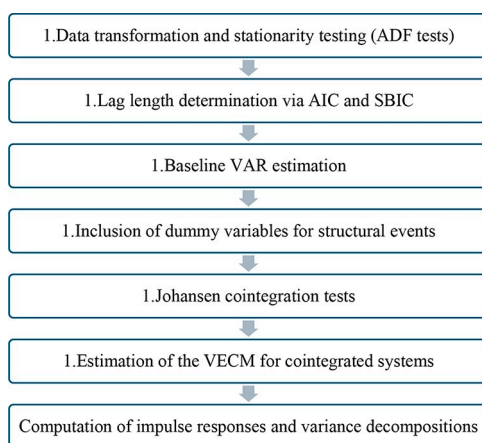


Figure 1. Sequential estimation procedure of the VAR-VECM framework

4. Data

4.1 Data and variables

This study uses monthly data covering the period from August 2010 to June 2025 for the USA and Saudi Arabia. The starting point reflects the availability of reliable Bitcoin market data, while the endpoint captures the most recent macro-financial and market conditions.

The data set includes the following variables:

- Bitcoin returns (BTC): Calculated from logarithmic changes in Bitcoin prices to capture cryptocurrency market performance, with data obtained from CoinMarketCap.
- Equity indices: The S&P 500 representing the US equity market and the TASI for Saudi Arabia, sourced from the Federal Reserve Economic Data (FRED) and the Tadawul official website, respectively.
- Global oil prices (OIL): Monthly Brent crude oil prices, serving as a proxy for global energy market conditions, retrieved from the US Energy Information Administration (EIA).
- Inflation (CPI): US consumer price index, representing domestic price dynamics, collected from the Bureau of Labor Statistics (BLS).
- Monetary policy (FED): Effective federal funds rate, capturing US monetary stance, obtained from FRED.
- Gross domestic product (GDP): US real GDP at constant prices, reflecting overall economic activity, sourced from FRED.

All variables are transformed into logarithms where appropriate to stabilize variance and improve interpretation in percentage terms.

To ensure clarity and consistency in the empirical design, all variable transformations are explicitly defined. Bitcoin (BTC) and the S&P 500 (SP500) are expressed as logarithmic returns, reflecting their use as return series in the VAR-VECM system. By contrast, the TASI is included in logarithmic levels, consistent with its role as a price index rather than a return measure. All macroeconomic variables – consumer prices (CPI), oil prices (OIL), the federal funds rate (FED) and real GDP – are expressed in logarithmic levels, and their changes are

incorporated into the models through first-difference transformations (DCPI, DOIL, DFED, DGDGP) when required for estimation. This explicit clarification ensures transparency in variable construction and avoids any ambiguity regarding the transformations applied in subsequent tables and empirical results.

4.2 Event dummies and structural shocks

To account for discrete structural shocks beyond continuous macroeconomic and financial variables, we augment the baseline VAR framework with three event-specific dummy variables. These dummies capture the impact of major events that are well-documented drivers of Bitcoin market dynamics and allow us to test whether such shocks produce statistically significant deviations in Bitcoin's return behavior (Corbet *et al.*, 2018):

- Bitcoin halving events (Dummy1): Occurring approximately every four years, halving events reduce the block reward for Bitcoin miners by 50%, introducing a predictable supply shock. These events are typically associated with heightened speculation, increased media coverage and abnormal returns in Bitcoin markets (CoinMarketCap, 2020).
- Bitcoin ETF announcements (Dummy2): Regulatory approvals or announcements regarding Bitcoin exchange-traded funds (ETFs) mark milestones in cryptocurrency institutionalization. Such announcements often generate surges in Bitcoin prices due to increased legitimacy and expectations of broader adoption [Lyócsa *et al.*, 2020; Securities and Exchange Commission (SEC), 2021].
- Federal Open Market Committee announcements (Dummy3): US monetary policy decisions, particularly on interest rates and liquidity, strongly influence global financial markets. Previous research indicates that unexpected FOMC shocks can spill over into Bitcoin, as investors reassess risk and liquidity across asset classes (Klein *et al.*, 2018).

The inclusion of these three event dummies strengthens the empirical design in two ways. First, it improves model fit by accounting for structural breaks that cannot be explained by autoregressive dynamics alone. Second, it enhances economic interpretation by linking Bitcoin's return behavior to supply adjustments (halvings), institutional adoption milestones (ETFs) and monetary policy shocks (FOMC). This distinction allows us to separate endogenous market-driven dynamics from exogenous event-driven responses.

4.3 Data analysis

We present the time-series behavior of all variables used in the empirical model, Bitcoin returns (BTC), the US equity market (S&P 500), the Saudi equity market (TASI), crude oil prices (OIL), US inflation (CPI), the federal funds rate (FED) and real GDP (GDP), over the study period. The visual inspection provides initial insights into the distinct characteristics of each series.

Figure 2 presents the evolution of the financial market variables. The BTC (Bitcoin) series shows pronounced volatility during the early period, with large spikes followed by relative stabilization, reflecting Bitcoin's speculative phase and gradual market maturity. The S&P 500 displays short-term cyclical fluctuations around a stable mean, indicative of moderate volatility typical of a mature equity market influenced by global risk sentiment. The TASI demonstrates an upward long-term trajectory punctuated by cyclical corrections, suggesting steady economic growth in Saudi Arabia with episodic market adjustments.

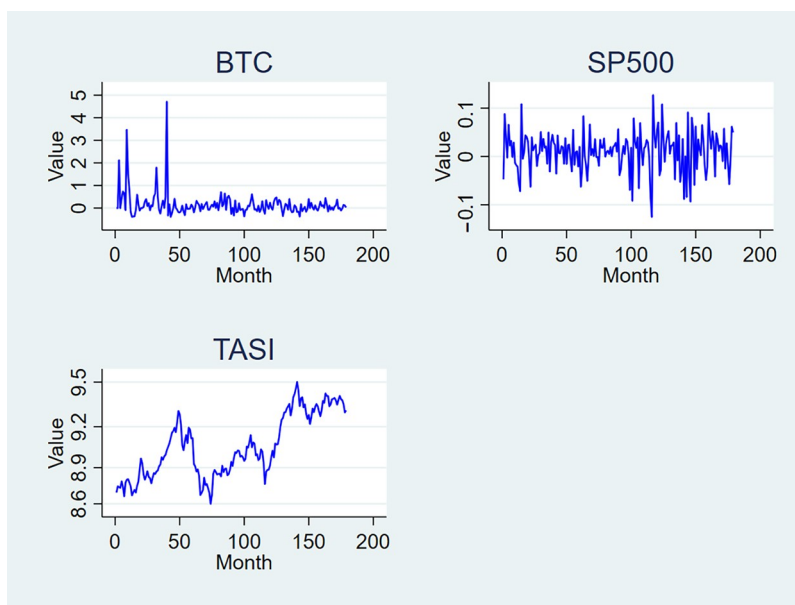


Figure 2. Time-series plots for financial markets

Figure 3 illustrates the evolution of the macroeconomic and commodity-related variables. The OIL series captures cyclical peaks and troughs associated with global supply–demand dynamics and geopolitical shocks. The CPI follows a persistent upward trend, confirming inflationary pressure over the sample period. The FED rate exhibits distinct policy phases, a prolonged low-rate environment, a tightening phase in the mid-sample and a subsequent rise, consistent with US monetary policy responses to inflation and economic cycles. The GDP series records a steady growth path interrupted by a sharp contraction likely corresponding to the COVID-19 pandemic, after which it resumes its prior trend.

Together, these figures show that financial variables (BTC, S&P 500, TASI) display varying degrees of volatility and cyclical movements, while macroeconomic variables (CPI, FED, GDP) reveal long-term structural trends driven by policy and economic fundamentals.

4.3.1 Stationarity analysis. The ADF test results (Table 1) indicate that most macroeconomic and financial variables – CPI, oil prices, the federal funds rate, TASI and GDP – are non-stationary at levels but become stationary after first differencing, implying they are integrated of order one [I(1)]. Bitcoin returns are weakly stationary at levels, while the S&P 500 is stationary without differencing. These findings validate the presence of mixed integration orders among the variables and justify using the VAR–VECM framework to capture both short-run dynamics and long-run cointegrating relationships. Ensuring stationarity before model estimation avoids spurious regressions and provides reliable inference about intermarket linkages.

4.3.2 Multicollinearity and descriptive analysis. Multicollinearity diagnostics using the variance inflation factor (VIF) reveal low correlation among regressors (mean VIF = 1.38 for the BTC–S&P 500 model; mean VIF = 1.33 for the BTC–TASI model), confirming the absence of redundancy and ensuring robust estimation.

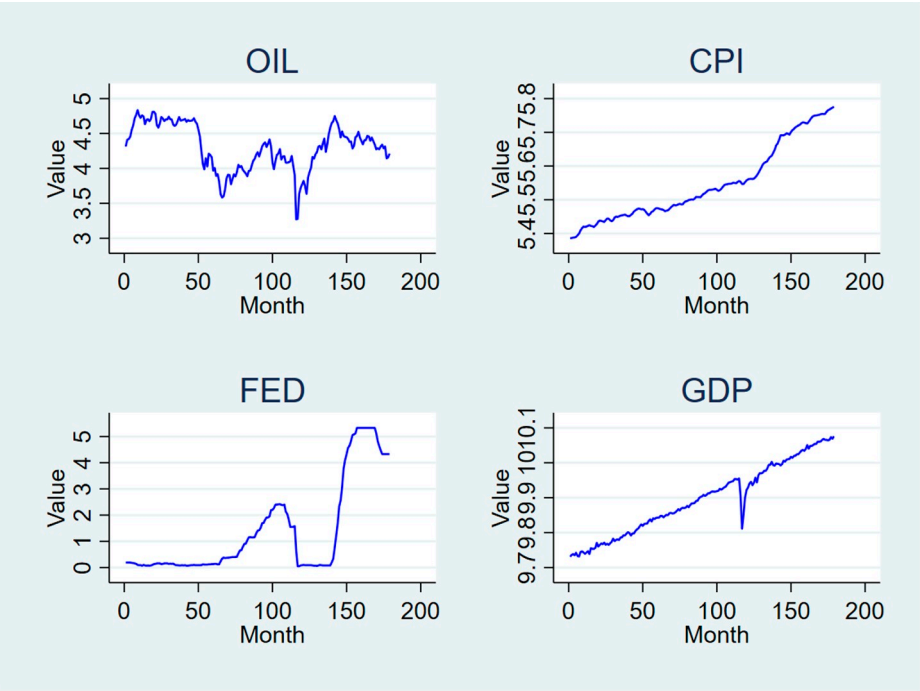


Figure 3. Time-series plots for macro-financial variables

Table 1. ADF test results

Variable	Level Z(t)	p-value	Diff Z(t)	p-value (diff)
BTC	-2.9210	0.0433	-9.3870	0.0000
SP500	-11.3760	0.0000	-18.0670	0.0000
CPI	1.1170	0.9954	-6.8390	0.0000
OIL	-2.3180	0.1663	-9.3230	0.0000
FED	-0.8140	0.8148	-5.2010	0.0000
TASI	-1.6540	0.4552	-9.9030	0.0000
GDP	0.1880	0.9716	-7.4650	0.0000

Source(s): Author’s own work

Descriptive statistics (Table 2) show that Bitcoin returns exhibit the highest volatility (mean = 0.1471, SD = 0.5371), reflecting the cryptocurrency market’s inherent instability. Traditional financial and macroeconomic indicators display much lower variability: the S&P 500 has a mean monthly return of 0.0106 (SD = 0.0414), TASI averages 9.0532 (SD = 0.2317), CPI averages 5.55 (SD = 0.11), OIL prices average 4.31 (SD = 0.33) and GDP averages 9.94 (SD = 0.21). The federal funds rate shows the widest range (mean = 1.37, SD = 1.80), consistent with major shifts in US monetary policy.

4.3.3 Correlation analysis. The correlation matrix (Table 3) confirms that Bitcoin returns have weak linear associations with traditional financial and macroeconomic

Table 2. Descriptive statistics

Variable	Obs	Mean	SD	Min.	Max.
BTC	179	0.1471	0.5371	-0.3887	4.7094
SP500	179	0.0106	0.0414	-0.1251	0.1268
TASI	179	9.0532	0.2317	8.6347	9.5276
CPI	179	5.5457	0.1118	5.3859	5.7763
OIL	179	4.3057	0.3309	3.2715	4.8354
FED	179	1.3748	1.7956	0.0500	5.3300
GDP	179	9.9389	0.2051	9.6289	10.3077

Note(s): The unusually high maximum value of BTC (4.7094) reflects Bitcoin's extreme historical price spikes during early market phases, particularly in 2013, when monthly price surges exceeded 1,000%. This value arises directly from the log-return calculation and is consistent with Bitcoin's well-documented early-period volatility

Source(s): Author's own work

Table 3. Correlation matrix of main variables

Variable	BTC	SP500	CPI	OIL	FED	TASI	GDP
BTC	1.0000						
SP500	0.1750	1.0000					
CPI	-0.1861	0.0001	1.0000				
OIL	0.1407	0.0077	-0.0713	1.0000			
FED	-0.1141	0.0264	0.8313	0.017	1.0000		
TASI	-0.1745	0.0167	0.8363	0.1992	0.5993	1.0000	
GDP	-0.2147	-0.0106	0.8595	-0.2356	0.7726	0.7914	1.0000

Source(s): Author's own work

indicators, reinforcing their relatively independent behavior as a distinct asset class. The low positive correlations with the S&P 500 (0.1750) and oil prices (0.1407) suggest limited short-term co-movements and partial diversification potential. By contrast, CPI, FED, and GDP display high positive correlations (above 0.75), reflecting strong macroeconomic interdependence. The TASI correlates significantly with CPI (0.8363) and GDP (0.7914), capturing Saudi Arabia's integration with global macro-financial trends.

Taken together, the visual, descriptive and statistical analyses confirm that Bitcoin behaves as a stationary, high-volatility financial variable, while the macroeconomic and equity market indicators exhibit non-stationary trends consistent with long-run equilibrium relationships. These results provide a strong empirical basis for modeling Bitcoin's interconnections with global markets within a VECM framework, enabling the investigation of both short-run adjustments and long-run cointegration among cryptocurrency, equity and macroeconomic variables.

5. Results

We estimated two sets of VAR models to assess the dynamic interactions between Bitcoin and key financial and macroeconomic variables. The baseline models (Model 1–2) included Bitcoin, either the S&P 500 or TASI, together with US macroeconomic indicators (CPI, federal funds rate, GDP) and oil prices, capturing endogenous dynamics without discrete shocks. The extended models (Model 3–4) incorporated dummy variables for Bitcoin

halving events, ETF announcements and FOMC meetings. These additions modestly improved model fit (lower AIC and residual variance) while preserving the significance and direction of most predictors. However, several coefficients changed in magnitude and significance once event dummies were introduced, indicating that baseline effects partly absorbed discrete shocks. Overall, the dummy-augmented models provide a richer representation of Bitcoin’s return dynamics in both global (S&P 500) and regional (TASI) contexts.

5.1 Vector autoregression lag selection

The selection of the optimal lag length for the VAR models is presented in Table 4.

The results suggest that a lag length of 4 is optimal for capturing the dynamic relationships among the variables in the VAR models, balancing model complexity and predictive accuracy.

5.2 Vector autoregression model for Bitcoin with S&P 500, US macroeconomic variables and oil prices

Table 5 presents the baseline VAR model using Bitcoin returns, the S&P 500, US macroeconomic variables and oil prices. This serves as the starting point to examine the short-run dynamics between Bitcoin and major global financial and commodity drivers.

Bitcoin returns show strong persistence, with significant positive effects from their own lags (1 and 4), indicating short- and medium-term autocorrelation. The S&P 500 has a strong

Table 4. VAR lag selection table

Lag	LL	LR	Df	p-value	FPE	AIC	HQIC	SBIC
<i>Model 1. Model BTC with SP500</i>								
0	56.4836				2.30E-08	-0.5803	-0.5361	-0.4713
1	540.2100	967.4500	36	0.0000	1.30E-10	-5.7266	-5.4172	-4.9640
2	587.6110	94.8020	36	0.0000	1.20E-10	-5.8576	-5.2831	-4.4415
3	649.2480	123.2700	36	0.0000	8.60E-11	-6.1523	-5.3127	-4.0826
4	702.0300	105.5700*	36	0.0000	7.2e-11*	-6.34518*	-5.2404	-3.6219
<i>Model 2. Model BTC with TASI</i>								
0	-179.9610				3.40E-07	2.1375	2.1817	2.2464
1	486.6540	1333.2000	36	0.0000	2.40E-10	-5.1110	-4.80164*	-4.34844*
2	535.8060	98.3040	36	0.0000	2.10E-10	-5.2621	-4.6877	-3.8460
3	587.4690	103.3300	36	0.0000	1.80E-10	-5.4422	-4.6026	-3.3725
4	634.6140	94.2900*	36	0.0000	1.6e-10*	-5.57027*	-4.4655	-2.8470
<i>Model 3. Model BTC with SP500 with dummy variables</i>								
0	74.6762				2.30E-08	-0.5825	-0.4057	-0.1468
1	572.5600	995.7700	36	0.0000	1.10E-10	-5.8915	-5.44959*	-4.80216*
2	614.5670	84.0140	36	0.0000	1.00E-10	-5.9605	-5.2535	-4.2176
3	671.8880	114.6400	36	0.0000	8.20E-11	-6.2056	-5.2334	-3.8091
4	727.7110	111.65*	36	0.0000	6.6e-11*	-6.43346*	-5.1962	-3.3833
<i>Model 4. Model BTC with TASI with dummy variables</i>								
0	-162.2560				3.40E-07	2.1409	2.3176	2.5766
1	522.7610	1,370.0000	36	0.0000	2.00E-10	-5.3191	-4.87720*	-4.22977*
2	566.8230	88.1220	36	0.0000	1.80E-10	-5.4118	-4.7047	-3.6688
3	614.3020	94.9580	36	0.0000	1.60E-10	-5.5437	-4.5715	-3.1472
4	663.0230	97.442*	36	0.0000	1.4e-10*	-5.68991*	-4.4526	-2.6398

Note(s): *indicates the optimal lag length selected by each lag selection criterion. LR = Likelihood Ratio test, FPE = Final Prediction Error, AIC = Akaike Information Criterion, HQIC = Hannan–Quinn Information Criterion, and SBIC = Schwarz Bayesian Information Criterion

Source(s): Author’s own work

Table 5. VAR Model 1 BTC with S&P 500

Variable	Lag	Coefficient	SE	p-value
BTC	L1	1.1208	0.0750	0.0000
BTC	L2	-0.2373	0.1148	0.0390
BTC	L3	-0.1229	0.1157	0.2880
BTC	L4	0.2954	0.0787	0.0000
SP500	L1	-29,899.8100	9,539.3330	0.0020
SP500	L2	12,470.8600	9,716.5030	0.1990
SP500	L3	22,082.4700	9,893.9600	0.0260
SP500	L4	16,533.5500	9,265.3230	0.0740
DCPI	L1	-440,946.1000	18,6428.5000	0.0180
DCPI	L2	-87,184.1000	187,445.3000	0.6420
DCPI	L3	-154,595.6000	187,910.8000	0.4110
DCPI	L4	-60,003.0800	167,657.0000	0.7200
DOIL	L1	14,561.8300	4,419.1270	0.0010
DOIL	L2	-1,246.2350	4,988.1180	0.8030
DOIL	L3	1,270.6180	5,113.0020	0.8040
DOIL	L4	1,391.4990	4,885.3250	0.7760
DFED	L1	-12,207.3600	3,451.2960	0.0000
DFED	L2	5,744.8920	3,891.4970	0.1400
DFED	L3	-2,425.7460	4,086.6000	0.5530
DFED	L4	8,815.6240	4,026.8280	0.0290
DGDP	L1	40,614.1200	94,047.4100	0.6660
DGDP	L2	144,706.0000	116,396.1000	0.2140
DGDP	L3	-110,266.4000	98,559.2600	0.2630
DGDP	L4	32,592.5900	87,199.5700	0.7090
_cons		880.5789	712.9140	0.2170
Model characteristics				
Equation	RMSE	R ²	Chi2	p-value
BTC	4260.0100	0.9759	7,038.625	0.0000
VAR residual serial correlation				
Lag	χ^2 statistic		p-value	
1	42.9400		0.1981	
2	42.5600		0.2095	

Source(s): Author's own work

impact: Lag 1 is negative, while Lags 3 and 4 are positive, reflecting immediate divergence and delayed spillovers. Inflation (CPI) reduces Bitcoin returns only at lag 1, while oil prices increase them in the short run. Monetary policy matters: rate hikes lower returns at lag 1 but raise them at lag 4, suggesting delayed adjustment. GDP growth shows no significant effect.

Overall, Bitcoin dynamics are shaped mainly by persistence, equity markets, monetary policy and oil prices, while inflation and GDP exert weaker short-term effects. Diagnostic checks confirm model reliability with no residual autocorrelation.

Diagnostic checks confirm the reliability of these results: the LM test (Table 5) shows no significant serial correlation in the VAR residuals, indicating that the models are well-specified and that the estimated coefficients can be interpreted with confidence.

5.3 Vector autoregression model for Bitcoin with Tadawul All Share Index, US
macroeconomic variables and oil prices

Table 6 replaces the S&P 500 with TASI to capture the role of the Saudi equity market. This step allows us to compare whether Saudi market dynamics explain Bitcoin fluctuations differently from US equity market conditions.

Bitcoin returns show strong persistence, with significant own-lag effects at 1 and 4, indicating short- and medium-term autocorrelation. TASI affects Bitcoin with a delayed positive impact at Lag 3, followed by a negative effect at Lag 4, suggesting spillovers and later correction. Inflation (CPI) reduces returns at Lag 1, with weaker effects later. Oil prices raise returns only at Lag 1, showing short-run sensitivity to energy shocks. Federal funds rate hikes lower returns at Lag 1 but turn positive at Lag 4, reflecting delayed adjustment. GDP growth has no significant effect.

Table 6. VAR Model 2 BTC with TASI

Variable	Lag	Coefficient	SE	p-value
BTC	L1	1.0505	0.0737	0.0000
BTC	L2	-0.1702	0.1089	0.1180
BTC	L3	-0.1028	0.1091	0.3460
BTC	L4	0.2752	0.0767	0.0000
TASI	L1	-4,213.1750	7,179.3530	0.5570
TASI	L2	-1,676.0890	10,042.9900	0.8670
TASI	L3	20,003.0400	10,092.8400	0.0470
TASI	L4	-13,322.1200	7,470.1160	0.0750
DCPI	L1	-481,519.0000	190,353.8000	0.0110
DCPI	L2	-235,630.9000	195,106.3000	0.2270
DCPI	L3	-136,201.8000	201,224.0000	0.4980
DCPI	L4	-1,121.8680	170,015.5000	0.9950
DOIL	L1	12,314.1500	4,851.9830	0.0110
DOIL	L2	5,386.0230	5,296.3280	0.3090
DOIL	L3	2,406.7170	5,392.0360	0.6550
DOIL	L4	2,970.9990	4,758.3750	0.5320
DFED	L1	-12,977.7600	3,608.4090	0.0000
DFED	L2	6,494.9230	4,075.9010	0.1110
DFED	L3	-3,389.4680	4,373.3670	0.4380
DFED	L4	8,153.4260	4,270.5830	0.0560
DGDP	L1	32,156.7200	98,830.1100	0.7450
DGDP	L2	127,574.3000	121,846.5000	0.2950
DGDP	L3	-43,837.1100	103,513.4000	0.6720
DGDP	L4	32,206.1600	92,384.3600	0.7270
_cons		-5,861.4480	23,794.8300	0.8050
Model characteristics				
Equation	RMSE	R-squared	Chi2	p-value
BTC	4,468.4200	0.9735	6,381.498	0.0000
VAR residual serial correlation				
Lag	χ^2 statistic			p-value
1	49.2900			0.0690
2	50.7700			0.0623

Source(s): Author's own work

Diagnostic checks confirm model validity with no residual autocorrelation. Overall, Bitcoin returns are driven by momentum, monetary policy, oil shocks and delayed signals from TASI, reflecting exposure to both local and global financial conditions.

5.3.1 Comparison of S&P 500 and Tadawul All Share Index models. Both models show Bitcoin's strong persistence (Lags 1 and 4), short-run sensitivity to oil prices (Lag 1) and immediate and delayed effects from US monetary policy (Lags 1 and 4). Inflation reduces returns at Lag 1 in both models, with slightly stronger medium-term effects in the TASI model. GDP growth is insignificant.

The main difference is in equity markets: with the S&P 500, Bitcoin reacts immediately (negative Lag 1) and positively at Lags 3 and 4, while with TASI, effects emerge only later, positive at Lag 3 and negative at Lag 4, indicating slower transmission from Saudi equities.

Overall, Bitcoin is driven by momentum, oil shocks and US monetary policy, but cross-market spillovers differ, rapid from the USA, delayed from Saudi Arabia.

5.4 Vector autoregression model for Bitcoin with S&P 500, US macroeconomic variables, oil prices and dummy controls

[Table 7](#) extends the baseline VAR model by incorporating dummy controls for structural breaks and major global shocks. This specification tests whether the Bitcoin–US financial linkages remain robust when accounting for extraordinary market events.

Bitcoin returns remain highly autoregressive, with persistence at Lags 1 and 4 and a negative adjustment at Lag 2, reflecting momentum, mean reversion and medium-term autocorrelation. The S&P 500 exerts a strong influence: negative at Lag 1 (immediate inverse response) and positive at Lag 3 (delayed spillover). Inflation (CPI) reduces returns at Lag 1, while oil prices boost them at Lag 1, showing sensitivity to short-run shocks. Monetary policy is significant: rate hikes depress returns immediately (Lag 1) but turn positive at Lags 2 and 4, suggesting delayed market adjustment. GDP growth remains insignificant.

Of the dummy controls, only dummy2 is significant, indicating event-driven effects on Bitcoin. Overall, returns are shaped by persistence, equity spillovers, oil and inflation shocks, monetary policy and specific global events. Diagnostic checks confirm model validity with no residual autocorrelation.

The absence of serial correlation in VAR residuals (LM test, [Table 7](#)) validates the reliability of the estimated coefficients.

5.5 Vector autoregression model for Bitcoin with Tadawul All Share Index, US macroeconomic variables, oil prices and dummy controls

[Table 8](#) mirrors the extension in [Table 3](#), but with TASI included instead of the S&P 500. This progression highlights whether the Saudi equity–Bitcoin relationship is sensitive to structural breaks and extraordinary market conditions.

Bitcoin returns are strongly autoregressive, with persistence at Lags 1 and 4 and mean reversion at Lag 2. TASI shows no immediate effect but has a positive impact at Lag 3 and a marginally negative one at Lag 4, indicating delayed and unstable spillovers compared to the S&P 500. Inflation reduces returns at Lag 1, while oil prices raise them at Lag 1, confirming Bitcoin's short-run sensitivity to macro and energy shocks. The federal funds rate depresses returns at Lag 1 but turns positive at Lags 2 and 4, reflecting delayed adjustment. GDP growth remains insignificant.

Among dummy controls, only dummy2 is significant, showing event-driven effects on Bitcoin. LM tests confirm no residual autocorrelation. Overall, Bitcoin is shaped by persistence, US monetary and inflation shocks, oil prices and lagged TASI effects. Compared with the S&P 500, Bitcoin reacts more strongly and quickly to US markets, with weaker and slower responses to Saudi equities.

Table 7. VAR Model 3 BTC with S&P 500 and dummy controls

Variable	Lag	Coefficient	SE	p-value
BTC	L1	1.1387	0.0714	0.0000
BTC	L2	-0.2692	0.1096	0.0140
BTC	L3	-0.1407	0.1105	0.2030
BTC	L4	0.3311	0.0756	0.0000
SP500	L1	-24,734.9500	9,148.8580	0.0070
SP500	L2	12,042.0400	9,247.1000	0.1930
SP500	L3	23,406.7900	9,506.2360	0.0140
SP500	L4	14,493.4100	8,861.8460	0.1020
DCPI	L1	-450,321.1000	178,012.2000	0.0110
DCPI	L2	-68,921.1400	178,902.7000	0.7000
DCPI	L3	-187,899.2000	181,088.0000	0.2990
DCPI	L4	-175,829.2000	161,460.9000	0.2760
DOIL	L1	14,202.7500	4,275.4130	0.0010
DOIL	L2	351.9855	4,807.0090	0.9420
DOIL	L3	1,276.4410	4,953.8780	0.7970
DOIL	L4	1,881.6020	4,672.1070	0.6870
DFED	L1	-10,912.2500	3,292.9210	0.0010
DFED	L2	7,567.5800	3,811.1660	0.0470
DFED	L3	-3,005.3120	3,906.6400	0.4420
DFED	L4	7,513.5170	3,838.9670	0.0500
DGDP	L1	18,637.2500	89,521.5100	0.8350
DGDP	L2	68,706.6500	111,983.7000	0.5400
DGDP	L3	-75,807.6500	96,400.0100	0.4320
DGDP	L4	42,306.1100	82,910.0600	0.6100
DUMMY1		1,382.0290	2,572.2440	0.5910
DUMMY2		17,442.7300	4,045.9370	0.0000
DUMMY3		631.1169	651.1695	0.3320
_cons		744.4701	789.6272	0.3460
Model characteristics				
Equation	RMSE	R-squared	Chi2	p-value
BTC	4,086.6300	0.9782	7,824.6450	0.0000
Lag		χ^2 statistic		p-value
1		44.0100		0.1690
2		34.2500		0.5520
Source(s): Author's own work				

5.5.1 Comparison between the SP500 and Tadawul All Share Index models with dummy controls. Both models confirm Bitcoin's strong autoregressive persistence, amplified when dummy controls are included. Equity spillovers differ: the S&P 500 drives immediate responses, reflecting close integration with US markets, while TASI effects appear only at Lag 3 and reverse at Lag 4, indicating delayed and unstable linkages. Macroeconomic influences are consistent across models: oil shocks boost returns in the short run, while inflation and monetary policy reduce them immediately, with delayed monetary adjustments turning positive. Dummy controls refine results by absorbing extraordinary events, which slightly moderate S&P 500 effects and highlight delayed TASI spillovers. GDP growth remains insignificant. Overall, Bitcoin is more sensitive to US market shocks, while Saudi equities exert weaker, lagged influences.

Table 8. VAR Model 4 BTC with TASI and dummy controls

Variable	Lag	Coefficient	SE	p-value
BTC	L1	1.0824	0.0699	0.0000
BTC	L2	-0.2210	0.1035	0.0330
BTC	L3	-0.1082	0.1030	0.2940
BTC	L4	0.3049	0.0726	0.0000
TASI	L1	-3,320.8470	6,789.4750	0.6250
TASI	L2	-3,419.2230	9,536.0160	0.7200
TASI	L3	20,275.3300	9,700.5270	0.0370
TASI	L4	-13,190.6900	7,114.1080	0.0640
DCPI	L1	-478,037.4000	181,695.8000	0.0090
DCPI	L2	-217,169.1000	185,919.5000	0.2430
DCPI	L3	-150,166.2000	192,962.1000	0.4360
DCPI	L4	-143,607.4000	163,288.6000	0.3790
DOIL	L1	11,918.5300	4,626.3060	0.0100
DOIL	L2	6,746.3320	5,052.6070	0.1820
DOIL	L3	2,773.2970	5,157.6670	0.5910
DOIL	L4	2,838.0500	4,495.6210	0.5280
DFED	L1	-11,437.4100	3,422.8130	0.0010
DFED	L2	7,766.1560	3,999.7390	0.0520
DFED	L3	-3,853.6630	4,140.7430	0.3520
DFED	L4	7,260.3280	4,052.6170	0.0730
DGDP	L1	9,319.6620	93,457.8500	0.9210
DGDP	L2	56,709.1400	116,220.9000	0.6260
DGDP	L3	-25,631.6800	99,551.3800	0.7970
DGDP	L4	46,621.1800	87,238.2900	0.5930
DUMMY1		173.2574	2,687.0540	0.9490
DUMMY2		19,399.5500	4,175.2980	0.0000
DUMMY3		269.2404	675.9703	0.6900
_cons		-1,686.1230	22,533.7400	0.9400
Model characteristics				
Equation	RMSE	R^2	Chi2	p-value
BTC	4,257.4500	0.9764	7,195.6710	0.0000
VAR residual serial correlation				
Lag	χ^2 statistic		p-value	
1	54.6400		0.0240	
2	38.7100		0.3484	

Source(s): Author's own work

5.5.2 Comparison of vector autoregression results with and without event dummies. Adding event dummies (halving, ETF announcements, FOMC decisions) improves model fit by lowering information criteria and reducing residual variance. Core relationships with equities, US macro variables and oil remain stable, confirming robust dynamics. Event dummies capture exogenous shocks: halvings produce lasting effects, ETF news generates short-term spikes tied to institutional adoption and FOMC decisions spill into Bitcoin and equities. Augmented models thus disentangle structural events from underlying market interactions, providing clearer insights into Bitcoin dynamics.

5.6 Wald test

The Wald tests were conducted to examine the joint significance of event dummies in the VAR models. Specifically, the tests assess whether the three dummy variables, Bitcoin halving events, Bitcoin ETF announcements and FOMC announcements, jointly have a statistically significant impact on Bitcoin returns (BTC) and across all equations in the system (Table 9).

Results show that the dummies are highly significant in the Bitcoin equation in both models, rejecting the null that their coefficients are zero. They are also jointly significant across all equations, indicating that event shocks influence not only Bitcoin but also other macroeconomic and financial variables. These findings confirm that structural events meaningfully explain deviations in Bitcoin returns and broader market dynamics, justifying their inclusion in the VAR framework to capture exogenous shocks alongside endogenous interactions.

5.7 Johansen cointegration test

The Johansen cointegration test was applied to examine the existence of long-run equilibrium relationships among Bitcoin, equity indices and key macroeconomic variables (Table 10).

The trace statistic indicates that both models exhibit long-run equilibrium relationships. In the first model, up to four cointegrating vectors exist, while the second model suggests two to three, confirming significant long-term linkages among Bitcoin, macroeconomic

Table 9. Wald test results

Test	χ^2	<i>p</i> -value
<i>Model BTC with S&P 500</i>		
Joint significance of dummies in BTC equation	21.6100	0.0001
Joint significance of dummies in all equations	61.3200	0.0000
<i>Model BTC with TASI</i>		
Joint significance of dummies in BTC equation	18.9600	0.0003
Joint significance of dummies in all equations	55.2200	0.0000

Source(s): Author’s own work

Table 10. Johansen cointegration test results

Null hypothesis (<i>r</i> = rank)	Eigenvalue	Trace statistic	5% critical value
<i>Model BTC with S&P 500</i>			
<i>r</i> = 0 (no cointegration)	–	206.6300	94.1500
<i>r</i> ≤ 1	0.3389	134.6200	68.5200
<i>r</i> ≤ 2	0.2751	78.6400	47.2100
<i>r</i> ≤ 3	0.2116	37.2800	29.6800
<i>r</i> ≤ 4	0.1304	12.9700	15.4100
<i>r</i> ≤ 5	0.0558	2.9900	3.7600
<i>Model BTC with TASI</i>			
<i>r</i> = 0 (no cointegration)	–	163.1700	94.1500
<i>r</i> ≤ 1	0.3298	93.5200	68.5200
<i>r</i> ≤ 2	0.2452	44.5800	47.2100
<i>r</i> ≤ 3	0.1290	20.5600	29.6800
<i>r</i> ≤ 4	0.0681	8.2900	15.4100
<i>r</i> ≤ 5	0.0303	2.9400	3.7600

Source(s): Author’s own work

indicators and equity markets. These results support the use of a VECM or cointegration-augmented VAR framework to capture both short- and long-term dynamics.

5.8 Vector error-correction model for Bitcoin with S&P 500, US macroeconomic variables and oil prices

Table 11 shifts the analysis from short-run dynamics to long-run equilibrium by using a VECM with the S&P 500, US macroeconomic indicators and oil prices. This model captures both adjustment processes and cointegration effects in Bitcoin's relationship with global markets.

5.8.1 Long-run dynamics. The error-correction term ($_ce1$) is negative and highly significant, indicating strong mean reversion in Bitcoin returns toward long-run equilibrium. The coefficient magnitude suggests over-adjustment of about 108%, highlighting Bitcoin's sensitivity to macro-financial conditions. Within the cointegration relationship, the federal funds rate shows a positive long-run effect, implying higher Bitcoin returns under tighter US monetary policy, while GDP growth has a significant negative effect, consistent with reduced demand for Bitcoin when conventional assets are attractive.

5.8.2 Short-run dynamics. Lagged changes in the S&P 500 significantly depress Bitcoin returns, confirming delayed spillovers from US equities. Short-run monetary policy also matters: the first lag of D_dfed shows that rate hikes reduce Bitcoin returns, consistent with tighter liquidity conditions. Inflation (marginally negative), oil prices (positive but insignificant) and GDP growth remain weak predictors in the short run.

5.8.3 Overall findings. The VECM highlights Bitcoin's dual behavior, short-run responses to financial market and policy shocks and long-run integration with US macro-financial variables. The significant error-correction term confirms that Bitcoin systematically reverts to equilibrium, driven mainly by US monetary policy and economic growth.

5.9 Vector error-correction model for Bitcoin with Tadawul All Share Index, US macroeconomic variables and oil prices

Table 12 extends the VECM analysis by replacing the S&P 500 with the TASI, assessing whether Saudi equity and oil markets contribute to Bitcoin's long-run equilibrium.

5.9.1 Long-run dynamics. The error-correction term ($_ce1$) is negative and highly significant, confirming that Bitcoin systematically reverts to long-run equilibrium when deviations occur. Within the cointegration relationship, oil prices exert a strong and positive long-run effect on Bitcoin, highlighting Bitcoin's sensitivity to global energy markets. Other variables, including CPI, the federal funds rate, GDP growth and TASI, are not statistically significant in the cointegration equation, suggesting that their influence is mainly transmitted through short-run adjustments rather than persistent equilibrium linkages.

5.9.2 Short-run dynamics. Bitcoin returns exhibit significant short-term momentum, as indicated by the positive effect of their first lag. The federal funds rate exerts a strong negative effect in the short run ($DL1_dfed$), consistent with tighter US monetary policy dampening risk appetite. By contrast, TASI, inflation, oil prices and GDP growth show no significant short-run effects on Bitcoin, underscoring the dominant role of global financial conditions over domestic market factors.

For TASI, short-run sensitivity is again evident to global drivers, particularly US monetary policy, which significantly reduces Saudi equity returns. Inflation and oil price dynamics show persistence within their own equations, reflecting strong regional macro-financial interdependencies, but their direct influence on Bitcoin is limited.

5.9.3 Overall findings. The VECM with TASI confirms both short-run and long-run interactions between Bitcoin, Saudi equities and global variables. Long-run equilibrium is

Table 11. VECM BTC with S&P 500

Variable	Lag	Coefficient	SE	p-value
_ce1	L1	-1.0825	0.1687	0.0000
_ce2	L1	24,701.4000	26,845.5400	0.3580
_ce3	L1	121,335.0000	104,910.1000	0.2470
_ce4	L1	-1,882.7870	10,360.6100	0.8560
BTC	LD	0.2675	0.1367	0.0500
BTC	L2D	0.1789	0.1126	0.1120
BTC	L3D	-0.0633	0.0853	0.4580
SP500	LD	-52,834.3600	21,979.6500	0.0160
SP500	L2D	-38,254.1900	16,894.0200	0.0240
SP500	L3D	-15,058.6100	11,077.1000	0.1740
DCPI	LD	-347,101.0000	194,573.3000	0.0740
DCPI	L2D	-208,946.2000	181,587.6000	0.2500
DCPI	L3D	-140,320.2000	174,170.7000	0.4200
DOIL	LD	14,012.6000	8,905.4120	0.1160
DOIL	L2D	7,459.4460	7,542.3740	0.3230
DOIL	L3D	3,114.7730	5,277.8750	0.5550
DFED	LD	-8,287.5620	3,728.9240	0.0260
DFED	L2D	-3,640.5890	3,885.1240	0.3490
DFED	L3D	-7,325.7990	4,388.0620	0.0950
DGDP	LD	-76,585.7400	118,933.0000	0.5200
DGDP	L2D	93,747.3900	113,888.5000	0.4100
DGDP	L3D	21,608.3600	95,033.9100	0.8200
_cons		0.0000	334.1818	1.0000
Cointegrating equations				
Equation	Variable	Coefficient	SE	p-value
_ce1	BTC	1.0000	.	.
_ce1	SP500	0.0000	.	.
_ce1	DCPI	0.0000	.	.
_ce1	DOIL	0.0000	.	.
_ce1	DFED	6,771.0760	2,666.5490	0.0110
_ce1	DGDP	-240,873.7000	92,258.7500	0.0090
_ce1	_cons	177.3251	.	.
Wald test results for cointegration equation				
Equation	Chi2	p-value		
_ce1	9.683	0.0079		
Model characteristics				
Equation	RMSE	R ²	Chi2	p-value
D_BTC	4,388.42	0.5516	184.5572	0.0000

Source(s): Author's own work

anchored by oil prices, reinforcing the importance of global energy dynamics for Bitcoin. Short-run adjustments, however, are dominated by US monetary policy and Bitcoin's own momentum. TASI influences remain weaker and indirect, suggesting that while Saudi markets transmit some spillovers, they play a secondary role compared to global macro-financial conditions.

5.9.4 Comparison of vector error-correction model results: Tadawul All Share Index vs SP500. Comparing the VECM models with TASI and the S&P 500 reveals distinct patterns in Bitcoin's responses to domestic versus international equity markets. In the S&P 500

Table 12. VECM BTC with TASI

Variable	Lag	Coefficient	SE	P-value
_ce1	L1	−1.1982	0.1708	0.0000
_ce2	L1	4,378.7710	914.6298	0.0000
BTC	LD	0.2797	0.1381	0.0430
BTC	L2D	0.1688	0.1107	0.1270
BTC	L3D	−0.0748	0.0814	0.3580
TASI	LD	−6,772.4620	7,840.0160	0.3880
TASI	L2D	−9,463.7550	8,001.3290	0.2370
TASI	L3D	10,567.5400	7,909.1640	0.1820
DCPI	LD	56,578.7200	206,991.3000	0.7850
DCPI	L2D	−70,398.2300	190,400.7000	0.7120
DCPI	L3D	−117,034.8000	171,692.6000	0.4950
DOIL	LD	−8,101.8210	10,342.4700	0.4330
DOIL	L2D	−3,460.4090	7,954.1770	0.6640
DOIL	L3D	−1,988.6800	4,941.9750	0.6870
DFED	LD	−8,402.2830	3,664.1480	0.0220
DFED	L2D	−1,909.4420	3,985.8230	0.6320
DFED	L3D	−6,934.6300	4,471.7310	0.1210
DGDP	LD	−77,064.7500	92,909.9200	0.4070
DGDP	L2D	50,543.2500	97,385.9400	0.6040
DGDP	L3D	14,768.9500	86,502.5900	0.8640
_cons		0.0000	369.1645	1.0000
Cointegrating equations				
Equation	Variable	Coefficient	SE	p-value
_ce1	BTC	1.0000	.	.
_ce1	TASI	0.0000	.	.
_ce1	DCPI	−304,673.6000	283,176.6000	0.2820
_ce1	DOIL	46,460.8300	12,659.0100	0.0000
_ce1	DFED	3,534.4430	3,465.6520	0.3080
_ce1	DGDP	−141,588.9000	137,548.0000	0.3030
_ce1	_cons	0.0000	.	.
Wald test results for cointegration equation				
Equation	Chi2	p-value		
_ce1	14.645	0.0055		
Model characteristics				
Equation	RMSE	R ²	Chi2	p-value
D BTC	4,466.73	0.5293	170.9575	0.0000

Source(s): Author's own work

model, Bitcoin's short-run dynamics are strongly affected by US stock market fluctuations, with significant negative coefficients at the first and second lags, reflecting rapid reactions to global financial shocks and investor sentiment.

By contrast, the TASI-based model shows weaker short-run effects, as most TASI lagged coefficients are insignificant. This suggests that domestic stock returns have limited immediate impact on Bitcoin compared to US equity movements, likely due to differences in market size, liquidity and global integration.

Long-run dynamics further differentiate the two models. In the S&P 500 model, US equity movements play a significant role in maintaining equilibrium with Bitcoin and macroeconomic variables. In the TASI model, oil prices emerge as the primary long-run driver, while TASI itself is excluded from the main cointegration equation, indicating that commodity prices and macro-financial factors outweigh local equity indices in shaping Bitcoin’s long-term behavior.

Overall, Bitcoin is more sensitive to international equity shocks in the short run, whereas domestic factors – particularly oil prices – dominate long-run equilibrium. This highlights the importance of the geographic source of financial shocks when modeling cryptocurrency interactions with traditional markets and underscores Bitcoin’s dual global and regional connectivity.

5.10 Impulse response functions and variance decompositions

IRFs and FEVDs were computed over a ten-step horizon. The IRFs trace the dynamic response of Bitcoin to one-standard-deviation shocks in oil prices, consumer price inflation (CPI), the Federal Funds Rate (FED), the S&P 500 index and GDP, while the FEVD quantifies the relative contribution of each shock to Bitcoin’s forecast variance.

Figure 4 shows that Bitcoin reacts positively but only briefly to oil price shocks, while monetary tightening and inflation shocks exert sustained negative effects. The responses to stock market and output shocks are moderate, suggesting partial but non-trivial financial linkages. Overall, the IRFs confirm the presence of short-term spillovers from global macroeconomic and financial shocks to cryptocurrency dynamics.

Table 13 reports the FEVD for Bitcoin returns over a ten-step horizon.

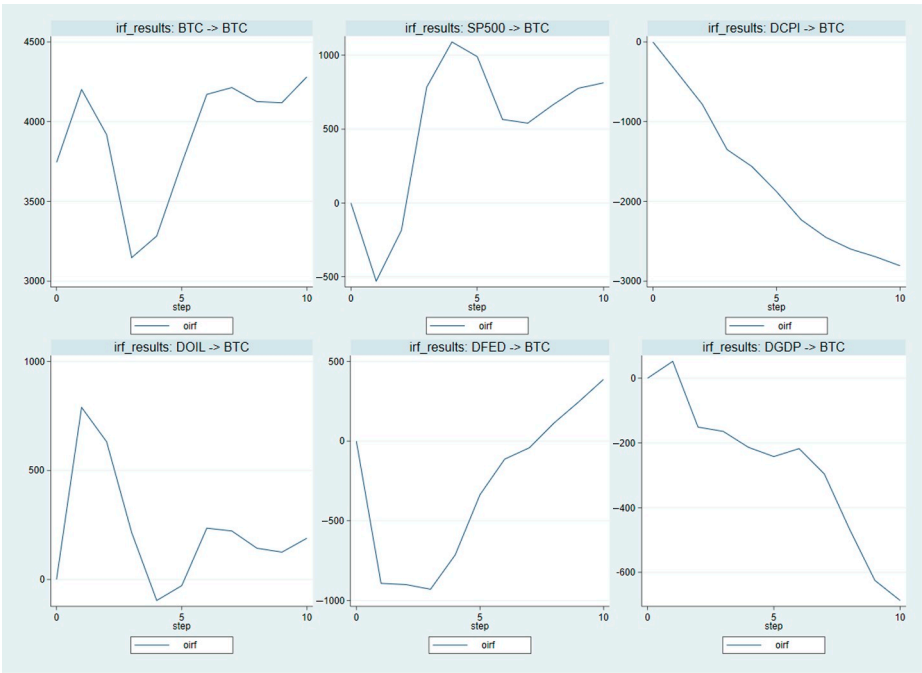


Figure 4. Impulse response functions (IRFs) of Bitcoin (BTC)

Source: Author’s own work

In the short term (Steps 1–3), Bitcoin’s own shocks dominate, explaining over 90% of its forecast variance, which indicates strong internal persistence in cryptocurrency markets. As the horizon extends, the share of Bitcoin’s own innovations gradually decreases from 94% (Step 2) to about 77.6% at Step 10, while the explanatory power of external shocks increases. Inflation (DCPI) emerges as the most influential macroeconomic factor, explaining roughly 17% of Bitcoin’s variance by Step 10. Smaller but non-trivial contributions arise from the S&P 500 ($\approx 2.5\%$), monetary policy shocks (DFED, $\approx 1.6\%$) and oil prices ($\approx 0.6\%$). GDP shocks remain negligible ($<0.5\%$).

Overall, these results suggest that while Bitcoin’s fluctuations are still largely self-driven, macroeconomic and financial conditions increasingly shape its medium-term volatility, with inflation and monetary policy dynamics playing particularly important roles.

6. Discussion

6.1 Discussion of vector autoregression results for SP500 and Tadawul All Share Index models

The VAR results provide insights into the determinants of Bitcoin returns and their interactions with equity markets, oil prices and US macro-financial conditions. Bitcoin exhibits strong autoregressive behavior, with L1 and L4 lags consistently significant, confirming short-term momentum and medium-term persistence (Tzeng and Su, 2024; Alokley *et al.*, 2024).

Equity market impact: Bitcoin responds almost immediately to S&P 500 shocks, with negative effects at Lag 1 followed by positive spillovers, reflecting partial hedging or risk-adjusted substitution for US equities (Katsiampa, 2019). By contrast, responses to TASI are delayed, emerging at Lag 3 and reversing at Lag 4, suggesting weaker and slower spillovers due to lower liquidity, smaller market size and limited integration (Alokley *et al.*, 2024).

Oil price sensitivity: Oil prices consistently produce positive first-lag effects on Bitcoin, highlighting sensitivity to commodity markets (Nzokem and Mounir, 2024). Later lags are generally insignificant, indicating immediate but not persistent responses.

US macro-financial conditions: Inflation negatively affects Bitcoin at Lag 1, consistent with reduced risk appetite (Bouri *et al.*, 2017). Changes in the federal funds rate show a short-run negative effect (Lag 1) and delayed positive adjustments, suggesting initial tightening dampens speculation, but investors reposition over time (Mahmoudi, 2023). GDP growth is largely insignificant, reflecting Bitcoin’s stronger responsiveness to financial and policy shocks than to real economic activity (Mensi *et al.*, 2023).

Effect of dummy variables: Including dummies for structural breaks or extraordinary events refines model fit. In both S&P 500 and TASI models, first-lag Bitcoin coefficients slightly

Table 13. Forecast error variance decomposition (FEVD) of Bitcoin (BTC)

Step	BTC (own)	SP500	DCPI	DOIL	DFED	DGDP
1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.9447	0.0084	0.0045	0.0186	0.0238	0.0001
3	0.9265	0.0062	0.0150	0.0201	0.0317	0.0005
4	0.8891	0.0145	0.0404	0.0167	0.0386	0.0008
5	0.8571	0.0268	0.0636	0.0136	0.0377	0.0012
6	0.8365	0.0317	0.0875	0.0110	0.0317	0.0016
7	0.8225	0.0284	0.1122	0.0094	0.0258	0.0017
8	0.8077	0.0256	0.1350	0.0082	0.0215	0.0020
9	0.7915	0.0245	0.1554	0.0071	0.0185	0.0030
10	0.7758	0.0245	0.1725	0.0063	0.0164	0.0046

Source(s): Author’s own work

increase, confirming robust short-run persistence. In the US model, dummies moderate equity and monetary policy effects; in the TASI model, they strengthen delayed spillovers, especially at Lag 3. Dummy2 consistently captures event-driven surges, emphasizing the need to account for extraordinary events to avoid biased estimates (Katsiampa, 2019).

Comparative insights: Baseline versus augmented VAR comparisons show that event dummies improve explanatory power, reduce residual variance and clarify Bitcoin's responses. Halving events induce persistent changes due to supply constraints, ETF announcements trigger short-term surges from institutional adoption and FOMC decisions generate spillovers to Bitcoin and equity markets (Lyócsa *et al.*, 2020).

Implications: Bitcoin reacts quickly to US equity and macro-financial shocks, whereas TASI produces delayed responses. Oil prices consistently influence returns, while inflation and monetary policy dampen short-term dynamics. Investors can exploit delayed responses to emerging markets for diversification, while policymakers should monitor both immediate and lagged cross-market spillovers to safeguard systemic stability. Event-driven shocks also play a decisive role in shaping Bitcoin's return dynamics, underscoring the need to account for structural breaks in forecasting and risk management (Corbet *et al.*, 2020).

In sum, Bitcoin exhibits dual dynamics: rapid reactions to US shocks, lagged responses to TASI, immediate sensitivity to oil prices and dampening from inflation and monetary policy. Dummies improve model accuracy, revealing nuanced short- and medium-term behavior and highlighting Bitcoin's integration into global and regional financial networks.

6.2 Discussion of vector error-correction model results for SP500 and Tadawul All Share Index models

The VECM results confirm long-term cointegration among Bitcoin, equity indices, inflation, oil prices, the federal funds rate and GDP. In the S&P 500 model, the first cointegration equation shows a highly significant error-correction term, indicating that deviations from long-run equilibrium are efficiently corrected over time, consistent with cointegration theory (Johansen, 1991).

By contrast, the TASI model displays slower adjustment. While the error-correction term remains significant, lagged differences of TASI are mostly insignificant, reflecting the slower responsiveness of an emerging market with lower liquidity and limited integration into global financial systems (Enders, 2010).

Short-run dynamics differ across markets. In the S&P 500 model, oil price changes positively affect Bitcoin adjustments, whereas the federal funds rate has a negative impact. In the TASI model, oil prices significantly influence GDP growth and inflation in the short run, highlighting emerging markets' heightened sensitivity to commodity and price shocks (Hamilton, 2003).

Overall, the VECM results indicate that while both US and Saudi equity markets are anchored in long-term macroeconomic equilibrium, the US market adjusts faster and exhibits stronger short-run responses. TASI, by contrast, shows slower adaptation and more gradual short-term responses, emphasizing the role of market structure and development in shaping financial and macroeconomic interactions across regions.

7. Conclusion

This study examined the dynamic linkages between Bitcoin returns, oil prices, equity markets and macro-financial indicators from both the USA and Saudi Arabia using VAR and VECM methodologies. The empirical findings reveal that Bitcoin is sensitive to macro-financial developments in both economies, particularly to US equity performance and monetary policy shocks. Oil prices also play a persistent role, linking the cryptocurrency market to global commodity cycles.

The results indicate that Bitcoin returns exhibit strong persistence in its returns, with significant autoregressive effects in both the VAR and VECM models. This underscores the importance of past Bitcoin performance in predicting short-term price movements. In the VAR models, Bitcoin returns respond immediately to shocks from the US equity market (SP500), oil prices and US monetary policy, whereas its response to the Saudi equity market (TASI) is delayed, emerging significantly only after several periods. These findings highlight the asymmetric effects of developed versus emerging markets on cryptocurrency dynamics and the critical role of geographic source in shaping financial spillovers.

The VECM results further reveal long-term cointegration relationships between Bitcoin, macroeconomic variables and equity indices. In the SP500 model, deviations from equilibrium are corrected efficiently, reflecting a strong adjustment mechanism typical of developed financial markets. By contrast, the TASI model demonstrates slower adaptation, with the domestic index exhibiting weaker short-run responses, consistent with emerging market characteristics. Notably, oil prices emerge as a key long-run determinant for Bitcoin in the TASI model, while US macro-financial variables, particularly the federal funds rate and equity shocks, dominate in the SP500 model. These findings underscore the importance of global macro-financial conditions in driving cryptocurrency behavior while also recognizing regional market influences.

The inclusion of dummy variables in both VAR and VECM specifications improves model accuracy by controlling for structural breaks and extraordinary events. This allows a clearer separation of normal market dynamics from event-driven shocks, providing a more reliable assessment of Bitcoin's short-run and long-run responses to financial and macroeconomic factors. The superiority of the VAR with dummies provides strong evidence for the role of event-driven shocks in shaping Bitcoin dynamics, underscoring the need to incorporate structural breaks into empirical cryptocurrency research.

From an investor perspective, the results suggest that Bitcoin exhibits dual characteristics: it reacts promptly to US market shocks and global commodity prices while responding more gradually to emerging market developments such as TASI. This behavior offers both opportunities and challenges for portfolio diversification and hedging strategies. Policymakers and regulators should also recognize the cross-border transmission of shocks to cryptocurrencies, which may affect market stability and financial risk management.

In conclusion, this study demonstrates that Bitcoin's dynamics are shaped by a combination of its own historical performance, global and regional equity markets, US macro-financial conditions and oil price fluctuations. The findings emphasize the importance of modeling both short-term shocks and long-run equilibrium relationships to fully capture Bitcoin's behavior. Future research could extend this analysis to other emerging markets or include additional macro-financial variables, such as exchange rates or interest rate spreads, to further understand the complex interactions between cryptocurrencies and traditional financial systems.

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Author's contributions

Ihsen Abid was responsible for the conceptualization, methodology, data collection, analysis, writing of the original draft, review, editing and overall supervision of the work.

Ethics statement

This study did not involve human participants, animals or sensitive data requiring ethical approval or informed consent.

Data availability

Data can be made available upon request to the corresponding author.

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Table A1. Comparative summary of key studies (2021–2025)

Author(s) and year	Markets/sample	Method	Main findings	Methodological limitations	Relevance to current study
Aliu et al. (2021a)	Visegrad equities + major cryptos (2017–2020)	Portfolio experiments/mean–variance tests	Crypto improves risk–return trade-offs	Static allocation; ignores tail risk and crisis behavior	Supports <i>H1</i> (global effects); motivates dynamic, state-dependent modeling
Aliu et al. (2021b)	Crypto-Index 20 vs EU indices (2015–2020)	Comparative diversification analysis	Moderate diversification benefits	Survivorship bias; linear risk metrics; no event controls	Reinforces <i>H1</i> ; justifies dummy-augmented VAR
Nuhuu et al. (2023)	Major cryptos (2018–2022)	Portfolio diversification and volatility analysis	Diversification gains shrink as volatility rises	Constant-parameter assumption; limited macro controls	Informs <i>H1–H3</i> (state dependence); supports dynamic modeling
Aliu (2025)	Top-15 cryptos (COVID-19 and Russia–Ukraine war)	Spillover/connectedness framework	Connectedness strengthens during crises	Identification sensitivity: window length affects robustness	Demonstrates need for structural dummies (<i>H3</i>)
Mahmoudi (2023)	BTC and US monetary-policy uncertainty (2010–2023)	Markov-Switching VAR	Policy uncertainty depresses BTC returns in both regimes	Regime count subjective; low-frequency data; within-regime linearity	Corroborates <i>H2–H3</i> ; motivates event-dummy design
Ullah (2024)	Russian financial market (2018–2023)	Dynamic connectedness/spillover index	Crypto–conventional linkages strengthen post-crisis	Short sample; limited asset coverage	Confirms cross-market contagion (<i>H1</i>)
Mensi et al. (2023)	Global crypto, gold, oil and stock markets (2016–2022)	Tail-risk spillover (TVAR)/quantile connectedness	Bidirectional tail spillovers between crypto and commodities	Tail dependence sensitive to quantile choice	Highlights asymmetric spillovers (<i>H3</i>)
Kayani and Hasan (2024)	US and Asian markets (2017–2023)	Wavelet-based coherence analysis	Bitcoin acts as short-term hedge for US; not for Asia	Non-causal method; ignores macro controls	Provides frequency-domain support for <i>H1–H2</i>
Nzokem and Mounir (2024)	BTC vs S&P 500 (2015–2023)	GARCH-type return–risk model	BTC offers higher returns with greater volatility	Risk not adjusted for tail events	Illustrates risk–return asymmetry (<i>H1</i>)

(continued)

Table A1. Continued

Author(s) and year	Markets/sample	Method	Main findings	Methodological limitations	Relevance to current study
Haider Ali <i>et al.</i> (2025)	TASI and G7 markets (2014–2023)	ARDL cointegration and causality	Increasing Saudi–global integration via oil channel	Limited crypto inclusion; single commodity driver	Motivates inclusion of TASI in VAR–VECM (<i>H1–H3</i>)
Benigno and Rosa (2023)	Major cryptos and macro news (2016–2022)	Event-study analysis	Crypto reacts more to sentiment than fundamentals	Short event windows; omitted volatility	Supports behavioral channels; linked to <i>H2</i>
Tzeng and Su (2024)	US macro variables and crypto (2017–2023)	VAR forecasting model	Inflation and interest rates predict crypto volatility	Linear specification; no structural breaks	Motivates dummy-augmented VAR (<i>H2</i>)
Sensoy (2019)	Bitcoin and altcoins (2015–2018)	High-frequency efficiency tests	Market inefficiency varies with liquidity conditions	Limited to short period; pre-DeFi era	Early evidence for state-dependence (<i>H3</i>)
Lyócsa <i>et al.</i> (2020)	BTC market (2013–2019)	EGARCH on news and hacking events	News and regulation significantly affect BTC volatility	No macro-integration context	Historical foundation for event dummies (<i>H3</i>)

About the author

Dr Ihsen Abid holds a PhD in Management Sciences with a specialization in Finance. She is an academic researcher and lecturer whose work focuses on finance, banking, financial management, and economic development. Her research examines financial sector dynamics, banking systems, and applied financial analysis, with particular attention to corporate finance and the role of financial institutions in supporting sustainable economic growth. Dr Abid has published in peer-reviewed journals, and her research is characterized by a strong policy-oriented and development-focused perspective. Ihsen Abid can be contacted at: isbaklouti@imamu.edu.sa