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Bitcoin as an econometric tool for asset co-movement: the relation index

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Abstract
This study proposes a methodological strategy composed of econometric techniques and time series modelling to analyse the dynamic asynchrony between Bitcoin and a basket of traditional sustainable financial assets and emerging markets over a 10-year period marked by major economic and financial changes. The centrepiece of this proposal is the Relation Index that combines vector autoregression and detrended cross-correlation analysis to capture linear and nonlinear dependencies, causality, and time-scale sensitive correlations. Thus, this research fills existing gaps in understanding cross-market interdependencies by integrating cryptocurrencies, sustainability indices, and emerging economies into a rigorous multivariate time series framework. Sustainability indices, emerging markets and Bitcoin have shown a growing correlation since 2020, with both interest rates and Bitcoin having strong autoregressive components. The findings indicate that emerging market equities have undergone a structural shift towards synchronisation with global risk assets, with a correlation index that frequently exceeds 0.6 in periods of systemic stress. This evolution highlights the decline in the advantages offered by diversification in developed and developing economies in a complex and interrelated financial environment.

Keywords Bitcoin · VAR · Asset interdependence · Portfolio diversification · Econometric modeling

Abbreviations

RI	Relation Index
ESG	Environmental, social, and governance
GDP	Gross domestic product
VAR	Vector Autoregression

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ADF	Augmented Dickey–Fuller
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
AIC	Akaike information criterion
BIC	Bayesian information criterion
HQIC	Hannan–Quinn information criterion
RMSE	Root mean squared error
MAPE	Mean absolute percentage error
DCCA	Detrended cross-correlation analysis

1 Introduction

The increasing integration of trade in the global economic environment has further strengthened the impact of financial markets on each other. This situation, which creates both opportunities and risks for investors, also reveals the need for more detailed global analysis by investors, regulators, and public policy makers (Lane and Milesi-Ferretti 2018).

A large and growing number of investors around the world are integrating environmental, social, and governance (ESG) to screen potential investments for their business operations (Amel-Zadeh and GS 2018; Giese et al. 2019). Environmental standards understand how a company operates as a steward of nature. Social criteria analyze how a company handles its relationships with employees, vendors, customers, and the communities in which it operates (Zhang et al. 2021). ESG indices (or sustainability indices) are stock market indices that track the performance of companies that meet high sustainability standards. ESG ratings, which measure the environmental, social and governance performance of corporate issuers, have become a focus of investors. ESG rating is one of the most important criteria for sustainable investment (Avramov et al. 2022).

The Nasdaq-100 stock market index is a collection of the 100 largest and most actively traded companies listed on the Nasdaq exchange. The index includes non-financial companies from a variety of sectors, including manufacturing, technology, healthcare, and others. The weights of the stocks in the index calculation are based on their market capitalization (Nasdaq 2025).

The S&P 500 Index, or Standard & Poor's 500 Index, is a stock market index that tracks the stock performance of 500 leading companies listed on stock exchanges in the US. Covers approximately 80% of the available market capitalization of publicly traded companies in the US, with a total market capitalization of over $49.8 trillion as of 31 March 2025 (S&P-500 2025). The S&P 500 index is considered one of the best indicators of the performance of the stock market in general.

Throughout human civilization, gold has long been the most important precious metal in circulation as a legal standard currency. Gold, as a safe haven asset, attracts investors around the world due to its historical significance, scarcity, high industrial value, and perceived stability. The gold market is a global financial market with various transaction formats, including the spot market, the futures market, the gold derivatives market, the gold ETF and the gold fund (Wang et al. 2024).

Interest rates are a significant factor that affects economic conditions, such as consumer spending, business investment, or overall economic growth (Zhao and Han 2025). Monetary policy, inflation, economic growth, market demand for credit, and commodity prices are the

main determinants of interest rates (Gouel et al. 2024; Audrino and Offner 2024). Therefore, interest rates and macroeconomic conditions mutually influence each other.

In recent years, crypto assets have emerged as a major global financial instrument. The rapid development of financial technologies over the past decade has given rise to a variety of crypto assets, including stablecoins, utility tokens, and non-fungible tokens (Almeida and Gonçalves 2024; Schwiderowski et al. 2024), and the global market value of crypto assets has reached $3 trillion (Coinmarketcap 2025). Bitcoin, the most important asset in this market, has a market value of $1.6 trillion as of March 2025. More recently, in 2024, the US Securities and Exchange Commission approved the listing of Bitcoin-based spot exchange-traded funds on exchanges, which has further increased interest in crypto assets.

In this study, we investigate the dynamic interactions between traditional financial assets, alternative digital assets, macroeconomic variables, and sustainability oriented investments over a 10-year period marked by major economic and financial changes. By integrating cryptocurrencies and sustainability indices into a rigorous multivariate time series framework, the research seeks to fill existing gaps in understanding cross-market dependencies and transmission mechanisms. The potential contributions of this study include advancing the empirical literature on financial interconnectedness, providing new insights into the role of sustainable and digital assets in portfolio diversification. In particular, a composite index (Relation Index) is designed to quantify the evolving relationship between time series. Thus, a robust and replicable methodology is proposed to examine complex financial systems.

From a theoretical standpoint, it is possible to explain the transmission mechanism between Bitcoin and ESG-focused assets through various complementary channels. First, Bitcoin increasingly behaves as a marker of macrofinancial trends, reflecting variations in global risk appetite and speculation, as well as liquidity conditions. Periods of heightened interest in Bitcoin tend to align with more extensive reallocations towards innovation-driven and sustainability-focused assets, particularly among institutional investors that incorporate ESG criteria. Secondly, Bitcoin has the capacity to act as a partial replacement for traditional or alternative safe-haven assets. This occurs when digital assets satisfy speculative demand and thus affect capital flows directed towards sustainability indices. Thirdly, the progressive institutionalisation of Bitcoin through ETFs and regulated investment vehicles – has made it less isolated from traditional financial markets, strengthening its informational relationship with ESG assets. In this context, the Granger causal effects seen between the sustainability index and Bitcoin are consistent with a directional information transmission system, rather than a simple contemporary correlation.

From a methodological point of view, this analysis contributes by suggesting a composite measure, called the Relation Index (RI), which incorporates dynamic dependence and directional predictability into a simplified and unified framework. Unlike existing spillover or connectivity indices, which are based on the decomposition of forecast error variance or purely correlational measures, the RI directly merges Granger causality-based information transmission with correlation dynamics that are sensitive to the time frame. This integration enables a better characterisation of the relationships between markets, especially in diverse systems comprising cryptocurrencies, ESG-targeted assets and macrofinance variables. Due to its construction, the IR is suitable for high-frequency financial data, replicable and transparent, in line with the methodological rigour that is emphasized in quantitative research in the social sciences.

The RI is not intended to be a structural or causal parameter, but rather a composite indicator created to synthesize the complementary aspects of financial interaction. Its role is primarily comparative and exploratory, rather than confirmatory. It is not about testing a single structural hypothesis, but rather capturing how patterns of integration, dependence and information transmission change over time in heterogeneous asset classes with markedly dissimilar market structures and investor bases. By comparing cryptocurrencies, sustainability-focused equities and traditional assets within an integrated empirical framework, the study highlights the relative disparities in the stability, persistence and intensity of market linkages. In this vein, the measures suggested are intended to uncover dynamic and changing connections over time that might not be correctly detected by static or purely parametric models. Thus, rather than a definitive causal classification, an informative map of financial interconnections is provided.

1.1 Literature review

The dynamic interactions and/or interconnections among varied financial instruments are important topics in the quantitative finance literature, and numerous studies have been conducted in this area in the last decade. These studies focused on the interconnectedness and spillover dynamics of green financial instruments, including green bonds and stocks, traditional major assets such as general stocks, crude oil, or gold, and digital assets such as bitcoin, and key macroeconomic variables such as gross domestic product (GDP), GDP growth rate, unemployment rate, inflation rate, and interest rates.

Recently, using a wavelet-based network approach, Ferrer et al. (2021) examined the relationship between green financial instruments and a set of major traditional assets, and demonstrated that green financial instruments are strongly connected to investment grade and Treasury bonds. More recently, in Papathanasiou et al. (2023), the linkages between a private equity ETF and a number of high-demand assets, such as bonds, stocks, crude oil, gold, commodities, currency, Bitcoin and shipping, were investigated. The results of this study indicated a moderate level of correlation between the markets studied, with volatility spillovers appearing to accelerate during turbulent periods. Moreover, Cetin and Bakirtas (2019) examined the long-run interactions among CO_2 emissions, real GDP, fossil fuel consumption, and financial development using heterogeneous dynamic panel data techniques. They found that the environmental Kuznets curve hypothesis is not working for developing markets and fossil fuel energy consumption negatively impacts the environmental quality of emerging markets. In another study, Hachicha et al. (2022) have explored dynamic connectivity and optimal hedging strategy among commodities and financial indices to find the best portfolio strategy to mitigate risk using the framework of Diebold and Yilmaz (2008). The empirical findings of this study highlighted the significance of volatility spillover effects in financial markets.

Pradhan et al. (2022) investigated the interconnections among financial market development, taxation propensity, and economic growth in OECD and non-OECD countries for the period 1961–2019. The most important finding of this study was that both the development of financial markets and the trend towards taxation promote economic growth in the long-term. They have also suggested that an integrated policy approach in developing financial markets and increasing taxation trends of countries will contribute to the economic growth of both OECD and non-OECD countries. Moreover, Yadav et al. (2023) have investigated

the dynamic connection between green bonds and OECD financial markets of European countries in the short, medium and long term, and have demonstrated that the results exhibit volatility in all frequency cycles. They also identified Brussel Stock Exchange and Euronext Amsterdam as high-risk markets in the OECD European market, and suggested that green bonds should be included in these financial markets only for shorter time horizons.

Chomicz-Grabowska and Orlowski (2020), using the Vector Autoregression (VAR) with impulse response functions, investigated the dynamic interactions and feedback effects between the risk of the financial market and key macroeconomic stability variables, including the rate of unemployment, headline inflation, and market-based inflation expectations. They found that the relationship between market risk and macroeconomic fundamentals is mostly neutral under normal and predictable economic conditions. Furthermore, Adarov (2021) have studied interactions between financial and macroeconomic imbalances based on a global sample of 24 countries spanning the period 1998–2012 using Bayesian and generalized method of moments panel VAR frameworks. The authors demonstrated the significant impact of financial cycles on macroeconomic imbalances and how expansions lead to economic overheating and downward pressure on public debt-to-GDP ratios.

Recently, there have been a few studies that concentrated on the connectedness of crypo-assets with other financial instruments. Abakah et al. (2023) have studied the dynamic price correlation and connectedness between the blockchain market (four cryptocurrencies, DeFi, NFTs) and green financial assets (the MSCI Global Environment Price Index and the S&P Green Bond Price Index) using rolling window wavelet correlation model and the quantile-based time-varying connectedness framework. They revealed that the correlation between the cryptocurrency market and green financial assets has strengthened during the COVID-19 pandemic. In addition, in Hanif et al. (2023), the connectivity in high-order moments between cryptocurrency, major stock markets (US, UK, Eurozone and Japan) and commodity (gold and oil) markets was examined. The findings of this study revealed that cryptocurrency, stock and commodity markets are strongly correlated in terms of volatility and volatility bounce component, while their correlations are weak in terms of skewness and kurtosis. The study also showed the potential of gold and oil as hedge investments and safe haven investments for other markets, given that they are least correlated with other markets at all times and investment horizons.

While previous studies have comprehensively examined cross-market linkages using the VAR, the Diebold and Yilmaz approach, wavelet transform-based techniques, dynamic panel data methods, or detrended cross-correlation analysis (DCCA), these approaches remain methodologically fragmented. VAR-based approaches can effectively identify directional relationships but primarily detect linear dependencies, while DCCA-based techniques effectively capture scale-dependent correlations and nonlinear co-movements but do not account for causality or multivariate feedback structures. These facts limit the ability of these approaches to characterize complex, multi-asset dependencies. This study fills this methodological gap by proposing a Relation Index that combines VAR dynamics with DCCA within a unified multivariate framework. Unlike traditional connectivity measures based solely on variance decompositions or correlation structures, the proposed relationship index jointly captures non-linear co-movement and predictive directionality within a unified and transparent framework. When evaluating asset classes that have different investor bases, trading methods, and ways of disseminating information, such as cryptocurrencies and ESG-focused equities, this distinction is particularly important. The proposed methodol-

ogy enables the simultaneous assessment of linear and nonlinear dependencies, directional effects, and time-scale-sensitive correlations across Bitcoin and a basket of traditional and sustainable financial assets. Therefore, this study reveals comprehensive results on cross-market dependencies and transmission mechanisms and, consequently, provides practical implications for portfolio managers, investors, policy makers, and market regulators.

2 Methodology

This study proposes a methodological strategy composed of econometric techniques and time series modelling to analyse the dynamic asynchrony between Bitcoin and a basket of traditional and sustainable financial assets. The centrepiece of this proposal is the Relation Index (RI), a composite index designed to quantify the evolving relationship between Bitcoin and other assets based on causality, mutual dependence, and dynamic correlation.

Financial data were obtained from Yahoo Finance for the following assets: Bitcoin ($BTC-USD$), $S[NONSPACE]\&P500$, Nasdaq, Gold ($GC=F$), the 13-week Interest Rate, and the Sustainability Index ($ESGU$). The selection of these assets is justified by their importance in financial markets and their relevance in previous studies on the interdependence and forecasting of financial time series (Cont 2001; Campbell et al. 1998; Wang et al. 2023). The analyzed period spans from January 1, 2015, to December 31, 2024, with daily frequency.

The methodological components and construction of the RI are presented as follows.

A logarithmic transformation is applied to stabilize the variance.

$$X_t = \log(P_t)$$

where P_t is the closing price at time t. First-order differencing is used to ensure stationary:

$$\Delta X_t = X_t - X_{t-1}$$

Normalization involved standardizing each time series by adjusting the data to have a mean of zero and a variance of one. This technique, obtained through transformation, facilitates comparability between variables at different scales.

$$X'_t = \frac{X_t - \mu}{\sigma}$$

In this context, μ and σ denote the empirical mean and standard deviation of the series, respectively. Data standardization is a typical preprocessing method in time series modelling to improve the robustness and effectiveness of statistical and machine learning models (Alsharef et al. 2022).

The stationarity of the series is assessed using the Augmented Dickey–Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests (Said and Dickey 1984).

The approach is structured in four stages:

1. Data Preprocessing: Frequency adjustment, logarithmic price transformation, and standardization are performed.
2. Dynamic Correlation Analysis: Detrended Cross-Correlation Analysis (DCCA) is used to measure local correlation within moving windows.
3. Construction of the Relation Index: The above information is synthesised into a unified index.

2.1 The relation index: formal and methodological positioning

The Relation Index (RI) is a synthetic measure that reflects the degree of interaction between two financial time series, taking into account dynamic dependence and directional predictive capacity. Let's assume that X_t and Y_t are two normalized and balanced time series.

First, directional dependence is measured through Granger causality tests based on VAR. For each moving window *t*, a normalized causality statistic $G_{X\to Y,t} \in [0,1]$ is calculated. This value indicates the robustness of the predictive data being passed from *X* to *Y* and whether its significance is statistical.

Second, dynamic correlation is used to quantify contemporary and multiscale dependence. This includes the DCCA coefficient, denoted as $\rho^{DCCA}_{X,Y,t}$, which is robust against non-stationarity and sensitive to correlations across various time scales.

The Relation Index is defined as:

$$RI_{X,Y,t} = \frac{1}{2}(G_{X\to Y,t} + |\rho^{DCCA}_{X,Y,t}|) \tag{1}$$

Both components are normalized to ensure comparability. The RI, by its nature, takes values in the range [0,1]; the higher the index value, the stronger and more lasting the relationships between the series.

At this point, it is useful to place the relationship index in explicit terms in relation to the perspectives that exist in the literature for measuring market connectivity. Although there are numerous studies that examine market connectivity using frameworks for decomposing forecast error variance (e.g., Diebold-Yilmaz-style spillover indices), wavelet-based networks, or exclusively correlational measures, the proposed Relationship Index is distinct at both the conceptual and operational levels. Spillover indices measure the contribution of shocks in markets, but they do not take into account contemporary non-linear dependence and are influenced by the specification and layout of the model. On the other hand, pure correlation or DCCA perspectives successfully capture scale-dependent co-movement; however, they do not take into account either the predictive structure or the transmission of directional information.

The RI addresses this methodological gap by explicitly incorporating two complementary dimensions: directional predictability, which is obtained from Granger causality statistics based on a VAR framework; and time-scale-dependent dependence, which is calculated using the DCCA coefficient. The RI provides a brief but informative summary of how assets move together and whether information flows asymmetrically between them by calculating the average of these normalised components.

It is important to emphasise that the IR is not intended to replace existing connectivity measures, but rather to complement them with a comprehensive and appropriate composite index for diverse systems that combine cryptocurrencies, ESG-targeted assets and macro-financial variables.

Conceptually, the RI differs from established connectivity metrics, such as contagion indices that use forecast error variance decomposition, because it explicitly merges directional predictability with dynamic correlation into a single measure. This makes it particularly appropriate for diverse financial systems, where assets may exhibit asymmetric information flows and nonlinear comovement patterns. The parsimonious structure of the RI, while maintaining methodological rigor, improves interpretability.

2.2 Modeling with VAR

The Vector Autoregression (VAR) model is utilised to understand the interconnected behaviour of financial assets. VAR models offer a robust and flexible multivariate framework that treats all variables in the system symmetrically. Each variable is explained by its own past values as well as the lagged values of all other variables. This approach is particularly effective for capturing complex interactions within financial markets, which are characterized by mutual influences and time-dependent interdependencies (Canova 2011; Christiano et al. 2006).

Initially proposed by Sims (1980), VAR models have become essential tools in empirical macroeconomics and financial econometrics due to their ability to represent the dynamic structure of data without imposing strong theoretical assumptions about causality or contemporaneous relationships. In financial time series analysis, they are especially valuable for studying the transmission of shocks, volatility spillovers, and co-movement patterns across different asset classes (Baruník et al. 2016; Forni et al. 2000).

The VAR(p) model is formally defined as:

$$Y_t = c + \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t \tag{2}$$

where:

- Y_t is a k-dimensional vector of stationary time series at time t,
- A_i are $k \times k$ coefficient matrices,
- c is a k-dimensional vector of constants (intercepts),
- ε_t is a vector process of white noise with zero mean and time-invariant covariance matrix Σ.

Before estimating the model, the time series are transformed to achieve stationarity, which is verified through the Augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. Once stationarity is confirmed, the optimal lag length p is selected using various information criteria–such as the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the Hannan–Quinn Information Criterion (HQIC)–which balance fit of the model and parsimony (Brockwell and Davis 2002).

To evaluate the predictive relationships between the variables, Granger causality tests were performed (Granger 1969). These tests assess whether the past values of one time series provide useful information for forecasting another. Formally, the null hypothesis represents the absence of Granger causality and is defined as follows:

$$H_0 : A_i = 0, \quad \forall i = 1, \ldots, p$$

where A_i denotes the coefficient matrices of the VAR(p) model. Under H_0, all lagged coefficients are jointly zero, implying that the process behaves as a vector white noise and that there is no Granger causality between the series.

This approach has been extensively used to identify lead–lag dynamics and contagion effects within international financial markets (Demirer et al. 2018; Billio et al. 2012). Furthermore, impulse response functions and forecast error variance decompositions can be derived from the estimated VAR to analyze the temporal impact and relative importance of shocks throughout the system (Lütkepohl 1990).

VAR models allow for examining the direction and statistical significance of the relationships between Bitcoin prices and those of other assets. For each pair (BTC, asset i), a VAR(p) model is estimated, and the Granger causality test is applied. A significance statistic $G_{i,t}$ is obtained for each time window t, normalized to the range [0, 1].

Although the use of orders with a relatively high delay in daily data may raise concerns about over-parameterization, the standard information criteria (AIC and HQIC) support the selected specification, as it has proven its effectiveness in high-frequency financial situations. Furthermore, daily financial markets tend to exhibit short- and medium-term patterns associated with weekly trading cycles and delayed information processing. The linear VAR model was adopted due to its clarity and interpretability, which are crucial for creating the Relation Index.

Supplementary diagnoses were considered due to the strong correlations currently observed among equity-based variables. The estimated VAR meets standard stability criteria, as demonstrated by the stability condition of the eigenvalue and variance inflation factors. Therefore, the results are analyzed with caution as indicators of predictability rather than structural dependence, particularly when there are regressors with very high correlation.

2.3 Forecasting with VAR

Six-day-ahead forecasts are generated using a recursive technique that takes advantage of the 12 preceding data points in the series. This rolling-origin forecast method emulates a real-time prediction environment by recalibrating the model whenever additional data become available, thus improving the robustness and practical relevance of the forecasting process (Tashman 2000).

Forecasts are produced by repeatedly applying the fitted VAR model. At each step of the forecasting process, the model's latest estimates are used to predict future values, preserving the dynamic relationships among the variables.

To assess predictive accuracy, both scale-dependent and percentage-based error metrics are employed:

- Root Mean Squared Error (RMSE), which penalizes large errors more heavily:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t - y_t)^2} \tag{3}$$

- Mean Absolute Percentage Error (MAPE), which expresses errors as a percentage of actual values:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{\hat{y}_t - y_t}{y_t}\right| \tag{4}$$

Although RMSE is effective for detecting outliers and useful when the forecast scale is important, MAPE is scale-independent, allowing for the comparison of series with different magnitudes. These metrics provide complementary insights into the model's forecasting performance (Hyndman and Koehler 2006).

The residuals of the model are analyzed to evaluate the validity of the underlying assumptions. Diagnostic checks include:

- The Jarque–Bera test for normality of residuals.
- The Ljung–Box Q-test for autocorrelation at multiple lags.

Conducting these diagnostics is essential to confirm that the model has adequately captured the structure of the data and that the residuals exhibit white-noise characteristics. If these assumptions are violated, it may indicate model misspecification, which can compromise the accuracy of the forecast (Lütkepohl 2005).

In addition, forecast uncertainty can be more comprehensively assessed by employing bootstrapped confidence or prediction intervals. These intervals, based on the estimated variance–covariance structure of the VAR model, effectively capture the dispersion of forecast errors over time (Kilian 1998).

It is crucial to emphasize that forecasting is not the primary focus of this research. Rather, forecasting serves as a diagnostic and verification tool to determine whether the calculated VAR structure reflects relevant dynamic relationships. In this context, percentage error measures, such as MAPE, may be overestimated in series with small absolute values, particularly short-term interest rates. Therefore, the accuracy of forecasts should be interpreted with caution, prioritizing scale-dependent metrics such as RMSE.

The six-day horizon is chosen because it is consistent with the moving window structure; it should not be considered an ideal forecast horizon in economic terms. It is not claimed that the predictions are better than simpler baseline predictions.

2.4 Dynamic correlation analysis

Dynamic correlations are assessed using a rolling-window approach (e.g., 12 days) with three primary correlation measures: Pearson, Spearman, and Detrended Cross-Correlation Analysis (DCCA) coefficients (Quesada et al. 2022; Zebende 2011; Zhou 2008). This approach enables monitoring how dependencies among financial assets evolve over time.

DCCA is used as a complement to, not an alternative to, standard correlation measures. While Pearson and Spearman correlations offer useful benchmarks, DCCA is particularly appropriate for assets with long memory characteristics and non-stationary behavior, such as Bitcoin. Combining these measures allows for a more detailed characterization of dynamic comovement.

The duration of the moving window is chosen to balance the statistical reliability of the daily data with short-term responsiveness. Different window dimensions are examined, yielding qualitatively similar patterns in the evaluation measurements and the resulting relation index. This suggests that the most relevant findings are not simply due to the randomness of the window duration.

2.4.1 Correlation measures

- Pearson correlation coefficient measures the linear dependence between two time series X_t and Y_t:

$$\rho_{X,Y} = \frac{\mathrm{Cov}(X_t, Y_t)}{\sigma_X \sigma_Y} = \frac{E[(X_t - \mu_X)(Y_t - \mu_Y)]}{\sigma_X \sigma_Y} \tag{5}$$

- Spearman rank correlation captures monotonic (not necessarily linear) relationships based on the ranked values $R(X_t)$ and $R(Y_t)$:

$$\rho_s = 1 - \frac{6 \sum_{t=1}^{n} (R(X_t) - R(Y_t))^2}{n(n^2 - 1)} \tag{6}$$

- DCCA coefficient, which is robust to nonstationarity and quantifies scale-dependent cross-correlations, is defined for a window size *s* as:

$$\rho_{\mathrm{DCCA}}(s) = \frac{F_{XY}^2(s)}{F_X(s) F_Y(s)} \tag{7}$$

where $F_X(s)$ and $F_Y(s)$ denote the fluctuation functions in detrend of *X* and *Y*, and $F_{XY}(s)$ represents the detrended covariance.

3 Data

For this paper, all financial time series are created using closing prices adjusted to account for dividends, splits, and other company actions. The tickers chosen are Bitcoin (BTC-USD), Gold, a US short-term interest rate, the ESGU exchange-traded fund, and the major US stock market indices (S&P 500 and Nasdaq) and Emerging markets. ESGU is used as a practical indicator (sustainability index) of ESG-focused equity investments, taking into account its mechanical correlation with major US equity indices and analyzing performance accordingly. The ESGU exchange-traded fund is used as a practical tool for equity investments that target sustainability. ESGU tracks a broad range of US equities selected

according to social, environmental and governance criteria. It also offers high liquidity, uninterrupted pricing and accessible data on a daily basis. These properties make it particularly suitable for econometric time series analysis and integration into a VAR framework. However, it should be noted that ESGU, as a market-based ESG indicator, automatically correlates with the most important stock market indices in the United States and reflects investors' opinions on sustainability, rather than direct social or environmental results. Therefore, the Sustainability Index presented in this research should be considered an indicator of how the financial market operates with ESG criteria, rather than a direct measure of sustainability performance.

To ensure consistency across assets with different trading calendars, all series are synchronized across the intersection of trading days, thus avoiding non-overlapping observations caused by market holidays. Missing values that arise during this synchronization process are addressed by removing incomplete observations within each moving estimation window. This ensures that the VAR system is estimated on balanced panels across the entire sample. This data processing enhances the transparency, internal consistency, and repeatability of the empirical analysis. All data is obtained from Yahoo Finance.

4 Empirical results

In this study, we propose a Relation Index (RI) to examine the dynamic interactions between traditional financial assets, alternative digital assets, macroeconomic variables, and sustainability index. We consider the period from January 1, 2015 to December 31, 2024, since it encompasses several economic cycles, including bull and bear markets, changes in monetary policy and macrofinancial shocks such as the COVID-19 pandemic and inflationary spikes, and thus will allow us to study the relationship between the assets considered under varied financial market conditions. We have obtained the data from Yahoo Finance. These assets are chosen not only for their economic importance and market capitalisation, but also for their frequent use in studies exploring interdependence, risk transmission, and forecasting in financial systems (Cont 2001; Wang et al. 2023). The inclusion of a sustainability index also introduces a modern perspective on green finance and its interplay with traditional markets.

Data preprocessing follows a structured pipeline that aimed to ensure the statistical properties required for reliable modelling. Adjusted closing prices are used to eliminate the impact of dividends, stock splits, and other corporate actions. Logarithmic transformation is applied to stabilise variance and reduce heteroskedasticity, a common feature in raw financial series. To induce stationarity, which is a prerequisite for most time series models, first-order differencing is performed. Subsequently, each series is standardised by subtracting its mean and dividing by its standard deviation. This normalisation ensures that all time series are on a comparable scale, which is especially important for multivariate models such as the VAR.

Stationarity is assessed using two complementary tests: the ADF test, which evaluates the null hypothesis that a unit root is present in the series (i.e. non-stationarity) and the KPSS test, which tests the null hypothesis of stationarity around a deterministic trend. The combination of both tests provides a robust diagnostic framework: a low p value in the ADF test indicates rejection of the unit root hypothesis, suggesting stationarity, while a high p value in the KPSS test indicates that the data do not significantly deviate from stationarity.

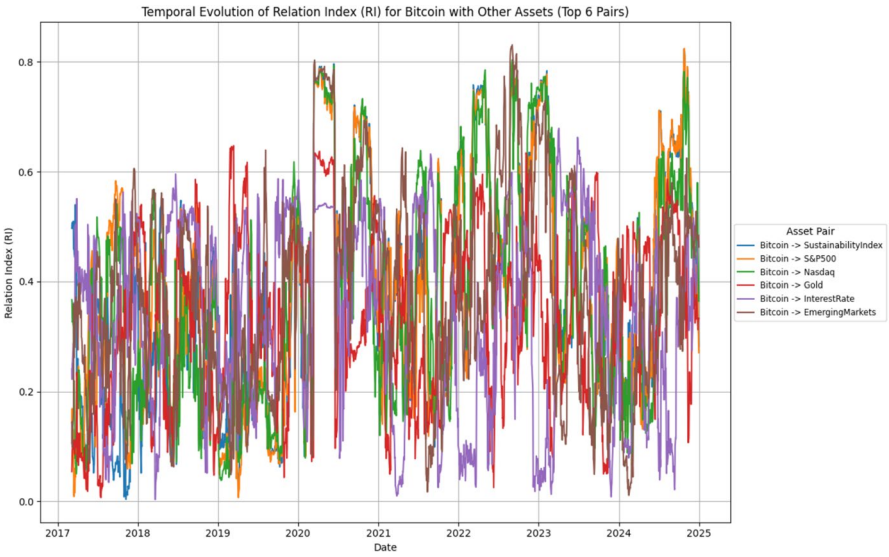


Fig. 1 Temporal evolution of RI for Bitcoin with other assets

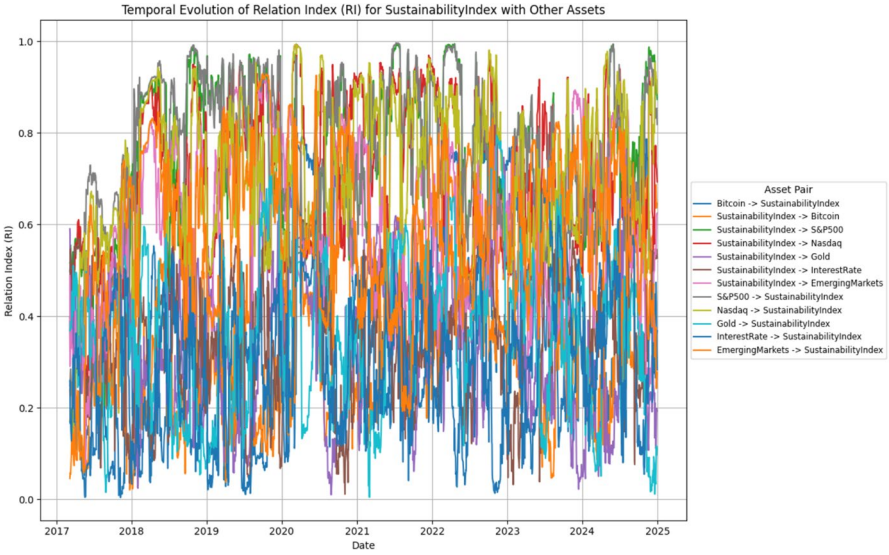


Fig. 2 Temporal evolution of RI for Sustainability index with other assets

Figures 1, 2,3, 4, 5 and 6, 7 show the Relation Index (RI), a dynamic measure that calculates the level of co-movement and dependence between key asset pairs from 2017 to the beginning of 2025. This set of visualizations shows how correlation structures are modified by systemic macroeconomic events and changes in market sentiment, challenging conventional diversification strategies and highlighting convergence processes between assets with different characteristics.

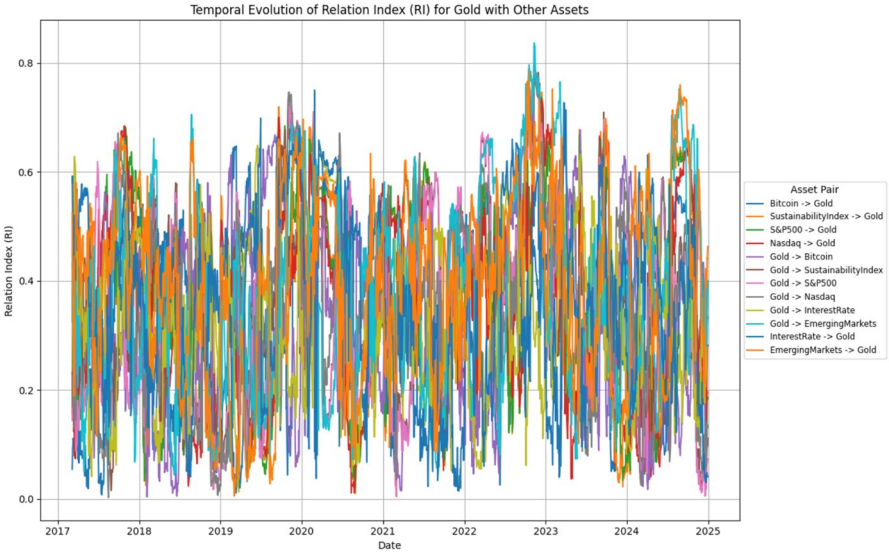


Fig. 3 Temporal evolution of RI for Gold with other assets

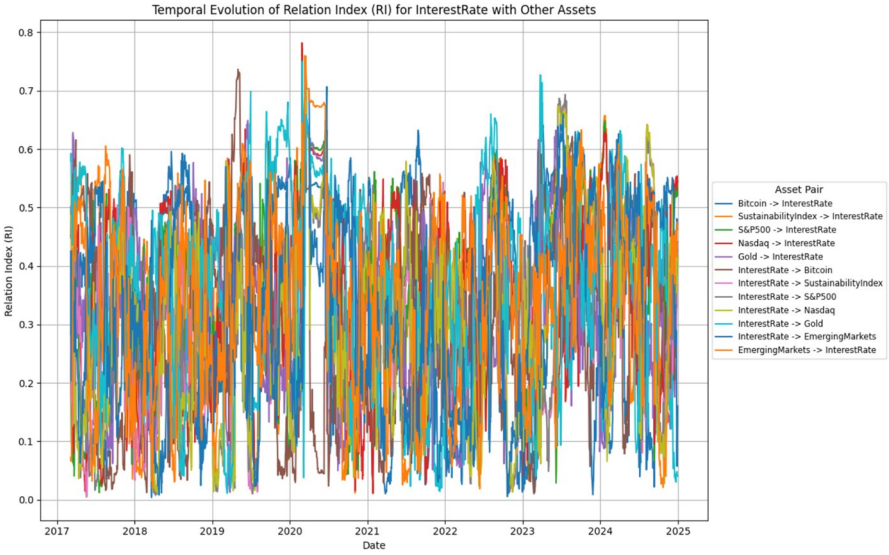


Fig. 4 Temporal evolution of RI for Interest Rate with other assets

Figure 1 illustrates how Bitcoin has evolved from an isolated asset to one with a high degree of integration. Its volatile sensitivity to interest rates and its increasingly strong correlation with equity indices (Nasdaq, S&P 500 and emerging markets) demonstrate that it is becoming a more mature, high-risk financial asset. An initial phase (2017–2019) of relatively low correlation is noticeable, during which it functioned almost idiosyncratically. However, the RI with the S&P 500, Nasdaq and emerging markets equities underwent a

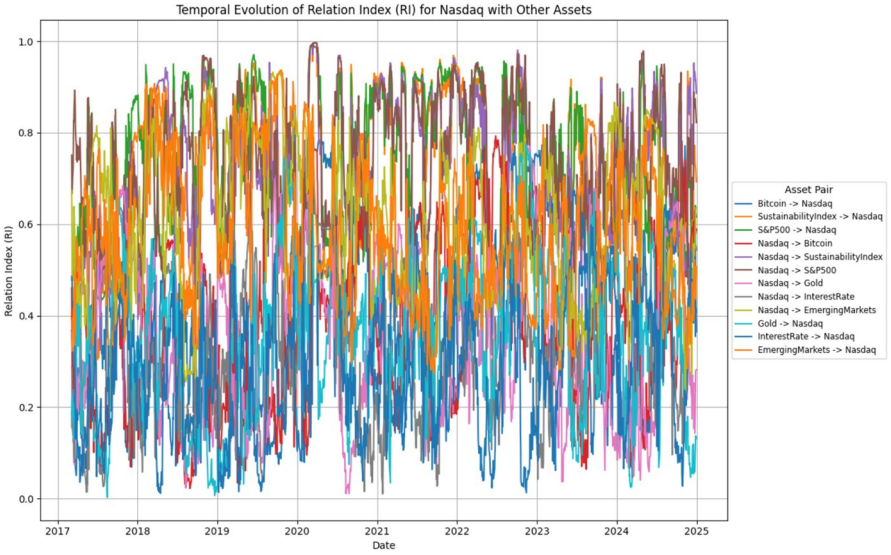


Fig. 5 Temporal evolution of RI for Nasdaq with other assets

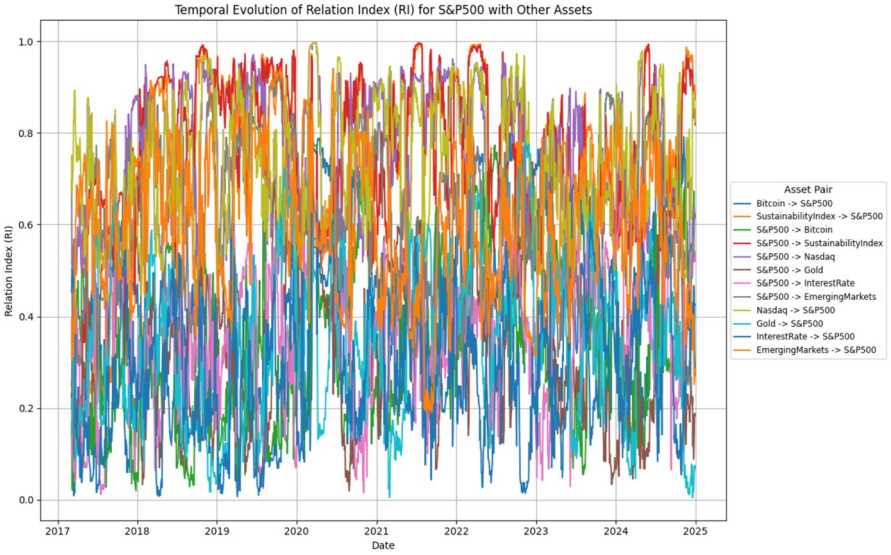


Fig. 6 Temporal evolution of RI for S&P 500 with other assets

structural change starting in 2020, often remaining above 0.6. This "persistent positive correlation" indicates that Bitcoin no longer has the characteristic of being an uncorrelated asset, which allowed it to function as a global liquidity detector and a risk-on asset sensitive to the emotions of the technology market and global growth sentiment.

Figure 2 demonstrates how ESG criteria are incorporated into portfolios worldwide. Figure shows an increasingly strong connection with traditional stock market indices and



Fig. 7 Temporal evolution of RI for Emerging Markets with other assets

emerging markets, suggesting that sustainable assets have moved beyond a niche market and now follow mainstream market trends. Initially, the sustainability risk index was more independent; however, after 2020 it became almost entirely aligned with traditional stock market indices and emerging markets equities. This shows that sustainable assets have moved beyond a niche market and become integrated into the dynamics of the general market, increasing their susceptibility to systemic risks across both developed and developing economies and indicating that they do not provide clear differential protection in situations of high volatility.

Figure 3 shows the enduring status of gold as an active safe haven, despite periods of erratic performance. It's RI tends to rise during crises of confidence, with peaks in its ratio to Bitcoin and emerging markets indicating periods when both competed for the "store of value" narrative or reacted to systemic stress. Figure 3 shows that gold remains a safe-haven asset, although its relationship structure is fragmented and reactive. Periods of geopolitical uncertainty and inflationary crises, and volatility in emerging economies coincide with peaks in the RI (beyond 0.7). A key finding is the instability of its relationship with Bitcoin: the market oscillates between digital assets and gold as a store of value, without one permanently prevailing over the other. This indicates that they compete for the safe-haven narrative depending on the prevailing volatility regime.

Figure 4 shows how monetary policy affects the global ecosystem. Since 2022, with the end of the zero-Interest Rate, structural transformations in the IR have been observed, recalibrating its relationship with crypto, technology assets and emerging markets. Asset valuation is affected by monetary policy, as this figure shows. After the monetary tightening cycle began in 2022, the RI between interest rates and growth assets (Nasdaq/Bitcoin) as well as emerging economies became highly volatile. These erratic movements demonstrate a "recalibration" phase, in which each macroeconomic data point causes drastic changes in

dependencies, highlighting that monetary policy is currently the main driver of instability in global correlations and critical factor in the risk appetite for emerging assets.

Figure 5 shows one of the most stable and strongest interdependencies, especially with Bitcoin, the S&P 500 and emerging markets. The high levels of RI (around 1.0) highlight the supremacy of the technology sector in global market management and its role as a liquidity regulator. It shows the most stable and highest levels of RI, particularly its relationship with the S&P 500, which is approaching unity (1.0). The figure illustrates how the Nasdaq influences other investments, including Bitcoin, sustainability indices and emerging market equities. The high level of interconnectedness highlights the dominant role of the technology sector in the overall market direction; technology risk has shifted from sectoral to systemic, deeply synchronizing with emerging economies and significantly diminishing the benefits of diversification.

Figure 6 is considered the benchmark for the market. It's RI figure is crucial for analyzing the phenomenon of financial "contagion," in which, during periods of high volatility, most assets (including Bitcoin and emerging markets) tend to fluctuate in parallel with this index. This figure, acting as a benchmark, allows for the visual detection of the "contagion footprint". Periods in which almost all RI lines converge simultaneously toward the 0.8–0.9 threshold, including the strong synchronization with emerging market equities are times of market capitulation. Diversification loses effectiveness during these episodes because the instability of the US market affects even assets with very different fundamentals, confirming the hypothesis that, during systemic crises, all correlations tend to become one across the entire global financial spectrum.

Figure 7 illustrates how the relationship index (RI) between emerging markets and different financial assets has evolved over the period 2017–2025. Each line indicates the direction and intensity of the relationship between a specific asset and emerging markets, both in terms of transmission to the latter and from them to other markets. The RI generally shows high variability over time, indicating that the interdependencies between emerging markets and other assets are not stable, but rather change according to global financial conditions. There are episodes with high indices, indicating greater transmission or integration of shocks, and others with lower indices. This shows periods of relative decoupling. This dynamic reveals that financial relationships vary over time and highlights the importance of examining the links between assets dynamically, rather than statically.

The analysis of the Relation Index (RI) between 2017 and 2025 shows that the boundaries between alternative and traditional assets have become much more blurred. The financialization of Bitcoin is a clear example, as it has ceased to be a marginal asset and now acts as a risk measure strongly correlated with the Nasdaq and the S&P 500 during times of systemic stress. Sustainability indices and emerging market equities are following a similar pattern, as they increasingly align with global risk assets, signalling deeper integration into broader financial dynamics. This structural synchronisation means that the benefits of diversification diminish just when they are most needed, as changes in global risk appetite and liquidity shocks spread rapidly across asset classes and regions. Therefore, these findings emphasise the limitations of static correlation schemes and highlight the need to employ dynamic analytical methods that can capture the changing and unstable nature of financial interdependencies over time in an increasingly interconnected global financial system.

Table 1 summarises the results of the ADF and KPSS tests applied to the preprocessed series. All assets exhibit extremely low p values in the ADF test, strongly rejecting the pres-

Table 1 Stationarity test results (p values)

Asset	ADF p value	KPSS p value
Bitcoin	2.68×10^{-28}	0.1
Sustainability Index	6.57×10^{-23}	0.1
S&P 500	8.29×10^{-25}	0.1
Nasdaq	4.42×10^{-23}	0.1
Gold	0.00	0.1
Interest Rate	1.80×10^{-13}	0.1
Emerging Markets	0.000000e+00	0.1

Table 2 Summary of VAR model estimation

Statistic	Value
Number of equations	7
Number of observations	2017
Log-likelihood	− 13243.1
Akaike information criterion (AIC)	− 6.62955
Hannan–Quinn information criterion (HQIC)	− 6.33754
Bayesian information criterion (BIC)	− 6.52237
Final prediction error (FPE)	0.00132076
Determinant of covariance matrix ($\mathrm{Det}(\Omega_{\mathrm{MLE}})$)	0.00125401

ence of a unit root, and thus confirming that the series are stationary after transformation. Similarly, the KPSS test yields p values of 0.1 for all assets, which means that we do not reject the null hypothesis of stationarity at the level of 10% significance. The consistency across both tests enhances confidence in the stationarity of the data, justifying their use in time-series models that assume weak stationarity.

These results validate the adequacy of the transformations applied and support the use of models such as the VAR, which rely on the assumption of stationarity for consistent parameter estimation and meaningful inference. Furthermore, ensuring stationarity is fundamental for avoiding spurious regression results and enhancing the interpretability of multivariate interactions across the selected assets.

Following the preprocessing steps and the verification of stationarity, a VAR model is estimated to capture the dynamic interactions among the seven financial time series: Bitcoin, Sustainability Index, S&P 500, Nasdaq, Gold, the US 13-week interest rate, and emerging markets. The model specification is selected on the basis of information criteria, ensuring parsimony without compromising explanatory power. Table 2 presents the key summary statistics of the estimated VAR model.

The most relevant statistical indicators of the VAR model estimate are shown in the table. It consists of seven equations corresponding to seven endogenous variables and is estimated with 2017 observations, a sample size large enough to ensure the reliability of the estimators obtained through Ordinary Least Squares. A log-likelihood value of −13,243.1, in addition to the information criteria, indicates that the model has a good fit in general terms. Specifically, the low HQIC and AIC values show an appropriate balance between parsimony and explanatory power; in contrast, the BIC, which is slightly less favourable, shows that its penalty for complexity in larger systems is greater. The low value of the final prediction error indicates an improvement in the predictive accuracy of the model, and the small determinant of the covariance matrix of the innovations suggests limited residual variance

and little contemporary correlation between the errors of the equations, which supports the stability and internal consistency of the VAR system with the new information.

These results confirm the suitability of the model to capture the joint dynamics of the financial series. It will be used in subsequent sections for forecasting, Granger causality testing, and scenario analysis. Details of the VAR estimation results for each asset considered are presented in the Appendix (see Tables 8, 9, 10, 11, 12, 13 and 14).

Based on the results of the estimated tables, the VAR model shows a complex structure of interdependencies and internal dynamics between financial variables. The autoregressive elements are particularly important for the Nasdaq, Gold, interest rates and the Sustainability Index, as they show both momentum and mean reversion. Bitcoin has a positive impact on the Sustainability Index and Emerging Markets with subsequent lags, suggesting delayed spillovers rather than instantaneous transmission. This dynamic is confirmed by the results of the Emerging Markets equation: the Nasdaq has a significant positive impact in the first lag, while the Sustainability Index and the emerging market lag itself exhibit negative effects, indicating internal adjustments; in the second lag, the Nasdaq has a negative effect and interest rates have a positive effect, highlighting the influence of global financial conditions and monetary policy.

Granger causality analysis suggests that Bitcoin acts as a leading indicator of market liquidity and expectations, anticipating changes that later manifest themselves in sustainable markets and ESG assets. This directional effect indicates that sustainability investment decisions take some time to react to information first incorporated by Bitcoin, supporting its role as a leading variable within the global financial system.

The correlations of the residuals after estimation show additional structural links that are not detected by autoregressive dynamics alone. This makes it possible to discern hidden co-movements and idiosyncratic behaviours among assets.

Finally, beyond the dynamic interactions captured by VAR, the analysis of residual correlations provides additional information on persistent structural relationships. This approach allows us to identify latent co-movements and dependencies that are not fully explained by the temporal dynamics of the model, thus complementing the evidence on the integration and relative autonomy of different financial assets.

A strong post-estimation dependence among traditional equity-based assets is observed in the residual correlation matrix shown in Table 3. In particular, the Sustainability Index exhibits high residual correlations with the Nasdaq and the S&P 500 (with correlation coefficients around or exceeding 0.94), indicating a marked structural co-movement that continues even after taking into account the dynamic interactions captured by the model.

Table 3 Correlation matrix of residuals

	Bitcoin	Sust. Index	S&P500	Nasdaq	Gold	Interest rate	Emerging markets
Bitcoin	1.000000	0.262217	0.267304	0.275093	0.096557	−0.008095	0.227929
Sust. Index	0.262217	1.000000	0.978794	0.935397	0.064718	0.054791	0.718205
S&P500	0.267304	0.978794	1.000000	0.946753	0.060666	0.058997	0.740330
Nasdaq	0.275093	0.935397	0.946753	1.000000	0.066422	0.030402	0.733019
Gold	0.096557	0.064718	0.060666	0.066422	1.000000	0.015084	0.172933
Interest rate	−0.008095	0.054791	0.058997	0.030402	0.015084	1.000000	0.110820
Emerging markets	0.227929	0.718205	0.740330	0.733019	0.172933	0.110820	1.000000

Table 4 Out-of-sample forecasting performance

Asset	RMSE	MAE	MASE
Bitcoin	0.0116	0.0116	0.258
Sustainability Index	0.0566	0.0566	5.219
S&P 500	0.0732	0.0732	6.761
Nasdaq	0.0897	0.0897	6.374
Gold	0.0497	0.0497	5.131
Interest rate	0.1008	0.1008	1.691
Emerging markets	0.0960	0.0960	7.194

Table 5 Variance decomposition from lagged values

Lag	S&P500	Nasdaq
0	0.0000	0.0000
1	0.1667	0.0833
2	0.8333	0.9167

Emerging markets also show fairly high residual correlations with the main stock market indices (close to 0.72−0.74), which highlights their close integration with global stock market dynamics. In contrast, Bitcoin and gold show relatively low residual correlations with most assets, indicating more idiosyncratic behaviour. Interest rates show correlations close to zero across the system, indicating that their incidence is captured mainly through model dynamics rather than contemporary residual dependence.

The following provides a statistical overview of the dynamics among key financial assets, including cryptocurrencies (Bitcoin), equity indices (S&P500, Nasdaq), Gold, Interest Rates, Sustainability Index and Emerging Markets (see Table 4). Specifically, we evaluate residual dependencies after model estimation, assess predictive performance using RMSE, MAE and MASE metrics, and analyse the temporal contribution of past lags through variance decomposition. In addition, we examine the contemporaneous correlation between Interest Rates and other asset classes. The aim is to uncover both structural and dynamic links that inform risk management, asset pricing, and policy implications.

RMSE and MAE calculate the average measure of forecast errors in the same units as the series, providing an indication of absolute predictive accuracy. MASE, which stands for Mean Absolute Scaled Error, is scale-invariant and compares model performance to a basic random walk, enabling a relevant comparison between diverse assets. If MASE values are less than 1, it means the VAR model improves a simple persistence forecast. If values are greater than 1, it indicates that the model does not outperform the benchmark. Bitcoin has a low MASE (0.258), revealing a remarkable predictive capacity. In contrast, stock market indices, gold, and the sustainability index have MASE values much higher than 1. This indicates that for these assets, simple benchmark indices are equally or more effective. Interest rates exhibit an intermediate performance (MASE 1.691), demonstrating that predictive gains are lower compared to a simple prediction. Emerging markets show the worst forecast performance (MASE = 7.194), indicating highly complex and unstable dynamics. This makes them particularly difficult to forecast with linear VAR specifications.

The decomposition indicates that more than 80% of the forecast variance for both S&P500 and Nasdaq is explained by the second delay (see Table 5). This result highlights the persistence and strong autoregressive behaviour in equity indices.

Table 6 Contemporaneous correlation with interest rate

Variable	Correlation with interest rate
Bitcoin	0.0886
Sustainability Index	0.1662
S&P500	0.1862
Nasdaq	0.2641
Gold	0.4691
Interest Rate	1.0000

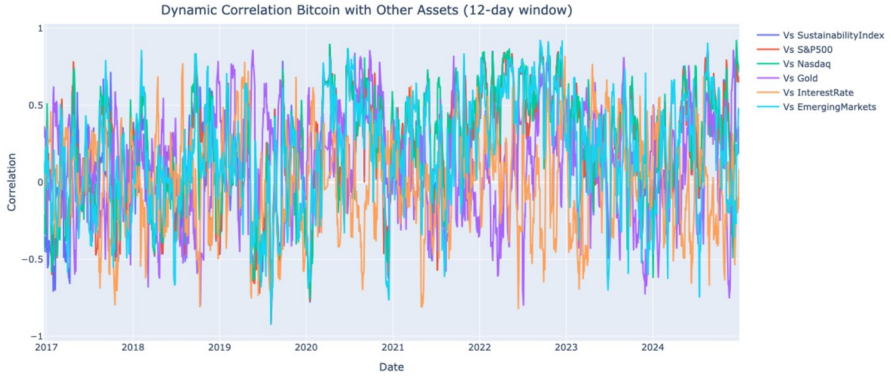


Fig. 8 Dynamic Correlation Bitcoin with other assets (2017–2024)

The Interest Rate shows a low contemporaneous correlation with most financial assets, with Gold showing the highest association ($\rho = 0.469$), possibly due to its traditional role as a hedge against monetary policy changes (see Table 6). These findings suggest that the effects of monetary policy may be predominantly lagged in nature, rather than instantaneous.

Although Spearman and Pearson correlations detect current linear and monotonic dependence, they are vulnerable to non-stationarity and trending behavior. DCCA, by capturing persistent joint movement under trending dynamics, adds value to these measures, which is especially important for Bitcoin and other financial series with long memory characteristics. Consequently, discrepancies between standard correlations and DCCA are considered informative, not redundant.

Figures 8, 9, 10, 11, 12, 13, 14 present the rolling correlations between pairs of financial assets over the period 2017 to 2024. The correlations are calculated using a fixed-size rolling window, providing insight into the time-varying co-movement patterns of each asset pair.

The dynamic correlation figures indicate a market structure marked by heterogeneity, in which Bitcoin stands out for its low and erratic levels, confirming its speculative nature and constant decoupling from traditional assets. In contrast, the Sustainability Index, the S&P 500 and the Nasdaq show a strong correlation, with figures close to 1, indicating joint exposure to global equity forces. Gold, meanwhile, retains inverse or weak connections with cryptocurrencies and equities, reinforcing its role as a hedging asset. In contrast, emerging markets and interest rates exhibit unstable and noisy behaviour due to regional risks and monetary policies. This discrepancy between the strong integration of stock market indices and the instability of alternative assets highlights that, in the face of fluctuations in instru-

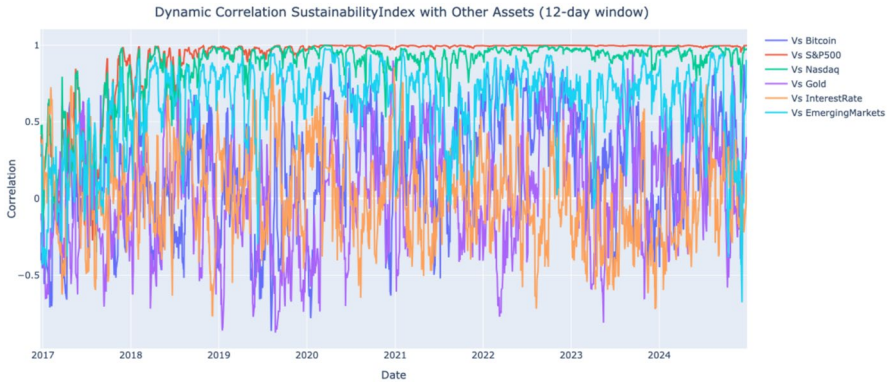


Fig. 9 Dynamic Correlation Sustainability Index with other assets (2017–2024)

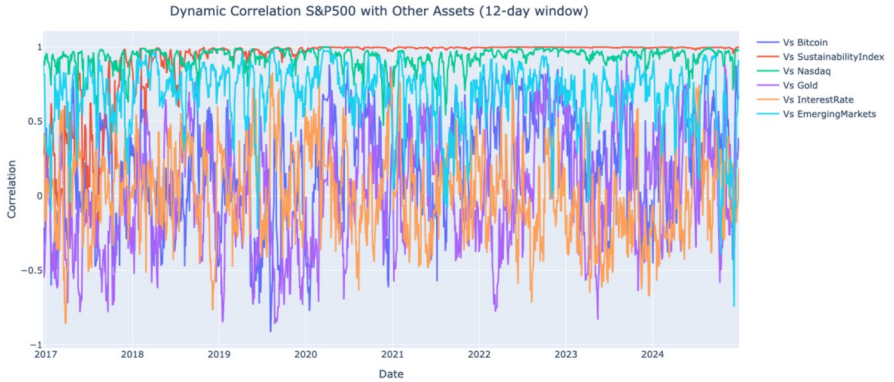


Fig. 10 Dynamic Correlation S&P 500 with other assets (2017–2024)

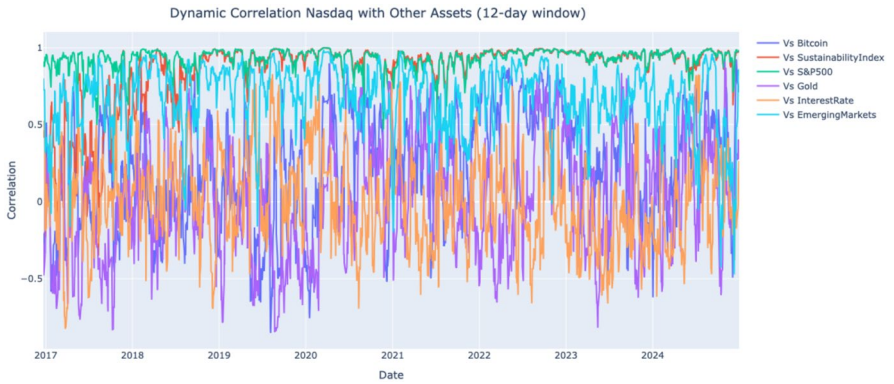


Fig. 11 Dynamic Correlation Nasdaq with other assets (2017–2024)

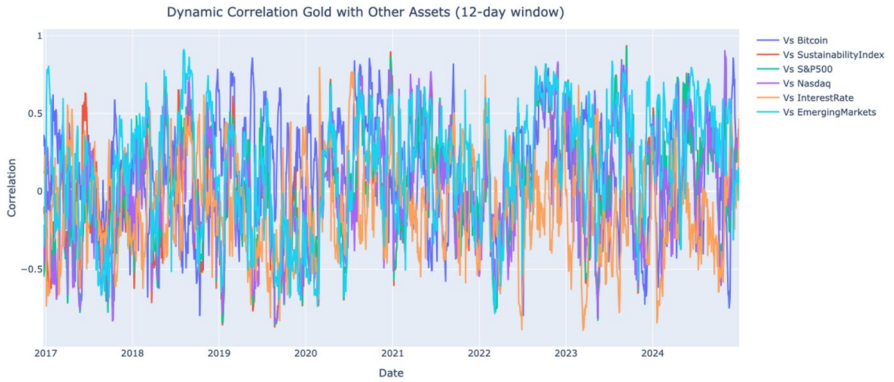


Fig. 12 Dynamic Correlation Gold with other assets (2017–2024)

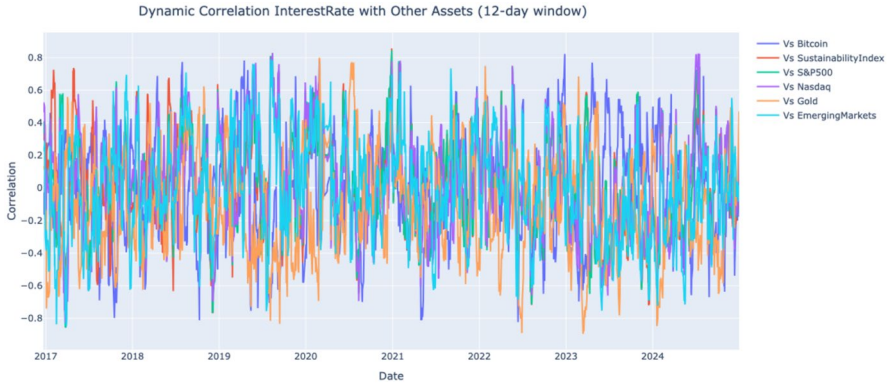


Fig. 13 Dynamic Correlation Interest Rate with other assets (2017–2024)

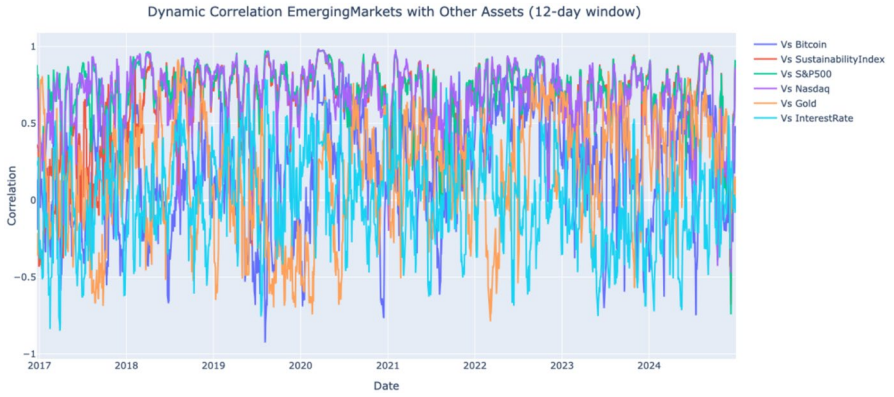


Fig. 14 Dynamic Correlation Emerging Markets with other assets (2017–2024)

ments such as Bitcoin, it is essential to implement specific diversification tactics for each type of asset.

To complement the visual representation of the rolling correlations shown in Fig. 8, we conducted a descriptive statistical analysis of the pairwise rolling correlations for all asset combinations during the period 2017–2024. Table 7 reports the mean, standard deviation, minimum, and maximum of these rolling correlations.

Traditional stock market indices (S&P 500, Nasdaq and Sustainability Index) show very strong and statistically robust correlations, with estimated coefficients ranging from 0.87 to 0.94. These high values, combined with rather narrow confidence intervals, indicate a remarkable level of co-movement and integration in global stock markets.

On the other hand, Bitcoin exhibits weak to moderate correlations with conventional financial assets. Its highest correlations are with stock indices, specifically the Nasdaq (0.228) and the S&P 500 (0.214). However, these relationships have wide confidence intervals that encompass negative values, indicating limited statistical stability. This pattern supports the idea that Bitcoin is a different asset class, with volatile and diverse connections to traditional markets over time.

Table 7 Summary statistics of rolling correlations (2017–2024)

Asset pair	Mean	Std. Dev.	Min	Max
Bitcoin - SustainabilityIndex	0.206908	0.249639	−0.399517	0.686356
Bitcoin - S&P500	0.213769	0.243216	−0.409354	0.674418
Bitcoin - Nasdaq	0.227741	0.243272	−0.392372	0.729406
Bitcoin - Gold	0.090422	0.185733	−0.329194	0.548597
Bitcoin - InterestRate	−0.002044	0.142619	−0.398712	0.475501
Bitcoin - EmergingMarkets	0.183682	0.239439	−0.373850	0.698318
SustainabilityIndex - S&P500	0.920650	0.191583	0.111579	0.999358
SustainabilityIndex - Nasdaq	0.871812	0.183709	0.135714	0.996128
SustainabilityIndex - Gold	0.019989	0.242432	−0.543117	0.610014
SustainabilityIndex - InterestRate	0.015116	0.145836	−0.395424	0.546278
SustainabilityIndex - EmergingMarkets	0.643987	0.184156	−0.041743	0.948856
S&P500 - Nasdaq	0.935291	0.041700	0.781720	0.995916
S&P500 - Gold	0.005437	0.248097	−0.554644	0.600022
S&P500 - InterestRate	0.021371	0.142773	−0.400546	0.544982
S&P500 - EmergingMarkets	0.697556	0.126401	0.072431	0.950277
Nasdaq - Gold	0.012676	0.230457	−0.540552	0.579747
Nasdaq - InterestRate	0.006755	0.141741	−0.378409	0.564857
Nasdaq - EmergingMarkets	0.698152	0.121777	0.105506	0.953573
Gold - InterestRate	−0.103928	0.139346	−0.557612	0.518042
Gold - EmergingMarkets	0.151389	0.253368	−0.521707	0.707172
InterestRate - EmergingMarkets	0.020788	0.157332	−0.413609	0.519272

Furthermore, correlations involving Bitcoin tend to show wider dispersion, supporting the notion of volatile and non-stationary dependency structures over time. Gold and interest rates have very low correlations with most other assets, which are often close to zero and statistically insignificant, consistent with their classic role as diversification or hedging instruments.

Overall, the combination of consistent and strong correlations between stock indices and unstable and weak correlations between Bitcoin and other alternative assets highlights the importance of time-varying correlation models and underscores the value of dynamic strategies for portfolio allocation in mixed-asset investment contexts.

Although the Appendix and the VAR estimate show a significant number of statistically significant coefficients (see Tables 8, 9, 10, 11, 12), their economic significance should be understood by considering broader financial mechanisms, not coefficient by coefficient. Specifically, Bitcoin's predictive capacity for the Sustainability Index, documented in Tables 8 and 9, can be interpreted as reflecting variations in the global willingness to take risks, experimentation with institutional portfolios, and the flow of information from digital markets to equity investments focused on sustainability. As Bitcoin increasingly functions as an indicator of market liquidity and speculative sentiment, fluctuations in its price dynamics can anticipate a reallocation toward ESG assets. These assets typically react with a delay because their structure is based on equities and their investment mandates. Similarly, the negative and delayed effects of Bitcoin on gold observed in the VAR estimates (see Table 12) are consistent with a substitution mechanism among alternative stores of value. This process causes demand for traditional safe-haven assets to decrease temporarily when digital assets are in higher demand. From this point of view, the coefficients that are reported in the Appendix are statistically significant and reflect interaction paths with economic importance, even though their individual values change depending on the lags.

5 Conclusion

This study provides robust empirical evidence on the dynamic interrelationships among traditional financial assets (S&P 500, Nasdaq, Gold), alternative assets (Bitcoin), macroeconomic variables (Interest Rates) and a sustainability index. Through a high-dimensional Vector Autoregression (VAR) model applied to rigorously preprocessed and stationary time series data, several significant insights have been obtained.

The results highlight the critical importance of autoregressive components in the price dynamics of Bitcoin, the Sustainability Index, and Interest Rates, suggesting persistent momentum or mean reversion behaviours across these assets. The effects of the cross-market are also selective but meaningful. Bitcoin exhibits a significant influence on both the Sustainability Index and Gold, suggesting an emerging link between digital and sustainable assets, as well as a potential substitution effect with traditional safe havens. Interest rate dynamics are primarily shaped by their own historical patterns, but equity market movements, particularly from the S&P 500 and Nasdaq, exert a measurable delayed impact, emphasising the interconnectedness of financial and macroeconomic environments.

Residual and rolling correlation analyses reveal a heterogeneous dependency structure: Although equity indices and the Sustainability Index are strongly and consistently correlated, Bitcoin and Gold remain largely idiosyncratic. This reinforces the value of digital

assets and commodities as diversification tools within portfolio management, particularly in increasingly integrated markets.

The results improve the comprehension of financial connections in a setting that includes traditional, sustainable and digital assets. We highlight the importance of adaptive and asset-specific risk management approaches, thereby adding to the expanding literature that bridges financial econometrics and sustainable finance. This research significantly advances the scientific discipline by merging modern sustainability aspects with high-frequency analysis of digital assets within a robust multivariate time series framework. It offers a replicable approach and delivers practical insights for scholars, investors, and policymakers aiming to understand the intricacies of today's financial markets.

Extending the analysis to emerging markets presents an encouraging opportunity for future research, particularly to determine whether Bitcoin plays a similar econometric role in less developed financial systems.

6 Limitations and future research

This study has limitations that must be acknowledged, despite its empirical richness and methodological contributions; however, these limitations also point to promising areas for future research.

First, the analysis focuses primarily on developed financial markets, particularly US stock indices and a sustainability-oriented exchange-traded fund. Although this choice is driven by data availability, liquidity, and the crucial role these markets play in global finance, it restricts the generalisation of the results. Emerging market financial systems often have different structural features, including greater instability, shallower market depth, and higher sensitivity to global shocks. Extending the scope of the Relation Index to frontier and emerging markets could provide useful insights into market integration, contagion dynamics, and opportunities for global diversification. The use of market indicators to reflect sustainability is another limitation. Although ESG-focused ETFs (such as ESGU) provide transparency, liquidity, and high-frequency data, they continue to be affected by overall stock market dynamics and investor sentiment. Therefore, ESG quality at the company level, actual environmental impact, or long-term sustainable results may not be fully reflected. By incorporating other ESG measures, such as composite sustainability ratings, company-level ESG scores, or non-market-related indicators, future research could expand the framework proposed. This would enable a more precise distinction between financial integration and genuine sustainability performance.

Secondly, the empirical framework uses linear vector autoregression (VAR) models to capture predictive relationships and dynamic interdependencies. Although VAR models remain a benchmark in financial econometrics due to their transparency and flexibility, they may not fully capture nonlinear dynamics, regime shifts, or structural breaks, which are particularly significant for cryptocurrencies and ESG-related assets. Future research has the potential to extend the suggested framework by including nonlinear or regime-switching models, such as threshold VARs, Markov switching VARs, or multivariate architectures based on machine learning, while maintaining the ability to interpret the Relation Index.

Thirdly, although the research incorporates dynamic correlation methods, such as DCCA, choosing the lengths and scales of the moving windows necessarily requires a certain degree

of arbitrariness. Although robustness checks indicate that the main patterns are stable, understanding short-, medium- and long-term dependency structures could be enriched by alternative window specifications or multiscale decompositions. Future research also has the potential to examine perspectives in the frequency domain or wavelet-based expansions of the Relation Index, with the aim of explicitly taking into account the temporal heterogeneity present in the various investment horizons. A natural extension of this analysis would be a scale-dependent exploitation of the DCCA, allowing for separate examination of short-, medium-, and long-term horizons. While this decomposition could provide additional information about diversity over time, it is not included in the present study, which prioritizes parsimony and comparability in constructing the Relation Index.

Fourth, in this research, Bitcoin is viewed as an econometric market variable that reflects the state of liquidity, risk perception, and investor expectations as a whole. However, technological advances in the Bitcoin network, such as changes in mining complexity, hash rate, transaction fees, or protocol updates, are not explicitly modelled. These elements have the potential to produce external shocks that affect asset relationships and price dynamics. The use of on-chain metrics and blockchain-specific indicators in the VAR-RI framework is a natural and encouraging extension of this research.

Fifth, forecasting is primarily incorporated as a validation tool rather than an autonomous predictive contribution. The accuracy of the prediction continues to be influenced by model specification and evaluation standards, even though different error metrics are used to address problems related to scale in low-level series, such as interest rates. Future work may compare the suggested multivariate framework with simpler univariate models, random walk processes, or various forecasting methodologies to further analyse its value as an incremental predictor.

Finally, the Relation Index is deliberately designed as a clear and parsimonious measure of systemic integration. While this simplicity improves replicability and interpretation, it also means that the index does not dissolve the relative contributions of directional predictability, correlation strength, and volatility transmission. Future research could explore weighted or decomposed versions of the RI, enabling a more thorough examination of the origins of financial connectivity.

Overall, these limitations do not diminish the main findings of the study; on the contrary, they highlight the flexibility and scalability of the proposed framework. When addressing these issues, future studies could further refine the Relation Index and extend its use to increasingly complex and diverse financial systems.

Appendix

Estimation results

Table 8 presents the regression results for the Bitcoin equation from the VAR model. The model includes coefficients, standard errors, t-statistics, and *p* values. The second lag of the Sustainability Index (L2.SustainabilityIndex) is positive and has a statistical significance level of 5% ($p = 0.040$). This result indicates that the past behaviour of sustainability-linked

Table 8 VAR model estimation results for the Bitcoin equation

Variable	Coefficient	Std. Error	t-Statistic	*p* value
const	− 0.000021	0.022298	− 0.001	0.999
L1.Bitcoin	− 0.014053	0.023305	− 0.603	0.547
L1.SustainabilityIndex	− 0.086628	0.109790	− 0.789	0.430
L1.S&P500	0.111063	0.123691	0.898	0.369
L1.Nasdaq	− 0.002424	0.072250	− 0.034	0.973
L1.Gold	0.003041	0.022939	0.133	0.895
L1.InterestRate	− 0.005774	0.022778	− 0.253	0.800
L1.EmergingMarkets	− 0.046157	0.035534	− 1.299	0.194
L2.Bitcoin	0.026652	0.023280	1.145	0.252
L2.SustainabilityIndex	0.223877	0.108943	2.055	0.040
L2.S&P500	− 0.181959	0.123707	− 1.471	0.141
L2.Nasdaq	− 0.025738	0.072288	− 0.356	0.722
L2.Gold	0.004028	0.022868	0.176	0.860
L2.InterestRate	−0.001283	0.022699	− 0.057	0.955
L2.EmergingMarkets	−0.021371	0.035413	− 0.603	0.546

Table 9 VAR model estimation results for the Sustainability Index equation

Variable	Coefficient	Std. Error	t-Statistic	*p* value
const	0.000209	0.021774	0.010	0.992
L1.Bitcoin	− 0.001445	0.022758	− 0.063	0.949
L1.SustainabilityIndex	− 0.510680	0.107210	−4.763	0.000
L1.S&P500	0.142562	0.120783	1.180	0.238
L1.Nasdaq	0.258474	0.070552	3.664	0.000
L1.Gold	0.020360	0.022400	0.909	0.363
L1.InterestRate	0.046102	0.022242	2.073	0.038
L1.EmergingMarkets	− 0.006302	0.034699	− 0.182	0.856
L2.Bitcoin	0.065220	0.022732	2.869	0.004
L2.SustainabilityIndex	− 0.101314	0.106382	− 0.952	0.341
L2.S&P500	0.317814	0.120799	2.631	0.009
L2.Nasdaq	− 0.205631	0.070589	− 2.913	0.004
L2.Gold	0.026441	0.022331	1.184	0.236
L2.InterestRate	0.069219	0.022165	3.123	0.002
L2.EmergingMarkets	0.046918	0.034581	1.357	0.175

stock markets could have a positive effect on Bitcoin in the long term, which could manifest itself in more extensive structural changes in capital allocation preferences or investor confidence. Overall, the findings corroborate the view that Bitcoin exhibits strong independence from conventional financial markets in the short term, with limited and delayed consequences stemming from sustainability-related factors. This supports the view that Bitcoin is an asset that is driven primarily by idiosyncratic dynamics rather than direct transmission processes of traditional macrofinancial variables.

Table 9 reports the VAR estimation results for the Sustainability Index equation. The first lag of the index itself (L1. Sustainability index) is strongly negative and highly significant ($p < 0.001$), indicating mean reversal behaviour. Significant positive effects are observed in the Nasdaq at lags 1 and 7 ($p < 0.001$ and $p = 0.014$), suggesting a connection between tech equities and sustainability sentiment. The lagged returns of Bitcoin (L2.Bitcoin, $p = 0.006$) also have a positive impact, possibly reflecting the speculative co-movement. Interest Rates

show mixed effects: positive in lags 2 and 4 and negative in lags 5 and 7, indicating sensitivity to monetary policy cycles. Furthermore, Gold exhibits a significant negative effect at lag 7 ($p = 0.021$), consistent with flight-to-safety behaviour. Overall, the results reveal complex interactions between the Sustainability Index and key financial variables, including cryptocurrencies, equities, Interest Rates, and commodities.

Table 9 presents the VAR estimation results for the Sustainability Index equation and reveals a combination of strong own-dynamics and selective cross-market spillovers. The first lag of the Sustainability Index is negative and highly significant ($p < 0.001$), indicating pronounced mean-reverting behaviour, while its second lag is not statistically significant. The sustainability index is affected by Bitcoin only with a lag, as the second lag of Bitcoin gains is positive and significant ($p = 0.004$). This indicates that there is a delayed spread from cryptocurrency markets to sustainability-focused stocks. The Nasdaq plays a significant role among traditional stock markets: its first lag has a strong positive effect ($p < 0.001$) and the second lag is negative and significant ($p = 0.004$), indicating a partial correction after a short-term boost. The second lag shows a positive contribution from the S&P 500 ($p = 0.009$), highlighting the broader influences of the stock market. Interest rates are equally important in both lags, with positive coefficients ($p = 0.002$ and $p = 0.038$), showing that sustainability-related assets are sensitive to monetary conditions. Conversely, gold and emerging markets do not show statistically significant effects. Overall, the findings indicate that the Sustainability Index is driven by robust internal dynamics and significant relationships with technology stocks, monetary policy variables and, to a lesser extent, lagging movements in Bitcoin.

Table 10 shows the results of the VAR estimation for the S&P 500 index and reveals that it is fundamentally affected by the short-term consequences of technology stocks and monetary conditions. The Nasdaq shows a significant positive effect in the first lag ($p = 0.001$), followed by a significant negative correction in the second ($p = 0.004$); this signals a short-term joint movement and subsequent adjustment dynamics. Bitcoin contributes positively with a delayed effect in the second lag ($p = 0.006$), indicating a delayed propagation of cryptocurrency markets. In both lags, interest rates are also important, as their coefficients are positive ($p = 0.041$ and $p = 0.001$), highlighting the importance of monetary policy in

Table 10 VAR estimation results for S&P500 equation

Variable	Coefficient	Std. error	t-stat	*p* value
const	− 0.000652	0.021787	− 0.030	0.976
L1.Bitcoin	− 0.000491	0.022771	− 0.022	0.983
L1.SustainabilityIndex	− 0.168027	0.107274	− 1.566	0.117
L1.S&P500	− 0.192001	0.120855	− 1.589	0.112
L1.Nasdaq	0.238616	0.070594	3.380	0.001
L1.Gold	0.021651	0.022414	0.966	0.334
L1.InterestRate	0.045510	0.022256	2.045	0.041
L1.EmergingMarkets	− 0.010879	0.034719	− 0.313	0.754
L2.Bitcoin	0.062637	0.022746	2.754	0.006
L2.SustainabilityIndex	0.121262	0.106446	1.139	0.255
L2.S&P500	0.100732	0.120871	0.833	0.405
L2.Nasdaq	− 0.203447	0.070631	− 2.880	0.004
L2.Gold	0.029031	0.022344	1.299	0.194
L2.InterestRate	0.072279	0.022178	3.259	0.001
L2.EmergingMarkets	0.040246	0.034602	1.163	0.245

stock market dynamics. In contrast, the lags of the S&P 500 and the Sustainability Index themselves, as well as those of emerging markets and gold, do not have statistically significant impacts; this indicates limited short-term persistence and the existence of selective interactions between markets.

Table 11 reports the results of the VAR estimate for the Nasdaq index and points out that the index is mainly driven by its own short-term dynamics and by some secondary macro-financial effects. The first lag of the Nasdaq is positive and highly significant ($p = 0.002$), followed by a significant negative adjustment in the second lag ($p = 0.006$), thus showing the initial momentum and subsequent correction. The S&P 500 has a weak short-term impact, with marginal significance in the first lag ($p = 0.054$). Interest rates have a significant positive impact in the second lag ($p = 0.015$), highlighting the importance of monetary conditions. Bitcoin has only a marginal delayed effect in the second lag ($p = 0.052$), but the Sustainability Index, gold, and emerging markets have no statistically significant effects.

Table 12 displays the VAR estimation results for the Gold equation. The first lag of Gold (L1.Gold) is negative and significant ($\beta = -0.0453$, $p = 0.046$), suggesting a short-term mean reversion without strong persistence. Bitcoin shows significant negative effects at lags 7 and 10 ($p = 0.018$ and $p = 0.022$), pointing to a delayed substitution effect between cryptocurrencies and Gold. Some positive coefficients in lags 4 and 8 approach significance, indicating a complex relationship. Other variables, such as the Sustainability Index, the Nasdaq and Interest Rates, show limited or inconsistent effects. A few S&P500 lags (e.g., lag 4, $p = 0.061$) suggest modest influence from the equity markets. Overall, Gold prices appear mainly driven by their own dynamics and selected Bitcoin lags, highlighting Gold's relative independence and sensitivity to crypto market developments.

Table 12 reports the VAR estimation results for the Gold equation and evidence that gold is mainly driven by its own short-term dynamics. The first lag for gold is negative and statistically significant ($p = 0.016$), indicating that in the short term there is a reversion to the mean. The first lag ($p = 0.038$) shows that interest rates have a positive and significant impact, indicating the sensitivity of gold's returns to monetary conditions. In contrast, Bitcoin, stock indices (S&P 500 and Nasdaq), the Sustainability Index, and emerging markets do not have statistically relevant impacts at conventional levels. Overall, the findings indi-

Table 11 VAR model estimation results for Nasdaq equation

Variable	Coefficient	Std. Error	t-stat	*p* value
const	− 0.000564	0.021907	− 0.026	0.979
L1.Bitcoin	− 0.000093	0.022897	− 0.004	0.997
L1.SustainabilityIndex	− 0.097076	0.107866	− 0.900	0.368
L1.S&P500	− 0.234568	0.121522	− 1.930	0.054
L1.Nasdaq	0.215479	0.070984	3.036	0.002
L1.Gold	0.020551	0.022537	0.912	0.362
L1.InterestRate	0.028517	0.022379	1.274	0.203
L1.EmergingMarkets	− 0.015119	0.034911	− 0.433	0.665
L2.Bitcoin	0.044496	0.022872	1.945	0.052
L2.SustainabilityIndex	0.131054	0.107033	1.224	0.221
L2.S&P500	0.076679	0.121539	0.631	0.528
L2.Nasdaq	− 0.195015	0.071021	− 2.746	0.006
L2.Gold	0.029316	0.022467	1.305	0.192
L2.InterestRate	0.054045	0.022301	2.423	0.015
L2.EmergingMarkets	0.030279	0.034793	0.870	0.384

cate that gold has a relatively independent role and modest short-term adjustment dynamics. Furthermore, they show that indirect effects between markets are limited.

Table 13 presents the VAR estimation results for the Interest Rate equation. The model reveals strong autoregressive behaviour, with multiple significant lags (e.g., lags 2, 3, 5, 6, 9, and 10), indicating cyclical and mean reverting dynamics. The S&P500 and Nasdaq indices exert significant influence at various lags, reflecting shifting market expectations. For instance, the S&P500 impacts Interest Rates at lags 2, 5, and 10, while the Nasdaq shows both negative (lags 2, 4, 5) and positive effects (lags 6 and 10), suggesting a nonlinear relationship. Gold has a positive impact in lags 2 and 3, and a marginally negative effect at lag 9, possibly linked to inflation expectations. Bitcoin influences Interest Rates only at lag 4, while the Sustainability Index remains largely insignificant. In sum, interest rate dynamics

Table 12 VAR model estimation results for Gold equation

Variable	Coefficient	Std. Error	t-stat	*p* value
const	− 0.000086	0.022195	− 0.004	0.997
L1.Bitcoin	0.016689	0.023198	0.719	0.472
L1.SustainabilityIndex	0.005864	0.109283	0.054	0.957
L1.S&P500	0.024271	0.123119	0.197	0.844
L1.Nasdaq	− 0.010167	0.071916	− 0.141	0.888
L1.Gold	− 0.054895	0.022833	− 2.404	0.016
L1.InterestRate	0.047035	0.022673	2.075	0.038
L1.EmergingMarkets	0.057908	0.035370	1.637	0.102
L2.Bitcoin	0.001476	0.023172	0.064	0.949
L2.SustainabilityIndex	0.129127	0.108440	1.191	0.234
L2.S&P500	− 0.054987	0.123135	− 0.447	0.655
L2.Nasdaq	− 0.048471	0.071954	− 0.674	0.501
L2.Gold	− 0.020843	0.022762	− 0.916	0.360
L2.InterestRate	0.030384	0.022594	1.345	0.179
L2.EmergingMarkets	0.049056	0.035250	1.392	0.164

Table 13 VAR model estimation results for Interest Rate equation

Variable	Coefficient	Std. Error	t-stat	*p* value
const	− 0.000093	0.021483	− 0.004	0.997
L1.Bitcoin	0.019435	0.022454	0.866	0.387
L1.SustainabilityIndex	− 0.279387	0.105778	− 2.641	0.008
L1.S&P500	0.204383	0.119170	1.715	0.086
L1.Nasdaq	0.077449	0.069610	1.113	0.266
L1.Gold	− 0.037727	0.022101	− 1.707	0.088
L1.InterestRate	− 0.046693	0.021945	− 2.128	0.033
L1.EmergingMarkets	− 0.068263	0.034235	− 1.994	0.046
L2.Bitcoin	0.003401	0.022429	0.152	0.879
L2.SustainabilityIndex	0.015108	0.104962	0.144	0.886
L2.S&P500	0.360025	0.119186	3.021	0.003
L2.Nasdaq	− 0.253126	0.069646	− 3.634	0.000
L2.Gold	0.046218	0.022033	2.098	0.036
L2.InterestRate	− 0.157878	0.021869	− 7.219	0.000
L2.EmergingMarkets	0.059406	0.034119	1.741	0.082

Table 14 VAR model estimation results for the Emerging Markets

Variable	Coefficient	Std. Error	t-stat	Prob
const	− 0.000818	0.021639	− 0.038	0.970
L1.Bitcoin	− 0.003197	0.022616	− 0.141	0.888
L1.SustainabilityIndex	− 0.232501	0.106545	− 2.182	0.029
L1.S&P500	− 0.131995	0.120034	− 1.100	0.271
L1.Nasdaq	0.267270	0.070114	3.812	0.000
L1.Gold	0.032635	0.022261	1.466	0.143
L1.InterestRate	0.039508	0.022105	1.787	0.074
L1.EmergingMarkets	− 0.070291	0.034484	− 2.038	0.042
L2.Bitcoin	0.063547	0.022591	2.813	0.005
L2.SustainabilityIndex	0.162647	0.105723	1.538	0.124
L2.S&P500	0.098629	0.120050	0.822	0.411
L2.Nasdaq	− 0.246265	0.070151	− 3.510	0.000
L2.Gold	0.019065	0.022192	0.859	0.390
L2.InterestRate	0.057591	0.022028	2.615	0.009
L2.EmergingMarkets	0.053295	0.034367	1.551	0.121

are primarily driven by their own history and selected equity and commodity market lags, highlighting sensitivity to financial conditions but limited exposure to ESG-related signals.

Table 13 reports the VAR estimation results for the Interest Rate equation and highlights intense internal dynamics and selective contagion in the financial market. A mean reversion dynamic is observed in interest rates, which show significant negative autoregressive behaviour in the first and second lags ($p = 0.033$ and $p < 0.001$). The sustainability index has a negative impact on the first lag ($p = 0.008$), and stock markets play an important role: the S&P 500 is significant in the second lag ($p = 0.003$) and the Nasdaq also has a strong negative impact in the same lag ($p < 0.001$). Gold also has a positive effect in the second lag ($p = 0.036$). In contrast, Bitcoin does not have any statistically significant effects. Interest rates are generally driven primarily by their own past values and by lagging movements in commodity and equity markets, with cryptocurrencies having a limited influence.

Table 14 shows the results of the VAR model evaluation for the emerging markets equation, revealing how their returns react to their own lags and other financial variables. The results show that the index has significant internal dynamics, with a negative impact on the first lag ($p = 0.042$), indicating that it can be corrected in the short term. Technology markets have significant spillovers, as the Nasdaq has a positive impact on the first lag ($p < 0.001$) and a negative impact on the second ($p < 0.001$), showing a pattern of momentum and correction. Bitcoin has a delayed positive effect on the second lag ($p = 0.005$), but the Sustainability Index has a significant negative impact on the first lag ($p = 0.029$). Interest rates also have a positive impact, albeit with a two-period lag ($p = 0.009$). In summary, the results indicate that emerging markets are subject to their own dynamics and to shocks from technological and monetary financial markets, as well as, to a lesser extent, from the cryptocurrency market.

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Data availability The real dataset used in this study is publicly available on Yahoo Finance. The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare no conflict of interest.

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