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When Bitcoin moves, who follows? State-dependent predictability across gold and green assets

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Abstract: This study examines whether Bitcoin contains economically meaningful predictive information for gold, green bonds, and renewable-energy assets and whether such relationships vary across market conditions. Using daily data from February 2018 to February 2023, we combine multi-horizon predictive regressions, volatility-state analysis, out-of-sample forecasting, local projections, forecast-error variance decomposition, and explainable machine learning. Bitcoin returns show no significant unconditional predictive power across the 1-, 5-, and 22-day horizons. State-dependent effects emerge selectively, with the strongest evidence for bio-clean fuel under high market uncertainty, but do not generalize across assets or horizons. Out-of-sample forecasting gains are modest and rarely statistically significant. Bitcoin shocks generate limited persistent responses and explain less than 1% of forecast-error variance across all assets. SHAP evidence further shows that Bitcoin features contribute relatively little to nonlinear forecasts. The findings characterize Bitcoin–green asset linkages as selectively state-dependent rather than persistently predictive.

Keywords: bitcoin; green assets; state-dependent predictability; machine learning; forecasting

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1. Introduction

Bitcoin's growing presence in investment portfolios has expanded the question of cryptocurrency risk beyond the digital-asset market itself. Of particular interest is whether Bitcoin movements carry information for assets that serve very different economic functions. Gold remains one of the most established defensive assets, while green bonds and renewable-energy equities have become increasingly important components of sustainable investment portfolios. Bitcoin sits differently within this landscape as it is highly volatile, digitally traded, sensitive to investor sentiment, and economically distinct from both traditional safe-haven assets and securities linked to the low-carbon transition (Baur & Dimpfl, 2021; Hairudin & Mohamad, 2024). Understanding whether information originating in Bitcoin is transmitted to these markets is therefore relevant to portfolio allocation, risk management, and assessing cross-market financial exposure.

The comparison with gold adds an important dimension to this question. Bitcoin has frequently been discussed as a potential alternative to gold because of its scarcity-based design and independence from conventional monetary systems. Empirical evidence, however, provides limited support for treating the two assets as equivalents. Baur et al. (2018) document substantial differences among Bitcoin, gold, and the US dollar in return, volatility, and correlation, while Klein et al. (2018) show that Bitcoin does not exhibit the same stable hedging and safe-haven properties as gold. Smales (2019) similarly questions Bitcoin's ability to function as a haven because of its volatility, liquidity, and market characteristics. These differences suggest that Bitcoin and gold are governed by distinct sources of price formation (Alexander & Heck, 2020; Baur & Dimpfl, 2021). An important question is therefore not simply whether they move together, but whether movements in Bitcoin contain information about subsequent gold returns.

The relationship between Bitcoin and green financial assets raises a different economic question. Green bonds and renewable-energy equities have become increasingly important as capital markets respond to climate-transition objectives and growing investor demand for sustainable assets (Esmaeili et al., 2024; Lucey & Ren, 2023). At the same time, Bitcoin has become connected to the environmental debate because proof-of-work mining requires substantial computational and energy resources. However, environmental relevance does not itself imply financial integration. Green bonds are primarily exposed to fixed-income conditions, credit and duration risk, and sustainability-oriented institutional demand. In contrast, renewable-energy equities depend on sectoral cash flows, financing costs, technological development, energy-market conditions, and climate and energy policies. A different combination of cryptocurrency-specific demand, liquidity, investor attention, and risk sentiment drives Bitcoin. Whether these markets transmit economically useful information to one another must therefore be established empirically rather than inferred from their common presence in debates surrounding technological and environmental change.

Research has increasingly documented linkages among these markets. Yadav et al. (2025) identify time- and frequency-varying relationships among green bonds, renewable energy, and cryptocurrency markets, showing that the strength and direction of transmission depend on the investment horizon. More broadly, studies of Bitcoin and conventional financial assets demonstrate that cryptocurrency dependence can change substantially across market conditions and frequencies (Candelon et al., 2021; Jiang et al., 2021; Maghyereh & Abdoh, 2020; Selmi et al., 2018), establishing that Bitcoin does not operate in complete isolation from other financial markets. It does not, however, answer a different question that is central to investors and forecasters: does information contained in Bitcoin returns improve the prediction of subsequent returns in gold and green assets?

This distinction between connectedness and predictability motivates the study. Correlation measures contemporaneous association, while connectedness and spillover measures identify how shocks or volatility are distributed across a system. Neither necessarily establishes incremental forecasting information. Two markets can become connected because they respond simultaneously to common macroeconomic or risk shocks without movements in one consistently preceding movements in the other. Similarly, statistically significant transmission need not be sufficiently persistent or economically large to improve out-of-sample forecasts. For Bitcoin, this distinction is especially relevant because its extreme volatility can produce visible episodes of cross-market association even when those relationships are unstable (Chan et al., 2022; Hairudin & Mohamad, 2024). Bianchi et al. (2023) show that predictability within cryptocurrency markets itself changes substantially over time, reinforcing the need to evaluate predictive relationships outside the estimation sample rather than infer them from contemporaneous dependence.

Market conditions also explain why average relationships may be incomplete. Bitcoin's interactions with other assets can change when uncertainty rises, investors rebalance portfolios, or cryptocurrency-specific volatility increases. Selmi et al. (2018) show that Bitcoin's hedging and diversification characteristics depend on market states, while Maghyereh and Abdoh (2020) find substantial variation in Bitcoin's dependence on financial assets across return quantiles and investment horizons. A relationship that is weak on average could therefore become more pronounced during periods of elevated uncertainty. Conversely, high volatility could weaken predictability if Bitcoin movements increasingly reflect idiosyncratic cryptocurrency shocks rather than information shared with other markets.

This study addresses this issue through state-dependent predictability. State dependence is defined specifically as variation in Bitcoin's predictive coefficient between low- and high-volatility conditions (Jiang et al., 2021; Lucey & Ren, 2023). We consider two distinct sources of uncertainty. VIX-based states capture changes in broader financial-market uncertainty, while Bitcoin realized-volatility states capture changes originating within the cryptocurrency market itself. This distinction separates general risk conditions from Bitcoin-specific turbulence and allows the analysis to determine whether either environment changes the information transmitted from Bitcoin to gold and green assets. Importantly, state dependence in this study does not refer to positive versus negative Bitcoin shocks or use "asymmetry" as a general description of nonlinear behavior. It refers explicitly to whether predictive relationships differ across observable volatility regimes.

The analysis focuses on gold, green bonds, and four renewable-energy equity segments: solar, wind, bio/clean fuel, and geothermal. These assets provide a useful setting because they differ substantially in economic function and exposure to market fundamentals. The study evaluates Bitcoin predictability at 1-, 5-, and 22-day horizons, distinguishing immediate effects from weekly and approximately monthly predictive relationships. All predictive and dynamic analyses are conducted using stationary daily log returns rather than price levels. This matters especially when comparing assets with strongly trending prices, because apparent level relationships can reflect common trends rather than economically meaningful return transmission.

The empirical design goes beyond identifying whether individual coefficients are statistically significant. Baseline predictive regressions first establish whether lagged Bitcoin returns contain incremental information for subsequent asset returns. State-dependent specifications then test whether this information changes between volatility regimes. Predictive usefulness is evaluated chronologically out of sample against historical-mean and autoregressive benchmarks, directly testing whether in-sample relationships translate into forecast gains. Recent evidence comparing econometric and machine-learning approaches also demonstrates the value of evaluating cryptocurrency predictability through genuine out-of-sample forecasting rather than relying exclusively on in-sample fit (Berger & Koubová, 2024; Saâdaoui, 2024). The study examines dynamic transmission using local projections, while forecast-error variance decomposition measures the quantitative contribution of Bitcoin innovations to uncertainty in each asset. Machine-learning models provide an additional test of nonlinear predictive information, and SHAP attribution determines whether Bitcoin features become important once nonlinearities and interactions are permitted.

The study then makes three contributions. First, it shifts the Bitcoin–green finance literature from evidence of co-movement and connectedness toward incremental return predictability. Existing evidence that cryptocurrency, green bonds, and renewable-energy markets are interconnected is important, but it does not establish that Bitcoin can forecast these markets. By evaluating predictive coefficients, out-of-sample performance, dynamic responses, and forecast-error variance within the same framework, the study establishes whether Bitcoin's statistical relationships with these assets translate into economically meaningful information.

Second, the study provides a precise assessment of state dependence. Rather than treating asymmetry as a broad property of cryptocurrency returns, the analysis directly tests whether Bitcoin's predictive relationship changes under high and low financial-market uncertainty and high and low Bitcoin-specific volatility. The distinction between VIX and Bitcoin-volatility regimes also economically separates external market stress from turbulence originating within the cryptocurrency market. Examining these states at multiple forecast horizons allows the analysis to determine not only whether conditional predictability exists, but whether it is persistent enough to matter beyond the immediate trading horizon.

Third, the study evaluates whether conclusions about Bitcoin's informational role hold up under increasingly demanding empirical tests. The study compares statistical predictability with genuine out-of-sample forecasting performance, complements dynamic responses with variance decomposition, and assesses linear evidence alongside nonlinear machine-learning models and explainable feature attribution. This triangulation is important because a significant coefficient, an impulse response, a forecast improvement, and high machine-learning feature importance represent different forms of evidence. Treating them jointly provides a more rigorous assessment of whether Bitcoin is genuinely informative for other asset markets.

The results show that Bitcoin's predictive role is substantially more limited than its volatility might suggest. Bitcoin returns provide no significant unconditional predictive information for any of the six assets at the 1-, 5-, or 22-day horizons. State dependence appears in selected cases, with the strongest evidence for bio-clean fuel under elevated VIX conditions, but these effects are not widespread across assets or horizons. Out-of-sample improvements are generally modest and rarely statistically significant. Unexpected Bitcoin movements generate predominantly weak and short-lived responses, while Bitcoin innovations explain less than 1% of forecast-error variance in every asset. The nonlinear evidence leads to the same conclusion: Bitcoin-related features account for only a limited share of predictive importance in the selected machine-learning models. The central empirical finding is therefore not complete market independence, but limited average predictive transmission accompanied by selective state dependence.

These findings matter for both investment and financial stability analysis. For investors, the results caution against treating large Bitcoin movements as leading signals for tactical allocation to gold or sustainable assets. Weak predictive transmission can coexist with diversification benefits, making it important to distinguish the two concepts. For policymakers, the evidence suggests that high Bitcoin volatility does not automatically imply economically important transmission to green financial markets. Monitoring remains relevant under stress, but regulatory assessments should distinguish isolated, state-dependent relationships from persistent systemic transmission.

The remainder of the paper is organized as follows. Section 2 presents the data and methodology. Section 3 reports the empirical analysis and results. Section 4 discusses the findings and relates them to the existing literature. Section 5 concludes the study and presents implications for policymakers and future research.

2. Data and Methodology

2.1. Data and return construction

The study uses daily observations for Bitcoin, gold, green bonds, four clean-energy indices, and the CBOE Volatility Index (VIX). The S&P Green Bond Index represents green bonds. In contrast, the clean-energy markets are represented by the NASDAQ OMX Solar Index (GRNSOLAR), NASDAQ OMX Wind Index (GRNWIND), NASDAQ OMX Bio/Clean Fuels Index (GRNBIO), and NASDAQ OMX Geothermal Index (GRNGEO). The sample extends from 2 February 2018 to 20 February 2023 and contains 1,286 synchronized daily price observations.

Because Bitcoin trades seven days per week whereas gold, green bonds, clean-energy indices, and the VIX follow conventional trading calendars, the series are aligned on common trading dates before return construction. The preprocessing procedure checks for missing observations, ensures consistent time-series intervals, and retains matched trading dates across all variables. This alignment avoids introducing artificial observations arising solely from differences in trading calendars.

Price levels are retained only for descriptive visualization. All subsequent econometric, forecasting, and dynamic analyses use continuously compounded daily log returns. For asset i, the daily return is calculated as:

$$r_{i,t} = 100\left[\ln\left(P_{i,t}\right) - \ln\left(P_{i,t-1}\right)\right] \quad (1)$$

Where P_{it} denotes the closing price or index level of the asset i on the trading day t. The transformation produces 1,285 daily return observations.

2.2. Preliminary analysis and stationarity testing

The preliminary analysis reports descriptive statistics and Pearson correlation coefficients to characterize the distributional properties and contemporaneous associations among the return series. The time-series properties of the variables are subsequently examined using the Augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1979) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Kwiatkowski et al., 1992).

The two tests provide complementary evidence because the ADF test evaluates the null hypothesis of a unit root, whereas the KPSS test evaluates the null hypothesis of stationarity. Both tests are applied to log price levels and daily log returns. The ADF specifications include a constant, with lag length selected using the Akaike Information Criterion, while the KPSS bandwidth is selected automatically. We then estimate the empirical models using daily log returns after establishing their stationarity.

2.3. Multi-horizon predictive regressions

The baseline analysis examines whether current Bitcoin returns contain incremental information for subsequent gold and green-asset returns after controlling for market uncertainty and short-run persistence in the dependent asset. For each asset i, the predictive specification is:

$$R_{i,t+h} = \alpha_{i,h} + \beta_{i,h} r_{BTC,t} + \gamma_{i,h} r_{VIX,t} + \delta_{i,h} r_{i,t} + \varepsilon_{i,t+h},\ h \in \{1, 5, 22\} \quad (2)$$

where $R_{i,t+h}$ denotes the forward return of asset *i* over horizon *h*, $r_{BTC,t}$ is the current Bitcoin return, $r_{VIX,t}$ captures changes in aggregate market uncertainty, and $r_{i,t}$ controls for the asset’s own current return.

For horizons exceeding one day, the dependent variable is constructed as the cumulative forward log return:

$$R_{i,t+h} = \sum_{j=1}^{h} r_{i,t+j} \quad (3)$$

The analysis considers 1-, 5-, and 22-trading-day horizons to distinguish immediate predictability from information emerging over approximately one trading week and one trading month. The coefficient of primary interest $\beta_{i,h}$ measures whether current Bitcoin returns contain incremental information about subsequent asset returns after accounting for VIX movements and the asset's own return.

Because cumulative returns at the 5- and 22-day horizons generate overlapping observations, inference is based on heteroskedasticity- and autocorrelation-consistent (HAC) Newey–West standard errors (Newey & West, 1987). The estimated coefficients represent predictive associations rather than causal effects.

2.4. State-dependent predictive regressions

Bitcoin's predictive content may vary with prevailing market conditions even when its unconditional predictive coefficient is weak. We therefore examine state dependence using two alternative measures of uncertainty: the VIX and Bitcoin realized volatility.

For a state indicator D_t the general interaction specification is:

$$R_{i,t+h} = \alpha_{i,h} + \beta_{L,i,h} r_{BTC,t} + \theta_{i,h} D_t + \beta_{\Delta,i,h}\left(r_{BTC,t} \times D_t\right) + \gamma_{i,h} r_{VIX,t} + \delta_{i,h} r_{i,t} + \varepsilon_{i,t+h} \quad (4)$$

7where $\beta_{l,i,h}$ measures Bitcoin predictability in the low-state regime. The corresponding Bitcoin coefficient in the high-state regime is:

$$\beta_{H,i,h} = \beta_{L,i,h} + \beta_{\Delta,i,h} \quad (5)$$

The interaction coefficient $\beta_{\Delta,i,h}$ therefore directly tests whether Bitcoin's predictive relationship differs between the two states.

2.4.1. VIX regimes

The first state classification captures broader financial-market uncertainty using VIX levels. Observations are divided at the sample median of 19.705, with $D\_t = 1\ when\ the\ VIX\ exceeds$ 19.705 $and\ zero\ otherwise$; the low-VIX coefficient in Equation (4) therefore measures Bitcoin predictability when the VIX is at or below the median, while Equation (5) provides the corresponding coefficient during high-VIX periods.

The regime-difference test evaluates:

$$H_0: \beta_{\Delta,i,h} = 0 \quad (6)$$

for each asset and forecast horizon. The models are estimated at the 1-, 5-, and 22-day horizons and include the VIX regime indicator, VIX return, the dependent asset's current return, and a constant.

2.4.2. Bitcoin-volatility regimes

The second classification captures uncertainty originating within the cryptocurrency market itself. Bitcoin realized volatility is calculated over a 22-trading-day window, and observations are classified into high- and low-volatility states relative to the sample median realized volatility of 4.1167. We estimate the same interaction structure in Equation (4) after replacing the VIX-state indicator with the Bitcoin-volatility-state indicator.

The low-volatility coefficient measures Bitcoin predictability during relatively tranquil Bitcoin-market conditions, whereas the sum of the baseline and interaction coefficients measures predictability during high-volatility conditions. The interaction coefficient formally tests whether the relationship changes across Bitcoin-volatility states.

HAC/Newey–West inference is used throughout. The one- and five-day models use five Newey–West lags, while the overlapping 22-day specifications use 21 lags.

2.5. Out-of-sample forecasting framework

An out-of-sample forecasting exercise complements the predictive regressions to determine whether the statistical relationships translate into economically meaningful forecast improvements. Observations are divided chronologically into 80% training and 20% testing samples without random shuffling. Preserving temporal ordering prevents future observations from entering model estimation and therefore avoids look-ahead bias.

Forecasts are generated at the 1-, 5-, and 22-day horizons using six competing approaches: the historical mean, autoregressive AR(1), ordinary least squares (OLS), least absolute shrinkage and selection operator (LASSO; Tibshirani, 1996), Random Forest (Breiman, 2001), and Gradient Boosting (Friedman, 2001). The historical mean provides a parsimonious no-predictability benchmark. At the same time, AR(1) represents a conventional time-series benchmark against which the incremental value of richer linear and nonlinear models can be evaluated. The inclusion of both econometric and machine-learning approaches follows the growing use of comparative forecasting designs for financial and cryptocurrency returns (Basak et al., 2019; Berger & Koubová, 2024).

The forecasting information set contains contemporaneously available and lagged information from Bitcoin, VIX, gold, green bonds, and clean-energy assets, together with rolling return and volatility measures. All predictor transformations are constructed using information available at or before the forecast origin to avoid information leakage.

Forecast accuracy is evaluated using root mean squared error:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2} \quad (7)$$

Moreover, mean absolute error:

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|y_t - \hat{y}_t| \quad (8)$$

where y_t denotes the realized return and $\hat{y}_t$ denotes its corresponding out-of-sample forecast.

Incremental forecast performance relative to the historical-mean benchmark is measured using the out-of-sample coefficient of determination:

$$R_{OOS}^2 = 1 - \frac{\sum_{t=1}^{T}(y_t - \hat{y}_{t,M})^2}{\sum_{t=1}^{T}(y_t - \hat{y}_{t,HM})^2} \tag{9}$$

where $\hat{y}_{t,m}$ denotes the forecast from the competing model M, while $\hat{y}_{t,hm}$ denotes the historical-mean forecast. Positive R^2_{oos} indicates that a model improves upon the historical-mean forecast, whereas a negative value indicates inferior out-of-sample performance.

2.6. Dynamic responses to Bitcoin shocks

The predictive regressions establish whether Bitcoin contains information about subsequent asset returns but do not reveal the temporal response following an unexpected Bitcoin movement. Dynamic transmission is therefore examined using local projections (Jordà, 2005) with HAC inference.

We first identify an unexpected Bitcoin-return shock as the standardized innovation from a Bitcoin return equation conditional on three lags of the complete return system. Let $U_{BTC,t}$ denote this innovation. The standardized shock is:

$$Shock_{BTC,t} = \frac{u_{BTC,t}}{\sigma(u_{BTC})} \tag{10}$$

For each asset i and response horizon h = 0,...,10, the local projection is estimated as:

$$r_{i,t+h} = \alpha_{i,h} + \theta_{i,h} Shock_{BTC,t} + \sum_{j=1}^{3} \Gamma'_{i,h,j} X_{t-j} + \varepsilon_{i,t+h} \tag{11}$$

where X_{t-j} contains lagged returns of the complete system. The sequence $\theta_{i,h}$ traces the response of asset i to a one-standard-deviation unexpected Bitcoin-return innovation.

Each horizon is estimated independently using HAC/Newey–West standard errors (Newey & West, 1987). This approach provides confidence intervals that accommodate heteroskedasticity and serial dependence and avoids imposing the complete set of dynamic restrictions required by conventional VAR impulse-response analysis.

2.7. VAR and forecast-error variance decomposition

The local-projection analysis is complemented by forecast-error variance decomposition (FEVD) to quantify the contribution of Bitcoin innovations to the forecast uncertainty of gold and green assets. The complete stationary return system is represented using a vector autoregressive framework (Sims, 1980).

$$X_t = c + A_1 X_{t-1} + A_2 X_{t-2} + A_3 X_{t-3} + \varepsilon_t \tag{12}$$

where:

$$X_t = [r_{BTC,t}, r_{Gold,t}, r_{GB,t}, r_{Solar,t}, r_{Wind,t}, r_{Bio,t}, r_{Geo,t}, r_{VIX,t}]' \tag{13}$$

Lag-selection criteria provide different recommendations: AIC and FPE select three lags, HQIC selects one lag, and BIC selects zero lags. We retain a VAR(3) specification based on the AIC and FPE criteria, and we verify model stability before variance decomposition.

The generalized forecast-error variance decomposition is used as the principal specification because it is invariant to variable ordering. The generalized contribution of innovation j to the H-step forecast-error variance of variable i is:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} e_i' \Psi_h \Sigma \Psi_h' e_i} \tag{14}$$

where Ψ_h denotes the moving-average coefficient matrix, Σ is the covariance matrix of VAR innovations, and e_i and e_j are selection vectors. Because generalized variance contributions do not necessarily sum to unity, normalized shares are calculated as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \times 100 \tag{15}$$

Bitcoin's contribution is evaluated at the 1-, 5-, 10-, and 22-day horizons. We also estimate an orthogonalized Cholesky FEVD with Bitcoin ordered first as a robustness check.

Although the VAR(3) system satisfies the stability condition, the residual Portmanteau test indicates remaining serial correlation. For this reason, the generalized FEVD serves as supplementary evidence on the relative contribution of Bitcoin innovations, while the HAC local projections constitute the principal dynamic-response analysis.

2.8. Explainable machine learning

Forecast accuracy does not reveal which information nonlinear models rely upon when generating predictions. SHapley Additive exPlanations (SHAP; Lundberg & Lee, 2017) are therefore employed to interpret the selected tree-based forecasting models.

For a prediction f(x), the SHAP representation is:

$$f(x) = \phi_0 + \sum_{j=1}^{M}\phi_j \tag{16}$$

where φ_0 denotes the model's expected prediction and φ_j represents the contribution of predictor *j* relative to that baseline.

Global feature importance is calculated from the mean absolute SHAP value:

$$I_j = \frac{1}{T}\sum_{t=1}^{T} | \phi_{j,t} | \tag{17}$$

Moreover, the corresponding percentage contribution is:

$$S_j = \frac{I_j}{\sum_{k=1}^{M} I_k} \times 100 \tag{18}$$

SHAP values are calculated on the held-out test observations rather than the training sample. We report detailed feature-level rankings for the selected tree-based forecasting models, while the main analysis groups predictors into Bitcoin information, VIX information, own-asset information, and other-asset information. This grouping allows direct assessment of whether Bitcoin is an economically important source of information in nonlinear forecasting models.

SHAP importance measures a predictor's contribution to the fitted model's forecasts. It does not establish causal effects or statistical significance. Explainable machine learning has increasingly been used to identify the information underlying cryptocurrency forecasting models (Saâdaoui, 2024).

3. Analysis and Results

3.1. Descriptive Statistics and Preliminary Analysis

Table 1 reports the descriptive statistics for the daily log returns of Bitcoin, gold, the S&P Green Bond Index, the four clean-energy indices, and the VIX. The results reveal substantial differences in return and risk characteristics across the markets. Bitcoin records a mean daily return of 0.050% and the highest standard deviation among the investable assets at 4.618%, compared with 0.952% for gold and 0.380% for green bonds. Among the clean-energy indices, solar energy exhibits the highest average daily return at 0.081% and a standard deviation of 2.520%, followed by wind (mean = 0.038%; standard deviation = 1.796%), geothermal (mean = 0.019%; standard deviation = 2.150%), and bio-clean fuel (mean = −0.007%; standard deviation = 2.317%). The VIX displays considerably greater variation, with a standard deviation of 8.369%.

The distributional characteristics further indicate substantial departures from normality. Bitcoin is negatively skewed (−1.166) and exhibits pronounced kurtosis of 15.829. Bio-clean fuel is similarly negatively skewed (−1.004), whereas geothermal and the VIX exhibit positive skewness of 0.549 and 1.533, respectively. Kurtosis exceeds the normal-distribution benchmark of three for every series, ranging from 7.481 for wind to 15.829 for Bitcoin. Consistent with these characteristics, the Jarque–Bera statistics reject normality at the 1% level for all return series. These distributional properties indicate substantial tail behavior and episodic volatility in the sample, particularly for Bitcoin and the clean-energy assets.

Table 1. Descriptive Statistics of Daily Log Returns

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque–Bera	Obs.
Bitcoin	0.050	0.087	19.182	-49.728	4.618	-1.166	15.829	10,687.43***	1,285
Gold	0.022	0.028	5.600	-5.122	0.952	-0.226	7.999	1,761.82***	1,285
Green Bond	-0.019	-0.011	2.262	-2.420	0.380	-0.328	9.296	3,025.67***	1,285
Solar Energy	0.081	0.091	12.051	-19.333	2.520	-0.539	8.452	2,353.78***	1,285
Wind	0.038	0.041	9.154	-11.828	1.796	-0.089	7.481	1,353.94***	1,285
Bio Clean Fuel	-0.007	0.018	13.393	-18.196	2.317	-1.004	12.459	6,111.72***	1,285
Geothermal	0.019	0.033	18.254	-13.391	2.150	0.549	12.760	6,522.85***	1,285
VIX	0.015	-0.352	76.825	-26.623	8.369	1.533	11.557	5,802.94***	1,285

Notes. Daily returns are computed as continuously compounded log returns, $100 \times [\ln(P_t) - \ln(P_{t-1})]$. Kurtosis is reported in its conventional (non-excess) form, where a value of three corresponds to the normal distribution. Jarque–Bera statistics test the null hypothesis of normality. *** denotes significance at the 1% level.

Figures 1 and 2 provide complementary evidence on the evolution of prices and returns. The normalized price series in Figure 1 shows marked differences in asset performance over the sample, with Bitcoin displaying particularly large price movements and pronounced reversals. The clean-energy indices also exhibit substantial variation, especially around and after 2020. Figure 2 shows that these movements translate into volatility clustering and occasional extreme daily returns rather than smooth changes in the return series. Bitcoin shows the most pronounced negative return, while sharp VIX movements concentrate around periods of heightened market uncertainty. The figures therefore reinforce the need to distinguish price-level movements from the stationary return dynamics used in the subsequent empirical analysis.

Table 2 reports the Pearson correlations among daily log returns. The most notable feature is the near absence of contemporaneous linear association between Bitcoin and the remaining assets. Bitcoin's correlations are −0.059 with gold, −0.018 with green bonds, 0.015 with solar energy, −0.010 with wind, −0.006 with bio-clean fuel, and 0.012 with geothermal. Its correlation with the VIX is also negligible at −0.004. These coefficients provide little preliminary evidence that Bitcoin systematically moves with either traditional defensive assets or the green-asset markets at the daily frequency.

Fig 1. Normalized Price Evolution of Bitcoin, Gold, Green Assets, and VIX

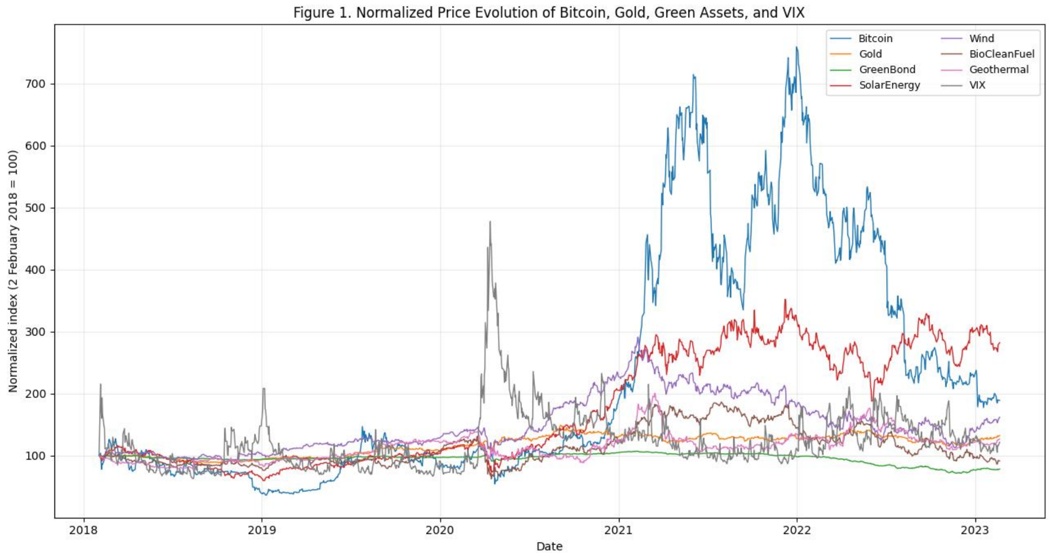
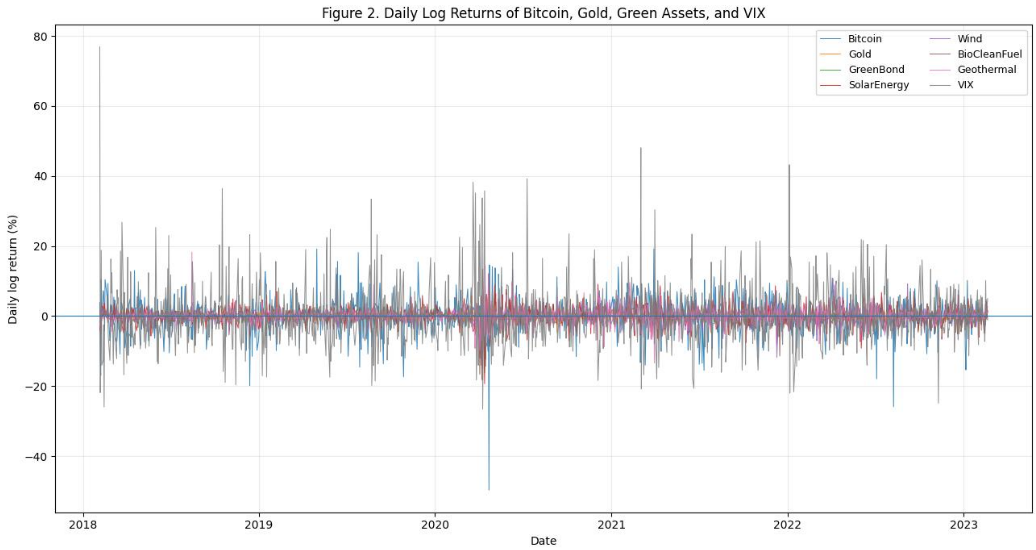


Fig 2. Daily Log Returns of Bitcoin, Gold, Green Assets, and VIX



Stronger relationships are observed within the non-Bitcoin asset set. Gold and green bonds correlate at 0.435. The clean-energy indices are also positively correlated: solar energy has correlations of 0.453 with wind, 0.514 with bio-clean fuel, and 0.395 with geothermal, while wind and bio-clean fuel are correlated at 0.349. These coefficients indicate common variation across renewable-energy equity segments without suggesting that the individual markets are interchangeable. The VIX, in contrast, is negatively correlated with all four clean-energy indices, with coefficients of −0.335 for solar, −0.209 for wind, −0.282 for bio-clean fuel, and −0.182 for geothermal. This pattern initially suggests that clean-energy returns are more closely associated with broader market-risk conditions than with contemporaneous Bitcoin returns.

Before estimating the predictive models, Table 3 examines the series' stationarity using the ADF and KPSS tests. For Bitcoin, gold, green bonds, solar energy, wind, bio-clean fuel, and geothermal, the ADF test fails to reject the unit-root null for log price levels, while the KPSS test rejects level stationarity. The evidence therefore consistently identifies these price series as non-stationary. The VIX level provides mixed evidence: the ADF statistic rejects the unit-root n=(p=0.001), whereas the KPSS statistic rejects stationarity.

Table 2. Pearson Correlation Matrix of Daily Log Returns

Variable	Bitcoin	Gold	Green Bond	Solar Energy	Wind	Bio Clean Fuel	Geothermal	VIX
Bitcoin	1.000	-0.059	-0.018	0.015	-0.010	-0.006	0.012	-0.004
Gold	-0.059	1.000	0.435	0.086	0.078	0.045	0.028	0.003
Green Bond	-0.018	0.435	1.000	0.101	0.159	0.086	-0.007	-0.032
Solar Energy	0.015	0.086	0.101	1.000	0.453	0.514	0.395	-0.335
Wind	-0.010	0.078	0.159	0.453	1.000	0.349	0.279	-0.209
Bio Clean Fuel	-0.006	0.045	0.086	0.514	0.349	1.000	0.395	-0.282
Geothermal	0.012	0.028	-0.007	0.395	0.279	0.395	1.000	-0.182
VIX	-0.004	0.003	-0.032	-0.335	-0.209	-0.282	-0.182	1.000

Notes. The table reports Pearson correlation coefficients computed from daily continuously compounded (log) returns. The diagonal elements equal one by construction.

The results become unambiguous after transforming the variables into daily log returns. The ADF test rejects the unit-root null at the 1% level for every return series, with statistics ranging from −8.813 for solar energy to −41.253 for the VIX. The corresponding KPSS statistics do not reject stationarity at conventional levels; the green-bond return series is the closest case, with a KPSS statistic of 0.437. The subsequent predictive regressions, forecasting models, and dynamic analyses are therefore estimated using daily log returns rather than price levels, avoiding inference based on non-stationary price series.

Table 3. Unit Root Tests

Variable	Form	ADF statistic	ADF p-value	KPSS statistic	KPSS p-value
Bitcoin	Log price level	−1.126	0.705	4.298	<0.01
Bitcoin	Daily log return	−11.634***	<0.001	0.195	>0.10
Gold	Log price level	−1.042	0.738	4.474	<0.01
Gold	Daily log return	−16.219***	<0.001	0.085	>0.10
Green Bond	Log price level	0.070	0.964	1.642	<0.01
Green Bond	Daily log return	−20.941***	<0.001	0.437	0.061
Solar Energy	Log price level	−0.609	0.869	5.281	<0.01
Solar Energy	Daily log return	−8.813***	<0.001	0.123	>0.10
Wind	Log price level	−1.515	0.526	3.310	<0.01
Wind	Daily log return	−18.789***	<0.001	0.143	>0.10
Bio Clean Fuel	Log price level	−1.804	0.378	2.838	<0.01
Bio Clean Fuel	Daily log return	−11.087***	<0.001	0.126	>0.10
Geothermal	Log price level	−2.299	0.172	3.245	<0.01
Geothermal	Daily log return	−10.784***	<0.001	0.037	>0.10
VIX	Log price level	−4.197***	0.001	1.370	<0.01
VIX	Daily log return	−41.253***	<0.001	0.018	>0.10

Notes. The ADF test has the null hypothesis of a unit root, whereas the KPSS test has the null hypothesis of stationarity. The tests include a constant. ADF lag length is selected using the Akaike Information Criterion, while KPSS bandwidth is selected automatically. *** denotes rejection of the ADF unit-root null at the 1% level.

These preliminary results establish three features that guide the subsequent analysis. First, Bitcoin is considerably more volatile and more heavily tailed than gold and green bonds. Second, its contemporaneous correlations with gold and the green assets are uniformly weak. Third, the price series are predominantly non-stationary, whereas their daily log returns are stationary. These properties motivate the return-based, multi-horizon framework used in the subsequent analysis and leave open the central empirical question of whether Bitcoin contains predictive information that is not apparent from contemporaneous correlations.

3.2. Multi-Horizon Bitcoin Predictability

Table 4 reports the baseline predictive regressions across the 1-, 5-, and 22-day horizons. The results provide little evidence that Bitcoin returns contain incremental predictive information for subsequent returns on gold, green bonds, or the four clean-energy assets. At the one-day horizon, the Bitcoin coefficient is statistically insignificant for all six assets. The same pattern persists at the five- and 22-day horizons, with no significant Bitcoin coefficient in any specification.

The control variables provide limited evidence of short-run return dynamics independent of Bitcoin. At the one-day horizon, green-bond returns are negatively associated with VIX changes ($\beta = -0.0062$, $p < 0.001$) and positively related to their own current return ($\beta = 0.1942$, $p = 0.001$). At the 22-day horizon, the own-return coefficient for gold is also positive and significant ($\beta = 0.0830$, $p = 0.017$). Beyond these cases, the control variables are generally insignificant. Model explanatory power is correspondingly modest, with R^2 values remaining low across assets and horizons.

Importantly, extending the forecast horizon does not strengthen Bitcoin's predictive relationship with the other markets. The Bitcoin coefficients vary in sign across assets and horizons, remain statistically insignificant in all 18 asset-horizon specifications, and are not accompanied by a systematic increase in explanatory power. Thus, the absence of predictability is not confined to short-run fluctuations; aggregating returns over approximately one week or one month does not reveal a stronger Bitcoin signal. The longer-horizon estimates account for the dependence generated by overlapping cumulative returns through HAC inference.

Table 4. Baseline Predictive Regressions

Panel A: One-Day Ahead Predictive Regressions				
Dependent Variable	Bitcoin	VIX	Lagged Return	R^2
Gold	0.0024 (0.715)	-0.0068 (0.102)	-0.0190 (0.559)	0.004
Green Bond	-0.0039 (0.269)	-0.0062 (0.000)	0.1942 (0.001)	0.061
Solar Energy	-0.0279 (0.222)	0.0123 (0.263)	-0.0622 (0.236)	0.010
Wind	-0.0122 (0.367)	-0.0053 (0.439)	0.0597 (0.097)	0.006
Bio Clean Fuel	0.0033 (0.883)	-0.0014 (0.885)	-0.0650 (0.320)	0.004
Geothermal	-0.0230 (0.127)	0.0036 (0.745)	-0.0684 (0.189)	0.008
Panel B: Five-Day Ahead Predictive Regressions				
Gold	-0.0005 (0.938)	0.0026 (0.480)	-0.0294 (0.337)	0.001
Green Bond	0.0030 (0.230)	-0.0019 (0.206)	-0.0040 (0.935)	0.003
Solar Energy	0.0150 (0.432)	-0.0066 (0.530)	-0.0123 (0.771)	0.001
Wind	-0.0018 (0.879)	-0.0054 (0.541)	-0.0144 (0.704)	0.001
Bio Clean Fuel	0.0114 (0.520)	-0.0028 (0.734)	0.0672 (0.290)	0.006
Geothermal	0.0067 (0.675)	-0.0007 (0.913)	0.0712 (0.117)	0.005
Panel C: Twenty-Two-Day Ahead Predictive Regressions				
Gold	-0.0004 (0.946)	-0.0013 (0.697)	0.0830 (0.017)	0.007
Green Bond	-0.0010 (0.654)	-0.0002 (0.857)	-0.0157 (0.710)	0.000
Solar Energy	-0.0042 (0.771)	0.0072 (0.481)	0.0233 (0.478)	0.001
Wind	-0.0035 (0.719)	0.0062 (0.376)	-0.0013 (0.964)	0.001
Bio Clean Fuel	-0.0019 (0.908)	-0.0034 (0.678)	-0.0339 (0.244)	0.001
Geothermal	0.0063 (0.585)	0.0045 (0.498)	0.0350 (0.265)	0.002

Notes. Entries are estimated coefficients with HAC (Newey–West) p-values in parentheses. The dependent variables are cumulative asset returns over the 1-day, 5-day, and 22-day forecast horizons, respectively. R^2 denotes the coefficient of determination.

The baseline evidence therefore indicates that Bitcoin does not provide stable unconditional predictive information for gold or the green assets over the sample period. This finding concerns average predictability and does not rule out relationships that arise under particular market conditions. The next analysis consequently examines whether Bitcoin's predictive content varies across VIX and Bitcoin-volatility states.

3.3. State-Dependent Bitcoin Predictability

Tables 5 and 6 examine whether the weak unconditional predictability documented in Table 4 changes across market states. The results provide some evidence of state dependence, although it is concentrated in particular assets and horizons rather than observed systematically across the green-asset set.

Under the VIX classification, there is little evidence of regime dependence at the one- and five-day horizons. Bitcoin coefficients generally remain insignificant across low- and high-VIX states, and the differences between regimes are statistically insignificant. The principal exception emerges for bio-clean fuel at the 22-day horizon. Its Bitcoin coefficient changes from −0.1325 in the low-VIX state to 0.1639 in the high-VIX state (p = 0.024), with a statistically significant regime difference of 0.2964 (p = 0.023). No comparable regime difference is detected for gold, green bonds, solar, wind, or geothermal.

Bitcoin's own volatility produces a somewhat different pattern. At the one-day horizon, solar energy exhibits a significant negative Bitcoin coefficient during high-volatility periods (β = −0.0515, p = 0.023), although the difference between the high- and low-volatility regimes is significant only at the 10% level (p = 0.094). The regime difference for bio-clean fuel is similarly marginal (p = 0.076). At the five-day horizon, the corresponding difference for green bonds is also marginally significant (p = 0.059), while the remaining assets show no meaningful regime variation. At the 22-day horizon, none of the regime differences is statistically significant.

Table 5. State-Dependent Bitcoin Predictability for High vs. Low VIX Regimes

Dependent variable	Low-VIX Bitcoin effect	High-VIX Bitcoin effect	Regime difference	R^2
One-Day Horizon				
Gold	0.0027 (0.622)	0.0023 (0.828)	−0.0004 (0.972)	0.004
Green Bond	−0.0019 (0.354)	−0.0053 (0.338)	−0.0034 (0.562)	0.061
Solar Energy	0.0030 (0.879)	−0.0472 (0.153)	−0.0502 (0.192)	0.016
Wind	0.0015 (0.920)	−0.0207 (0.279)	−0.0222 (0.361)	0.008
Bio Clean Fuel	0.0235 (0.197)	−0.0098 (0.773)	−0.0333 (0.388)	0.006
Geothermal	−0.0168 (0.269)	−0.0275 (0.237)	−0.0107 (0.701)	0.008
Five-Day Horizon				
Gold	0.0203 (0.169)	0.0226 (0.191)	0.0023 (0.919)	0.006
Green Bond	−0.0028 (0.548)	0.0062 (0.592)	0.0090 (0.464)	0.028
Solar Energy	0.0105 (0.792)	0.0791 (0.102)	0.0686 (0.272)	0.023
Wind	0.0208 (0.448)	0.0384 (0.243)	0.0176 (0.683)	0.009
Bio Clean Fuel	0.0051 (0.893)	0.0891* (0.053)	0.0840 (0.160)	0.010
Geothermal	−0.0179 (0.514)	0.0550 (0.368)	0.0730 (0.276)	0.002
Twenty-Two-Day Horizon				
Gold	0.0361 (0.372)	−0.0333 (0.203)	−0.0694 (0.147)	0.005
Green Bond	−0.0127 (0.352)	0.0194 (0.377)	0.0322 (0.212)	0.014
Solar Energy	0.0068 (0.949)	0.0448 (0.565)	0.0380 (0.779)	0.089
Wind	−0.0495 (0.371)	0.0013 (0.986)	0.0508 (0.580)	0.048
Bio Clean Fuel	−0.1325 (0.198)	0.1639 (0.024)	0.2964 (0.023)	0.035
Geothermal	0.0067 (0.916)	0.1344 (0.168)	0.1277 (0.275)	0.004

Notes. Values are estimated Bitcoin-return coefficients with HAC p-values in parentheses. The low-VIX coefficient measures Bitcoin predictability when the VIX is at or below 19.705. The high-VIX coefficient equals the sum of the baseline Bitcoin coefficient and its interaction with the high-VIX dummy. The regime-difference column reports the interaction coefficient. ** and * denote significance at the 5% and 10% levels, respectively. All regressions include the high-VIX dummy, contemporaneous VIX return, the asset's own current return, and a constant.

Table 6. State-Dependent Predictability Based on Bitcoin Realized Volatility

Dependent variable	Low-volatility Bitcoin effect	High-volatility Bitcoin effect	Regime difference	R^2
One-Day Horizon				
Gold	−0.0036 (0.811)	0.0031 (0.638)	0.0067 (0.648)	0.004
Green Bond	0.0001 (0.985)	−0.0061 (0.161)	−0.0062 (0.348)	0.062
Solar Energy	0.0144 (0.704)	−0.0515 (0.023)	−0.0660* (0.094)	0.016
Wind	−0.0029 (0.908)	−0.0169 (0.253)	−0.0140 (0.597)	0.006
Bio Clean Fuel	0.0515 (0.137)	−0.0162 (0.511)	−0.0677* (0.076)	0.010
Geothermal	−0.0047 (0.888)	−0.0285 (0.111)	−0.0238 (0.529)	0.008
Five-Day Horizon				
Gold	0.0183 (0.571)	0.0254* (0.052)	0.0071 (0.843)	0.007
Green Bond	0.0281 (0.117)	−0.0064 (0.286)	−0.0345* (0.059)	0.032
Solar Energy	0.0249 (0.776)	0.0408 (0.245)	0.0159 (0.867)	0.006
Wind	0.0252 (0.682)	0.0263 (0.238)	0.0011 (0.986)	0.003
Bio Clean Fuel	0.0634 (0.437)	0.0460 (0.188)	−0.0173 (0.845)	0.009
Geothermal	0.0345 (0.612)	0.0207 (0.657)	−0.0138 (0.865)	0.001
Twenty-Two-Day Horizon				
Gold	0.0005 (0.993)	−0.0056 (0.813)	−0.0061 (0.917)	0.012
Green Bond	0.0499 (0.142)	−0.0081 (0.546)	−0.0581 (0.112)	0.014
Solar Energy	−0.0044 (0.979)	0.0029 (0.961)	0.0073 (0.966)	0.004
Wind	−0.0297 (0.827)	−0.0379 (0.404)	−0.0082 (0.954)	0.005
Bio Clean Fuel	0.0401 (0.801)	0.0307 (0.651)	−0.0094 (0.956)	0.009
Geothermal	0.0418 (0.774)	0.0984 (0.213)	0.0565 (0.744)	0.003

Notes. Values are estimated Bitcoin coefficients with HAC p-values in parentheses. The high-volatility coefficient equals the sum of the baseline Bitcoin coefficient and its interaction with the high-Bitcoin-volatility dummy. The regime-difference column reports the interaction coefficient. ** and * indicate significance at the 5% and 10% levels, respectively. The one- and five-day models use five Newey–West lags; the overlapping 22-day models use 21 lags. All regressions include the volatility-regime dummy, VIX return, the dependent asset's current return, and a constant.

Across the two state classifications, significant regime differences are limited. The strongest evidence occurs for bio-clean fuel at the 22-day horizon under the VIX classification, where the regime difference is positive and significant at the 5% level. Under the Bitcoin-volatility classification, regime differences for solar energy and bio-clean fuel at the one-day horizon and green bonds at the five-day horizon are significant only at the 10% level. In contrast, no significant regime differences are observed at the 22-day horizon.

3.4. Out-of-Sample Forecasting Performance

Table 7 evaluates whether the limited in-sample predictability translates into meaningful out-of-sample forecasting gains. Across the 1-, 5-, and 22-day horizons, improvements over the historical-mean benchmark are generally small and vary across assets and models. At the one-day horizon, OLS produces the largest improvement for green bonds (R^2_{oos} = 0.0398), while AR(1) performs best for gold and wind. Gradient Boosting provides a modest gain for bio-clean fuel (R^2_{oos} = 0.0103), whereas the historical mean remains the best-performing model for solar energy and geothermal.

A similar pattern is observed at the five-day horizon. The largest gains remain modest: LASSO achieves R^2_{oos} = 0.0169 for green bonds and 0.0167 for geothermal, while Gradient Boosting performs best for wind (R^2_{oos} = 0.0153) and Random Forest for bio-clean fuel (R^2_{oos} = 0.0085). For gold and solar energy, none of the competing models improves upon the historical-mean forecast.

At the 22-day horizon, forecast improvements become even more limited. Random Forest performs best for gold, with an R^2_{oos} of 0.0205, while AR(1) provides only marginal gains for green bonds, wind, bio-clean fuel, and geothermal; the historical mean remains the preferred specification for solar energy. The complete forecasting results reported in Appendix Table A1 further show that several linear and machine-learning models generate negative R^2_{oos} values, particularly at the 22-day horizon. The complete out-of-sample results for all competing models are reported in Appendix Table A1. They confirm that the modest gains reported in Table 7 are not accompanied by consistently superior performance across alternative models, assets, or forecast horizons.

Table 7. Forecast Performance Comparison of Competing Models

Asset	Best model	RMSE	MAE	OOS R^2
Panel A: One-Day Horizon				
Gold	AR(1)	0.9568	0.7198	0.0011
Green Bond	OLS	0.6108	0.4711	0.0398
Solar Energy	Historical Mean	2.3922	1.8040	0.0000
Wind	AR(1)	2.3109	1.7799	0.0077
Bio Clean Fuel	Gradient Boosting	2.3861	1.8743	0.0103
Geothermal	Historical Mean	1.9868	1.3879	0.0000
Panel B: Five-Day Horizon				
Gold	Historical Mean	2.0825	1.6713	0.0000
Green Bond	LASSO	1.6691	1.2792	0.0169
Solar Energy	Historical Mean	5.8617	4.6102	0.0000
Wind	Gradient Boosting	5.2880	4.1555	0.0153
Bio Clean Fuel	Random Forest	5.9367	4.8291	0.0085
Geothermal	LASSO	4.7078	3.3154	0.0167
Panel C: Twenty-Two-Day Horizon				
Gold	Random Forest	4.2240	3.4702	0.0205
Green Bond	AR(1)	4.3227	3.7621	0.0012
Solar Energy	Historical Mean	13.5803	11.7048	0.0000
Wind	AR(1)	11.7715	9.7885	0.0001
Bio Clean Fuel	AR(1)	12.3133	10.0652	0.0002
Geothermal	AR(1)	11.0487	8.8373	0.0004

Notes. The best model is selected using the lowest test-sample RMSE. R^2 is computed relative to the historical-mean forecast. Forecasts are generated from a chronological 80/20 training–testing split. One- and five-day test samples contain 256 observations, while the 22-day test sample contains 252 observations.

The out-of-sample evidence therefore shows that forecast improvements are generally modest and rarely statistically significant. No single linear or machine-learning model performs consistently best across assets and horizons, while simple benchmarks remain competitive in several cases.

3.5. Dynamic Responses to Bitcoin Innovations

Table 8 and Figure 3 report the HAC local-projection responses of gold and the green assets to a one-standard-deviation unexpected Bitcoin-return shock over horizons from 0 to 10 trading days. The responses are generally small, short-lived, and statistically insignificant, with no common response pattern across the six assets.

Gold and green bonds show no statistically significant response at any horizon. The clean-energy indices display greater short-run variation, but most estimates also remain insignificant. The main exceptions are geothermal, which records a positive response at horizon 3 ($\beta = 0.1130$, $p < 0.10$), and wind, which shows a negative response at horizon 10 ($\beta = -0.1028$, $p < 0.10$). Neither response reaches the 5% significance level. Bio-clean fuel exhibits a relatively large positive coefficient at horizon 4 (0.2006), but the estimate is statistically insignificant.

Figure 3 reinforces the absence of a persistent dynamic pattern. Responses fluctuate around zero across the projection horizon rather than exhibiting sustained movements following the Bitcoin shock. The confidence intervals generally encompass zero, consistent with the limited statistical significance reported in Table 9.

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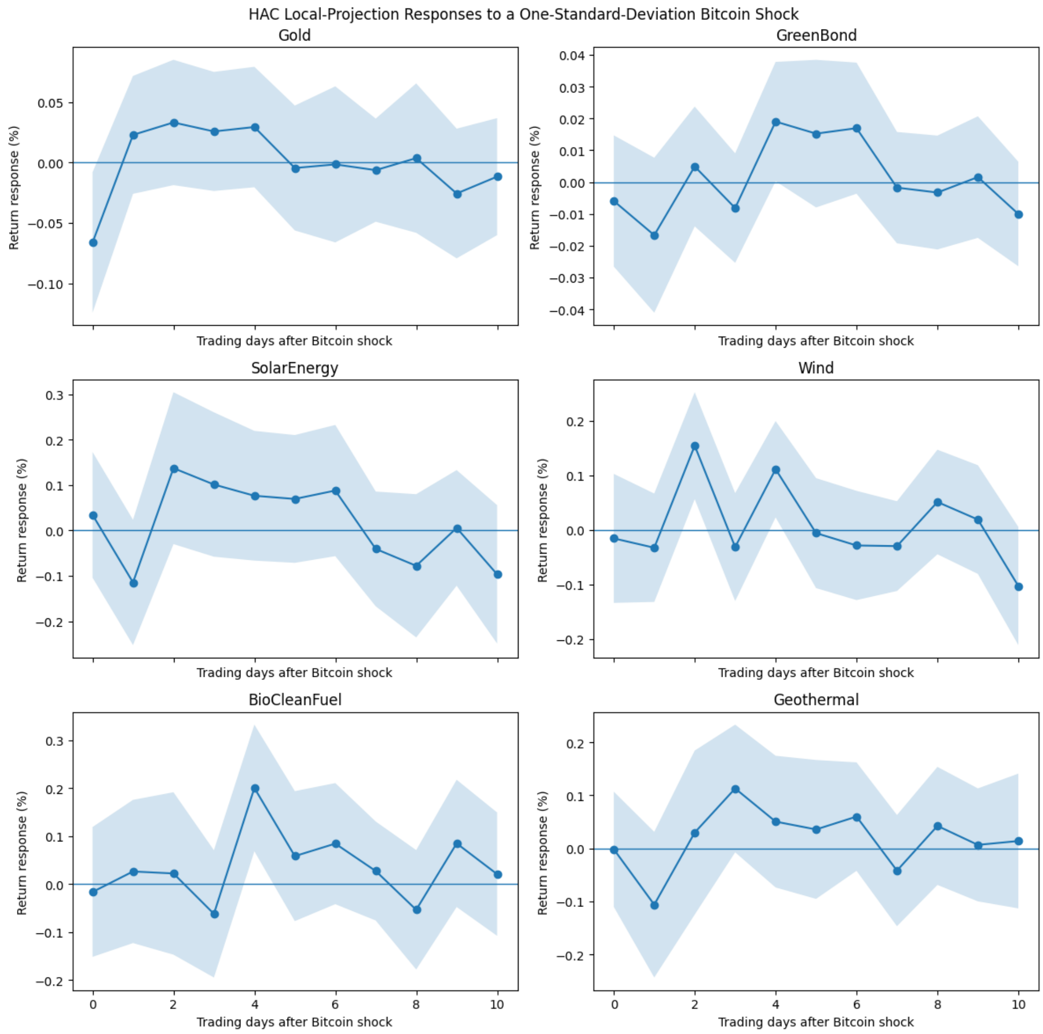
Fig 3. HAC Local Projection Responses to One-Standard-Deviation Bitcoin Shock



The local-projection estimates therefore provide limited evidence of persistent return transmission from unexpected Bitcoin movements to gold or the green assets. The few marginally significant responses are isolated by asset and horizon rather than sustained across the projection period.

3.6. Bitcoin's Contribution to Forecast-Error Variance

Table 9 and Figure 4 report the generalized forecast-error variance decomposition from the VAR(3) return system. Across all assets and horizons, Bitcoin innovations account for only a small proportion of forecast-error variance. At the one-day horizon, the contribution ranges from effectively zero for geothermal to 0.434% for gold, with contributions below 0.03% for green bonds, solar energy, wind, bio-clean fuel, and geothermal.

Bitcoin's contribution increases somewhat as the forecast horizon expands but remains below 1% for every asset. At the 22-day horizon, the largest shares are observed for gold (0.628%) and wind (0.562%), followed by solar energy (0.384%), geothermal

(0.313%), green bonds (0.208%), and bio-clean fuel (0.104%). The variance shares also stabilize relatively quickly, with little change between the 10- and 22-day horizons.

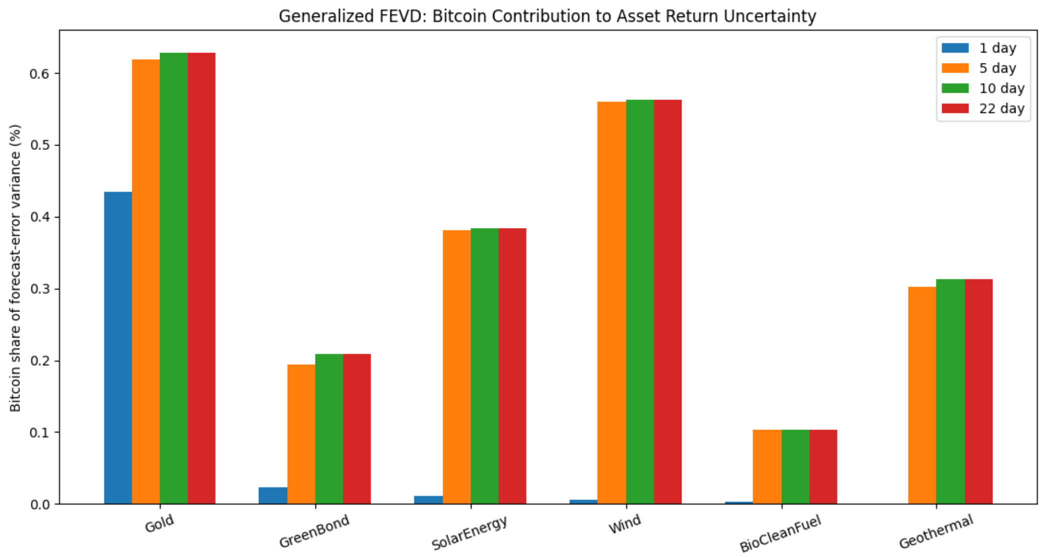
Figure 4 illustrates the same pattern across forecast horizons: Bitcoin-related variance shares rise from their initially low levels but remain quantitatively small throughout the forecast window. The robustness analysis in Appendix Table A2 produces slightly larger shares under the orthogonalized decomposition, but Bitcoin's 22-day contribution remains below 1% for every asset. The generalized and orthogonalized specifications therefore yield the same qualitative pattern.

Table 8. HAC Local-Projection Responses to a Bitcoin Shock

Horizon	Gold	Green Bond	Solar Energy	Wind	Bio Clean Fuel	Geothermal
0	−0.0662	−0.0060	0.0342	−0.0156	−0.0165	−0.0017
1	0.0229	−0.0167	−0.1146	−0.0327	0.0262	−0.1063
2	0.0332	0.0049	0.1370	0.1540	0.0221	0.0297
3	0.0258	−0.0082	0.1010	−0.0315	−0.0623	0.1130*
4	0.0294	0.0190	0.0763	0.1110	0.2006	0.0504
5	−0.0045	0.0152	0.0692	−0.0060	0.0583	0.0357
6	−0.0015	0.0169	0.0877	−0.0286	0.0844	0.0599
7	−0.0063	−0.0018	−0.0408	−0.0297	0.0272	−0.0420
8	0.0037	−0.0033	−0.0780	0.0510	−0.0537	0.0423
9	−0.0257	0.0015	0.0055	0.0188	0.0848	0.0065
10	−0.0117	−0.0101	−0.0968	−0.1028*	0.0206	0.0138

Notes. Responses are percentage-return-point changes following a one-standard-deviation unexpected Bitcoin-return shock. ** and * indicate significance at the 5% and 10% levels, respectively. All specifications include three lags of the complete return system and use HAC/Newey–West standard errors.

Fig 4. Generalized FEVD



As a robustness check, Appendix Table A2 compares the generalized FEVD with an orthogonalized decomposition in which Bitcoin is ordered first. Although the orthogonalized shares are somewhat larger, Bitcoin's 22-day contribution remains below 1% for every asset, leaving the qualitative result unchanged.

3.7. Explainable Machine-Learning Evidence

Table 10 and Figure 5 report grouped SHAP importance for the selected tree-based forecasting models. Across the three models, Bitcoin-related features account for a relatively small share of total predictive importance. Bitcoin contributes 4.42% of total SHAP importance in the 22-day Random Forest model for gold, 6.38% in the five-day Gradient Boosting model for wind, and 2.46% in the five-day Random Forest model for bio-clean fuel.

The models instead draw most of their predictive information from other financial and green assets. Other-asset information accounts for 88.58% of total importance in the gold model, 65.01% in the wind model, and 75.31% in the bio-clean-fuel model. VIX information is more prominent for wind (10.61%) and bio-clean fuel (14.40%) than for gold (1.79%), while own-asset information contributes 5.22%, 18.00%, and 7.83%, respectively.

The feature-level results reported in Appendix Table A3 provide further detail on these grouped contributions. Green-bond volatility is the dominant predictor in the gold model, accounting for 53.98% of total SHAP importance, while green-bond information also ranks prominently in the wind and bio-clean-fuel models. Bitcoin five-day volatility appears among the ten highest-ranked predictors for wind, with a 4.20% share, but Bitcoin features do not dominate any of the selected models. The corresponding SHAP summary plots are presented in Appendix Figures A1–A3 for gold, wind, and bio-clean fuel, respectively.

Table 9. Bitcoin's Contribution to Forecast-Error Variance

Asset	1-day	5-day	10-day	22-day
Gold	0.434	0.618	0.628	0.628
Green Bond	0.024	0.194	0.208	0.208
Solar Energy	0.012	0.381	0.384	0.384
Wind	0.006	0.560	0.562	0.562
Bio Clean Fuel	0.003	0.103	0.104	0.104
Geothermal	0.000	0.302	0.313	0.313

Notes. The table reports generalized forecast-error variance decompositions from the VAR(3) return system. Generalized FEVD is reported because it is not affected by the ordering of the variables. Values are expressed as percentages.

Table 10. Grouped SHAP importance

Model	Bitcoin	VIX	Own-asset information	Other asset information
Gold, 22-day RF	4.42%	1.79%	5.22%	88.58%
Wind, 5-day GB	6.38%	10.61%	18.00%	65.01%
Bio Clean Fuel, 5-day RF	2.46%	14.40%	7.83%	75.31%

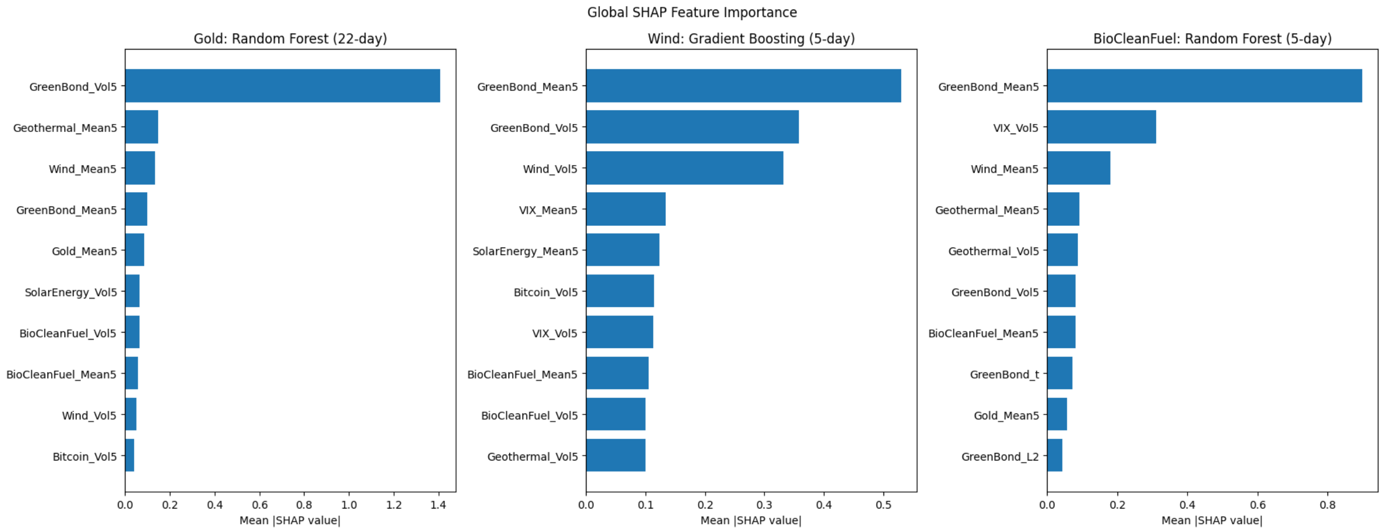
Notes: The table reports grouped global SHAP importance for the selected tree-based forecasting models. Importance is calculated from mean absolute SHAP values and expressed as a percentage of total feature importance within each model. Bitcoin comprises all Bitcoin-related features, VIX comprises all VIX-related features, Own-Asset Information comprises features constructed from the return history of the respective dependent variable, and Other-Asset Information comprises features derived from the remaining financial and green assets. The percentages in each row sum to 100%. RF and GB denote Random Forest and Gradient Boosting, respectively.

The SHAP results therefore show that Bitcoin-related information plays a limited role in the selected nonlinear forecasting models. Predictive importance is concentrated primarily in information from the other financial and green assets, with VIX and own-asset information contributing to varying degrees across the three models.

4. Discussion of Empirical Results

The findings indicate that Bitcoin's substantial volatility does not translate into systematic predictive influence on gold and green assets. Across the different empirical approaches, Bitcoin provides little incremental information for subsequent returns, generates limited persistent responses, and explains only a small proportion of forecast uncertainty in the other markets. Large fluctuations in Bitcoin can attract considerable investor and regulatory attention without necessarily transmitting information that is useful for forecasting assets whose prices are formed through different economic channels.

Fig 5. Grouped SHAP Feature Importance



The weak relationship with gold is particularly relevant given the frequent comparison of Bitcoin with traditional safe-haven assets. The absence of consistent Bitcoin predictability for gold, together with its small contribution to gold's forecast-error variance, suggests that the two assets retain distinct return-generating processes. This is consistent with Klein et al. (2018), who find fundamental differences between Bitcoin and gold in their volatility, correlation, and portfolio characteristics, particularly during market distress. Baur et al. (2018) similarly show that Bitcoin differs substantially from gold in its return, volatility, and correlation properties. The present findings extend this distinction from contemporaneous market characteristics to predictive transmission: movements in Bitcoin do not provide a stable signal for subsequent gold returns.

The evidence for green assets points to a similar separation, although the economic mechanisms differ. Green bonds are primarily fixed-income instruments whose valuation is closely connected to interest rates, credit conditions, duration risk, and institutional demand for sustainable securities (Esmaeili et al., 2024; Lucey & Ren, 2023). Renewable-energy equities, in contrast, are exposed to sector-specific fundamentals such as financing costs, technological development, energy-market conditions, and environmental policy. Bitcoin has no direct claim on the underlying cash flows of either market. Consequently, even substantial movements in cryptocurrency valuations need not alter the expected cash flows or discount rates governing green-asset prices. This provides an economic explanation for the weak unconditional predictive coefficients and the very small contribution of Bitcoin innovations to forecast-error variance.

These results complement rather than contradict evidence that cryptocurrency and sustainable-asset markets can be interconnected. Yadav et al. (2025) document time- and frequency-dependent linkages among green bonds, renewable energy, and cryptocurrency markets, while finding limited short-run volatility transmission from green bonds to energy and cryptocurrency markets. The present results show why connectedness should be distinguished from predictability. Markets may share common shocks, exhibit episodic co-movement, or become more connected at particular frequencies without one market consistently containing incremental information about the future returns of another. In this study, whatever interdependence exists between

Bitcoin and green assets does not generally translate into stable Bitcoin-led return predictability.

The state-dependent evidence adds an important qualification. Bitcoin's predictive relationship is not completely invariant to market conditions. The strongest regime effect occurs for bio-clean fuel at the 22-day horizon during high-VIX periods, while several weaker differences emerge under Bitcoin's own volatility classification. Such variation is consistent with the broader evidence that cryptocurrency relationships depend on market states and investment horizons. Maghyereh and Abdoh (2020), for example, show that dependence between Bitcoin and conventional financial assets varies across return quantiles and frequencies. Selmi et al. (2018) similarly demonstrate that the hedging and diversification properties of Bitcoin depend on prevailing market states. These studies support the economic intuition that relationships involving Bitcoin can change when uncertainty, risk perceptions, and portfolio rebalancing intensify.

The important feature of the present results, however, is that heightened uncertainty does not produce a general increase in Bitcoin's predictive influence. Significant regime differences are concentrated in particular assets and horizons. This suggests that market stress can alter specific transmission channels without integrating Bitcoin systematically with the broader green-finance complex. Renewable-energy subsectors themselves differ considerably in their economic exposures, market depth, investor composition, and sensitivity to policy and financing conditions. It is therefore plausible that a common shift in risk sentiment produces a detectable relationship in one segment, such as bio-clean fuel, without generating comparable responses in solar, wind, or geothermal markets. State dependence in this setting is consequently better understood as selective rather than pervasive.

The out-of-sample results provide a further economic test of whether these relationships are sufficiently stable to be useful. Although several linear and machine-learning specifications produce positive out-of-sample gains, the improvements are generally small, vary across assets and horizons, and are rarely statistically distinguishable from simple benchmarks. This result is consistent with the time-varying nature of cryptocurrency return predictability documented by Bianchi et al. (2023). A relationship observed within a particular sample or market environment need not remain sufficiently stable to improve forecasts when applied to new observations. The competitiveness of the historical-mean and autoregressive benchmarks in the present analysis therefore indicates that additional model flexibility does not automatically generate economically useful forecasts.

The explainable machine-learning evidence strengthens this conclusion. If Bitcoin contained important nonlinear information that was simply missed by the linear predictive regressions, Bitcoin-related features should become substantially more important once flexible tree-based algorithms are allowed to exploit nonlinearities and interactions. This is not observed. Bitcoin features account for only a small proportion of SHAP importance in the selected models, while information from other financial and green assets accounts for substantially larger shares. The weak Bitcoin signal therefore cannot readily be attributed to linear-model misspecification alone. Rather, Bitcoin appears to contribute relatively little incremental forecasting information even when nonlinear relationships are permitted.

In this way, the forecasting, local-projection, variance-decomposition, and machine-learning evidence also clarifies the distinction between statistical association and economic transmission. A statistically observable relationship between two financial markets does not necessarily imply that shocks originating in one market materially determine uncertainty or future returns in the other. The finding that Bitcoin accounts for less than 1% of forecast-error variance across all six assets is particularly informative in this respect. Combined with the absence of persistent responses in the local projections, it indicates that Bitcoin is not a quantitatively important source of return variation in these markets over the sample period. This interpretation is consistent with the broader literature showing that Bitcoin's relationships with conventional financial assets are conditional and differ substantially across assets, states, and investment horizons (Klein et al., 2018; Maghyereh & Abdoh, 2020).

The findings have practical implications for portfolio management. Investors should distinguish between an asset's diversification potential and its predictive value. Weak transmission between Bitcoin and gold or green assets can preserve diversification opportunities, but it does not imply that Bitcoin is a useful leading indicator for tactical allocation across these markets. Maghyereh and Abdoh (2020) similarly show that Bitcoin's diversification properties depend on return conditions and investment horizons. Portfolio managers should therefore avoid interpreting large Bitcoin movements as general signals for subsequent movements in sustainable assets. The evidence instead favors asset-specific information sets, with market uncertainty and sector fundamentals considered alongside, rather than replaced by, cryptocurrency indicators.

The state-dependent results nevertheless have implications for risk management. Because some relationships become stronger under elevated VIX or Bitcoin-volatility conditions, average full-sample relationships may understate exposures that arise temporarily during stressed markets. Investors managing combined cryptocurrency and green-asset portfolios may therefore benefit from monitoring regime conditions rather than relying exclusively on unconditional correlations. This implication is consistent with Selmi et al. (2018), who demonstrate that the portfolio properties of Bitcoin can differ substantially across market states. The present results add an important qualification: regime sensitivity exists, but it should not be interpreted as evidence of uniformly stronger contagion or predictability during periods of stress.

The policy implications are similarly measured. The results do not support treating ordinary Bitcoin return shocks as an important source of systematic return transmission to gold or sustainable financial markets during the sample period. Bitcoin's small variance contributions and limited dynamic responses imply that regulatory concern about cryptocurrency markets should not automatically be translated into assumptions of substantial spillover to green-finance assets. At the same time, the state-dependent findings suggest that surveillance frameworks should remain responsive to market conditions. Episodes of elevated uncertainty may temporarily strengthen particular cross-market relationships even when average transmission remains weak. For financial-stability monitoring, the economically relevant question is therefore not simply whether cryptocurrency and green markets are connected, but whether such connections become sufficiently large, persistent, and widespread to generate material cross-market risk.

5. Conclusion and Implications

This study examines whether Bitcoin contains economically meaningful predictive information for gold, green bonds, and renewable-energy assets, and whether this relationship changes across market conditions. By combining multi-horizon predictive regressions, volatility-state specifications, out-of-sample forecasting, local projections, forecast-error variance decomposition, and explainable machine learning, the analysis distinguishes between average predictability, state dependence, dynamic transmission, and nonlinear predictive importance.

The findings provide limited evidence of systematic Bitcoin-led predictability. Bitcoin returns do not significantly predict any of the six assets at the 1-, 5-, or 22-day horizons in the baseline regressions, and extending the forecast horizon does not strengthen the relationship. State dependence is present but selective. The strongest evidence occurs for bio-clean fuel at the 22-day horizon under high-VIX conditions, while the Bitcoin-volatility regimes produce only marginal differences for a small number of asset-horizon combinations. Thus, changes in market uncertainty can modify particular relationships without producing a general strengthening of Bitcoin's predictive influence.

The out-of-sample evidence reinforces this conclusion. Forecast improvements over simple benchmarks are generally modest, vary across assets and horizons, and are rarely statistically significant. The dynamic analysis leads to a similar result. Responses to unexpected Bitcoin movements are predominantly insignificant and short-lived, while Bitcoin innovations explain less than 1% of the forecast-error variance of every asset even at the 22-day horizon. Moreover, the SHAP analysis shows that Bitcoin-related features account for only a small share of predictive importance in the selected nonlinear models, indicating that the weak Bitcoin signal is not simply a consequence of imposing linear relationships.

These findings have implications for investors. Bitcoin should not be treated as a general leading indicator for tactical allocation across gold, green bonds, or renewable-energy equities. Its limited predictive transmission does not, however, eliminate potential diversification benefits; predictive usefulness and diversification value represent different dimensions of cross-asset relationships. Portfolio managers should therefore rely on asset-specific information and market fundamentals rather than infer subsequent movements in green or traditional assets directly from Bitcoin returns. The evidence of selective state dependence also suggests that risk assessment should allow cross-market relationships to vary during periods of elevated uncertainty rather than relying exclusively on full-sample average relationships.

For policymakers and financial regulators, the results provide little evidence that ordinary Bitcoin return innovations constitute an important source of systematic return transmission to the green-finance markets examined here. Bitcoin's very small contribution to forecast uncertainty and the absence of persistent dynamic responses suggest that cryptocurrency-market volatility should not automatically be interpreted as a source of material instability for sustainable financial assets. Nevertheless, the state-dependent findings support monitoring cross-market exposures during periods of heightened financial and cryptocurrency volatility, when isolated transmission channels can become more pronounced. Regulatory surveillance should therefore distinguish between temporary market-state effects and persistent systemic transmission.

The study also carries implications for empirical research on cryptocurrency connectedness. Correlation, state dependence, forecastability, dynamic transmission, and machine-learning importance capture different dimensions of financial interdependence and should not be treated as interchangeable evidence. The results demonstrate that Bitcoin can exhibit conditional relationships with other markets while providing little stable incremental forecasting information. This distinction is particularly relevant when evaluating claims that statistically detectable cryptocurrency–green-finance linkages necessarily imply economically meaningful transmission.

Several limitations provide opportunities for further research. The analysis covers February 2018 to February 2023 and therefore captures important episodes of financial and cryptocurrency-market stress but cannot establish whether the documented relationships persist under subsequent market structures. Future studies could extend the sample, examine alternative measures of financial and cryptocurrency uncertainty, and investigate whether the identified state dependence changes across more extreme market regimes. Additional work could also incorporate climate-policy uncertainty, energy prices, interest-rate conditions, and investor sentiment to identify the economic channels underlying the selective relationships observed across renewable-energy sectors. Finally, alternative nonlinear and time-varying frameworks could examine whether predictive information emerges in the tails of the return distribution even when average and volatility-state predictability remains weak.

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Data Availability Statement: The author has no permission to share the data due to subscription-based collected data. We encourage all authors to share their research code and data to facilitate further work on the same topic. In this section, the author should provide details regarding where data from the study can be found. This may include links to datasets that are publicly archived or that were utilized or created in the course of the study. Even if no fresh data was produced or if data is inaccessible due to confidentiality or ethical constraints, it remains necessary for the author to make a statement.

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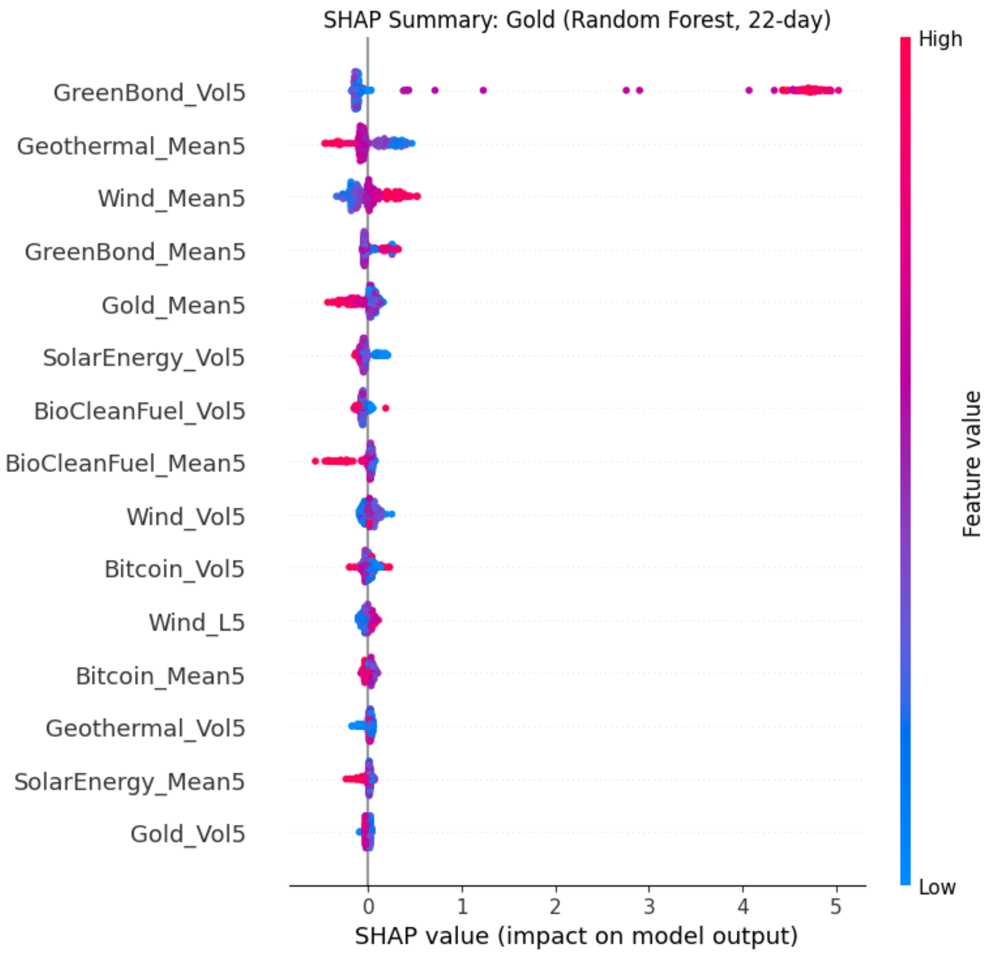
Appendices

Appendix Table A1. Complete Out-of-Sample Forecasting Performance (R^2_{OOS})

Asset	AR(1)	OLS	LASSO	Random Forest	Gradient Boosting
One-day horizon					
Gold	0.0011	-0.0314	-0.0151	-0.0148	-0.0028
Green Bond	0.0271	0.0398	0.0320	0.0208	-0.0155
Solar Energy	-0.0420	-0.0225	-0.0213	-0.0476	-0.0352
Wind	0.0077	0.0007	0.0051	0.0038	-0.0221
Bio Clean Fuel	-0.0550	-0.0812	-0.0600	0.0004	0.0103
Geothermal	-0.0356	-0.0454	-0.0334	-0.0339	-0.0376
Five-day horizon					
Gold	-0.0097	-0.0566	-0.0424	-0.0471	-0.0062
Green Bond	0.0161	-0.0067	0.0169	-0.0219	-0.0320
Solar Energy	-0.0003	-0.0506	-0.0444	-0.0523	-0.0441
Wind	-0.0006	-0.0180	-0.0138	0.0072	0.0153
Bio Clean Fuel	-0.0004	-0.0062	-0.0033	0.0085	-0.0088
Geothermal	-0.0001	0.0160	0.0167	-0.0166	-0.0120
Twenty-two-day horizon					
Gold	0.0007	-0.0026	-0.0005	0.0205	0.0128
Green Bond	0.0012	-0.1051	-0.0776	-0.1335	-0.1074
Solar Energy	-0.0009	-0.0222	-0.0186	-0.0229	-0.0096
Wind	0.0001	-0.0008	-0.0012	-0.0026	-0.0039
Bio Clean Fuel	0.0002	-0.0185	-0.0162	-0.0507	-0.0447
Geothermal	0.0004	-0.0525	-0.0519	-0.0087	-0.0091

Notes. This table reports the complete out-of-sample forecasting performance of all benchmark and machine-learning models for the 1-day, 5-day, and 22-day forecast horizons. Entries represent the out-of-sample coefficient of determination relative to the historical-mean benchmark. Positive values indicate that a model outperforms the historical-mean forecast, whereas negative values indicate inferior forecasting performance. Forecasts are generated using a chronological 80/20 training–testing split to avoid look-ahead bias. Bold values identify the best-performing model for each asset and forecast horizon.

Appendix Fig. 1. SHAP Summary – Gold

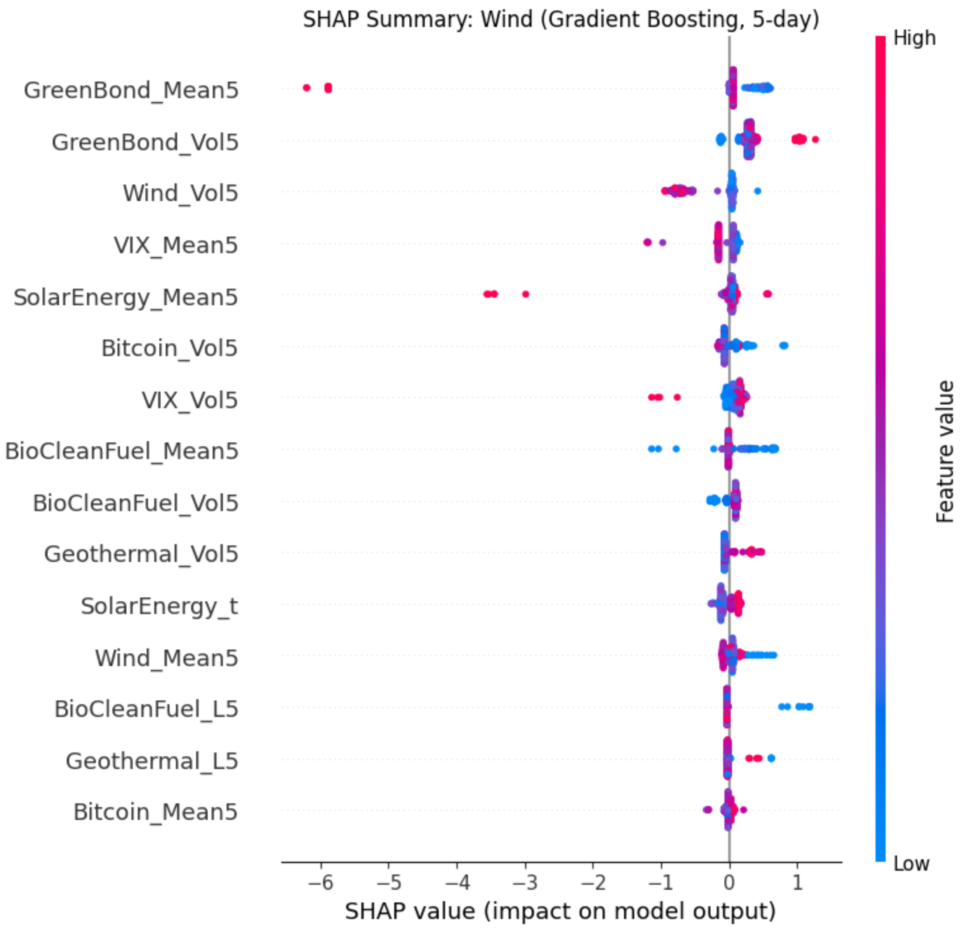


Appendix Table A2. Robustness Comparison of Orthogonalized and Generalized FEVD

Asset	Orthogonalized 22-day	Generalized 22-day
Gold	0.767	0.628
Green Bond	0.276	0.208
Solar Energy	0.642	0.384
Wind	0.791	0.562
Bio Clean Fuel	0.170	0.104
Geothermal	0.448	0.313

Notes. The table compares Bitcoin's contribution to the 22-day forecast-error variance under orthogonalized and generalized FEVD. The orthogonalized decomposition is based on a Cholesky identification with Bitcoin ordered first, whereas generalized FEVD is invariant to variable ordering. Values are expressed as percentages. The qualitative conclusion of a limited Bitcoin contribution is unchanged across the two specifications.

Appendix Fig. 2. SHAP Summary – Wind



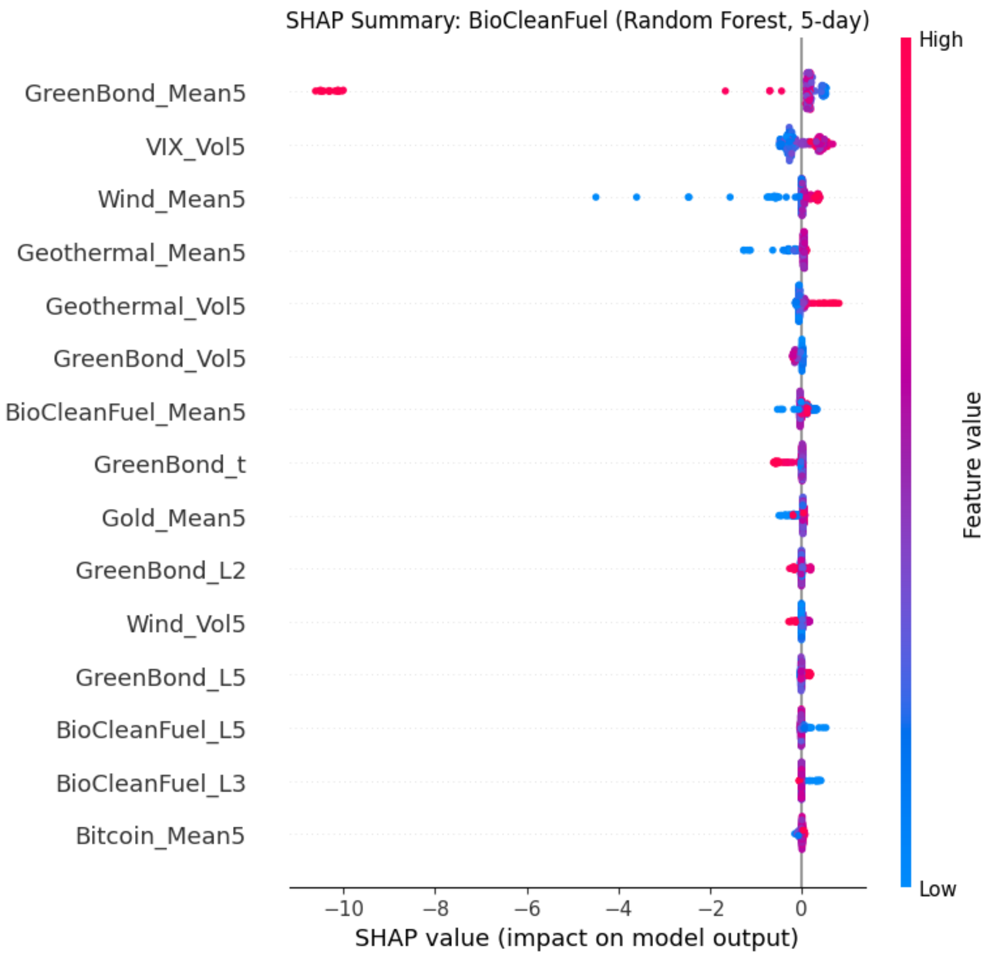
Appendix Table A3. Detailed SHAP Global Feature Importance Rankings

Panel A: Gold, 22-day Random Forest		
Rank	Predictor	Importance share
1	Green Bond 5-day volatility	53.98%
2	Geothermal 5-day mean return	5.72%
3	Wind 5-day mean return	5.14%
4	Green Bond 5-day mean return	3.77%
5	Gold 5-day mean return	3.25%
6	Solar Energy 5-day volatility	2.51%
7	Bio Clean Fuel 5-day volatility	2.50%
8	Bio Clean Fuel 5-day mean return	2.27%
9	Wind 5-day volatility	1.94%
10	Bitcoin 5-day volatility	1.61%
Panel B: Wind, 5-day Gradient Boosting		
Rank	Predictor	Importance share
1	Green Bond 5-day mean return	19.38%
2	Green Bond 5-day volatility	13.11%
3	Wind 5-day volatility	12.14%
4	VIX 5-day mean	4.89%
5	Solar Energy 5-day mean return	4.52%
6	Bitcoin 5-day volatility	4.20%
7	VIX 5-day volatility	4.14%

8	Bio Clean Fuel 5-day mean return	3.84%
9	Bio Clean Fuel 5-day volatility	3.68%
10	Geothermal 5-day volatility	3.65%
	Panel C: Bio Clean Fuel, 5-day Random Forest	
Rank	Predictor	Importance share
1	Green Bond 5-day mean return	37.38%
2	VIX 5-day volatility	12.98%
3	Wind 5-day mean return	7.48%
4	Geothermal 5-day mean return	3.87%
5	Geothermal 5-day volatility	3.69%
6	Green Bond 5-day volatility	3.40%
7	Bio Clean Fuel 5-day mean return	3.40%
8	Current Green Bond return	3.01%
9	Gold 5-day mean return	2.36%
10	Green Bond return, lag 2	1.78%

Notes. The table reports the ten highest-ranked predictors based on global SHAP importance for the selected tree-based forecasting models. Global importance is calculated as the mean absolute SHAP value of each predictor across the out-of-sample test observations and is expressed as a percentage of total feature importance within each model. Panel A reports the 22-day Random Forest model for Gold, Panel B the 5-day Gradient Boosting model for Wind, and Panel C the 5-day Random Forest model for Bio Clean Fuel. Higher importance shares indicate a greater contribution of the predictor to the model's forecasts but do not indicate the direction of its effect or establish statistical significance. RF and GB denote Random Forest and Gradient Boosting, respectively.

Appendix Fig. 3. SHAP Summary – Bio Clean Fuel



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