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Three Essays on Predictability, Hedging, and Financial Contagion in the Crypto Market

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Dissertation Overview

In 2008, amid the profound uncertainty triggered by the global financial crisis, a group of activists and computer scientists operating under the pseudonym Satoshi Nakamoto released the Bitcoin *white paper* (Nakamoto, 2008). The paper introduced a peer-to-peer electronic payment system in which the security and traceability of transactions do not rely on a bank, but instead on the individuals who participate in, maintain, and validate the network. In a turbulent environment shaped by inflation concerns and unconventional monetary policies implemented by the U.S. Federal Reserve, Nakamoto proposed a system with a limited, algorithmically determined supply, in which participants can operate pseudonymously. This architecture became known as the *blockchain*, and the digital asset used to exchange value within that network was named Bitcoin.

From that point to the present, the evolution of *blockchain* and Bitcoin has been unprecedented. In 2010, the first transactions took place at prices around USD 0.07 on early exchange platforms that were later linked to illicit markets and, in some cases, vanished with users' funds. By late 2025, by contrast, one bitcoin was trading in the iconic financial district of Wall Street at roughly USD 125,000. This sustained appreciation has gone hand in hand with major advances in adoption, as Bitcoin increasingly became a viable alternative for both retail and institutional investors. If the 2017 boom was largely explained by the widespread use of *blockchain* for smart-contract programming and the proliferation of decentralized projects, momentum in 2021 was driven by support and participation from U.S. technology firms such as Tesla, MicroStrategy, and Coinbase. By late 2024, the phenomenon also gained a political and governmental dimension when presidential candidate Donald Trump stated during his campaign that he would establish a major U.S. cryptocurrency reserve. In March 2025, once in office, he signed an executive order aimed at fulfilling that promise, following a trend already adopted by countries such as China and the United Kingdom.

It is therefore unsurprising that the academic community has turned its attention to the Bitcoin phenomenon. A simple search for the term "Bitcoin" in Google Scholar suggests a sharp expansion in scientific output: between 2010 and 2015, more than 15,000 documents were associated with the topic, whereas between 2016 and 2025 the results exceed 179,000 documents. According to Web of Science, among the most highly cited articles within the cryptocurrency literature, prominent themes include risk, returns, sentiment, and prediction. This doctoral dissertation is directly connected to these research themes and contributes to the frontier of knowledge through three articles focused on Bitcoin and cryptocurrency markets.

The first article, "*A Comprehensive Look at Bitcoin Return Predictability*," addresses a central gap in the cryptocurrency forecasting literature: despite the rapid growth of studies proposing return predictors, there is still no unified evaluation that identifies which signals generate out-of-sample forecasting gains and meaningful economic value. Using daily data from September 2014 to April 2025, we assemble 141 predictors grouped into four families: technical, fundamental, sentiment-based, and macroeconomic. We evaluate these predictors through a two-stage framework aligned with the classic approach of Welch and Goyal (2008). First, we screen predictors in sample and retain those with statistically significant coefficients. Second, we subject each surviving variable to an extensive out-of-sample battery that compares forecasting performance against benchmark models across different evaluation windows, training schemes, and forecasting horizons. To address model uncertainty and the instability of individual signals, we also construct a parsimonious composite factor using principal component analysis (PCA) based on the statistically significant variables, compressing dispersed information into a single indicator.

Our results underscore how difficult it is to identify signals that deliver robust out-of-sample forecasting gains in Bitcoin: although 67 variables exhibit in-sample significance, only 29 improve out-of-sample performance at least at one horizon, and just 4 beat the random-walk benchmark consistently across different horizons. Predictive content is concentrated in technical indicators, especially trend-based measures, while sentiment proxies perform the worst and most erratically. By contrast, fundamental and macroeconomic variables provide only episodic improvements in accuracy, often confined to specific horizons or subsamples. Importantly, aggregation improves robustness: PCA-based factors, particularly those dominated by trend information, tend to outperform their constituent variables. In addition, trading strategies based on these forecasts deliver economically meaningful improvements relative to a buy-and-hold benchmark, although their effectiveness varies across market regimes, underscoring both the practical relevance and the inherent fragility of Bitcoin return predictability.

The second article, "*Gold vs. Bitcoin as Safe Havens Across U.S. Sectors: Evidence from the Latest Equity Market Crashes*," It re-examines the "digital gold" hypothesis, that is, the idea that Bitcoin could play a role similar to gold by preserving value and hedging equity risk during periods of financial stress. The analysis is motivated by evidence that gold's safe-haven role varies across U.S. industries and has weakened in some recent subperiods, as well as by the argument that Bitcoin, as a non-sovereign asset, could in principle provide protection when stress reflects banking fragility, doubts about monetary-policy credibility, capital controls, or disruptions to payment infrastructure. Because shocks do not propagate uniformly across equities, the paper evaluates gold and Bitcoin across the 11 U.S. GICS sectors, focusing on the five most severe U.S. equity drawdowns and using Bitcoin's full history as a tradable market instrument. The empirical strategy combines time-varying conditional correlations estimated with a DCC–GARCH model, directional interdependence measures based on an R^2-connectedness framework, and left-tail tests that condition on extreme sectoral drawdowns, where a safe haven requires co-movement to become negative precisely when risk materializes.

The results indicate that Bitcoin does not behave as a sector-level safe haven, whereas gold exhibits a more defensive profile during stress episodes. DCC–GARCH estimates show that Bitcoin is positively correlated with all 11 sectors and that these correlations rise sharply from 2020 onward; by contrast, gold correlations are systematically lower, often near zero, and turn negative in key cyclical sectors, most notably Financials. This divergence strengthens in crisis windows: Bitcoin's correlations rise and remain positive, while gold remains less correlated than Bitcoin across several sectors, including Communication Services, Consumer Discretionary, Financials, Industrials, and Information Technology, even during the "Liberation Day" shock (when President Trump announced reciprocal tariffs and U.S. equities fell sharply, with the S&P 500 dropping about 5% in a single session). Left-tail evidence further suggests that gold's protection is state dependent: conditioning on the worst 5% of sectoral outcomes, gold decouples more strongly in a way consistent with flight-to-quality behavior, but in the most extreme 1% tail this effect attenuates and can partly reverse in some industries. Overall, the findings imply that gold delivers more stable sectoral decoupling under stress, whereas Bitcoin behaves largely as a procyclical risk asset, offering selective, time-varying diversification rather than robust crisis insurance.

The third article, "*The Moby Dick effect: Contagious Bitcoin Whales in the Crypto Market*," examines a behavioral channel of contagion in cryptocurrency markets by studying whether the activity of large Bitcoin holders, commonly referred to as "whales," propagates to the broader crypto ecosystem. In the paper, we define whales as investors holding 500 bitcoins or more. The core idea is that these movements should not be interpreted solely as mechanical order-flow events, but as highly visible signals that can coordinate expectations and trigger herding, particularly in an environment with weak fundamental anchors and real-time transparency of on-chain transfers. To test this mechanism, we build a novel hourly dataset that merges Whale Alert records of whale movements from April 22, 2022 to May 7, 2025 with returns for Bitcoin and the 15 largest cryptocurrencies by market capitalization, and we classify whale activity by the direction of the transfer and the type of wallet involved. This classification separates potentially informative movements, such as withdrawals from exchanges (interpreted as holding or accumulation signals) and transfers to exchanges (interpreted as selling-pressure signals), from neutral placebo movements with limited informational content.

Empirically, we quantify time-varying spillovers using a TVP-VAR model and generalized forecast error variance decompositions at 1-, 6-, and 24-hour horizons. The results show that whale-induced contagion is modest on impact but strengthens over time and becomes economically relevant at longer horizons, particularly for transfers to exchanges: average spillovers rise from about 2.5% after 1 hour to about 6.3% after 24 hours, and the Whale Hit ratio increases from roughly 1.9% to 50%, indicating that whale shocks become among the dominant sources of variance for a large share of major crypto assets. Exchange withdrawals also generate increasing spillovers, though of smaller magnitude, consistent with a slower diffusion of accumulation signals. A direct comparison across the four whale types confirms that informative movements (exchange withdrawals and transfers to exchanges) produce significantly stronger contagion than neutral placebo movements, and that the relative strength of signals varies with the horizon, with sell-related transfers becoming the most contagious at 24 hours. Overall, the findings imply that monitoring whale activity is important for investors, exchanges, and regulators because it provides real-time indicators of evolving cross-asset connectedness and potential systemic stress in crypto markets.

Taken together, these three articles provide complementary evidence on predictability, hedging properties, and contagion mechanisms in Bitcoin and cryptocurrency markets. The remainder of this dissertation presents the complete development of each study, including the theoretical motivation, data construction, empirical methodology, main results, robustness analyses, and their implications for investors, policymakers, and future research.

Chapter 1

A Comprehensive Look at Bitcoin Return Predictability

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Abstract

This paper assesses the predictive power of 141 variables widely used to forecast Bitcoin returns. Using daily data from September 2014 to April 2025, we assess out-of-sample performance across various training and forecasting windows, including multi-step-ahead forecasts. Predictive gains are measured using the R^2_{oos} statistic to evaluate sample-level predictive ability, and the Clark and West test to assess population-level predictive ability, comparing each model with two benchmarks: a random walk and an autoregressive process. We also examine the economic value of signal-based strategies using annualized returns and Sharpe ratios. Results show that trend-based technical indicators consistently outperform benchmarks, while macro and fundamental variables yield mixed results. Additionally, we construct indices via principal component analysis that summarize the most informative signals in each group, offering a scalable tool for active investors and portfolio managers.

Keywords: Bitcoin, Forecasting, Cryptocurrencies, Technical analysis

1. Introduction

Which variables predict Bitcoin returns? This is a $50 billion question, roughly the amount traded daily in Bitcoin[1]. Not surprisingly, scholars are increasingly interested in this issue. As documented by John et al. (2024), 1,819 scientific articles on cryptocurrency price prediction have been published over the past decade, with nearly 80% focusing specifically on Bitcoin. Market participants, from institutional investors to retail traders and speculators, rely on a wide range

[1] According to updated data from https://coinmarketcap.com/currencies/bitcoin/.

of predictors to anticipate price movements and make investment decisions. We classify these predictors into four categories: technical, fundamental, sentiment-based, and macroeconomic (M. Chen et al., 2025; Naeem et al., 2021; Tzeng & Yi-Kai, 2024). While numerous studies suggest that incorporating such variables can improve forecasting performance (Pečiulis et al., 2024), empirical evidence also reveals that traders employing active strategies tend to underperform passive approaches, such as simply buying and holding (Hudson & Urquhart, 2021; Rink, 2023). This paper provides a comprehensive evaluation of the predictive power of 141 variables proposed in the literature and identifies which of them are useful in terms of statistical accuracy and economic value.

The task of forecasting Bitcoin returns has evolved considerably since its emergence as a financial instrument. In its early stages, characterized by the absence of traditional economic fundamentals and structurally high volatility (Cheah & Fry, 2015), predictive models relied mainly on technical analysis and univariate econometric approaches, such as ARIMA and GARCH (Dyhrberg, 2016; Munim et al., 2019), with trend and momentum indicators central to anticipating price movements (Corbet et al., 2019). Intrinsic blockchain variables, including block size, mining difficulty, and hash rate, were also explored to capture the dynamics of price formation in a decentralized and underregulated environment (Jang & Lee, 2018). Behavioral finance later highlighted the role of sentiment, emphasizing that collective perceptions and investor biases can amplify volatility and create feedback dynamics in prices. Within this framework, measures such as the Fear and Greed Index, Google search trends, and Twitter activity were incorporated as proxies for market mood and investor attention toward Bitcoin (Gradojevic et al., 2023; Kraaijeveld & De Smedt, 2020). In recent years, Bitcoin's growing integration with traditional financial markets has increased the relevance of macroeconomic factors in its price dynamics, including global equity returns, major exchange rates, commodity prices, and measures of uncertainty, which have demonstrated the ability to anticipate movements in the crypto market (Demir et al., 2018; Panagiotidis et al., 2024; Y. Zhou et al., 2025).

The challenge of forecasting financial returns has been an open debate since at least the 1980s. R. Meese and Rogoff (1988) and R. A. Meese and Rogoff (1983) show that most proposed predictors fail to outperform a simple random walk. After four decades, the consensus remains that financial returns are extremely difficult to predict, with any detectable predictability often being fragile, episodic, and subject to rapid change over time (Timmermann, 2008). Extensive studies in exchange rates (Rossi, 2013) and in the equity premium (Goyal et al., 2024; Welch & Goyal, 2008) confirm that even sophisticated models rarely deliver consistent gains over the driftless random walk benchmark[2]. While this literature has provided rigorous and systematic evaluations of proposed predictors in traditional asset classes, no comparable effort exists for Bitcoin. This paper fills that gap by conducting a comprehensive assessment of predictive variables in the cryptocurrency market.

[2]The driftless random walk benchmark is equivalent to a no-change forecast in first log differences.

To this end, we assemble a daily dataset covering the period from September 2014 to April 2025, comprising 141 predictors. In the first stage, we evaluate the in-sample fit and retain only predictors with statistically significant coefficients (Goyal et al., 2024). In the second stage, we assess the out-of-sample forecasting performance of each variable against benchmark models across different evaluation windows, training schemes, and forecasting horizons (Hardy et al., 2023). Additionally, in this stage, we further evaluate a factor constructed from the statistically significant variables using principal component analysis (PCA) (Stock & Watson, 2006). Finally, we assess the economic value of predictors by implementing forecast-based trading strategies and evaluating their annualized returns and Sharpe ratios, following the frameworks of Anatolyev and Gerko (2005) and Neely et al. (2014) and Y. Wang et al. (2020).

Our results are in line with the common knowledge that financial returns are very difficult to predict. Out of 141 variables, 67 show in-sample predictive value; however, only 29 deliver significant out-of-sample gains at least at one forecasting horizon, and just 4 predictors outperform the random walk benchmark throughout the different horizons. Nevertheless, our results indicate that technical indicators improve forecasting performance, consistent with the findings of Neely et al. (2014) for the U.S. equity risk premium. In particular, we document that trend-based indicators deliver especially strong predictive power, surpassing standard benchmarks in both in-sample and out-of-sample evaluations. For the remaining predictor categories, results are mixed. Evidence from fundamental and macroeconomic variables suggests only limited predictive content in terms of accuracy, with gains confined to time periods or forecasting horizons. Sentiment variables perform the worst, showing limited and inconsistent forecasting ability across the different exercises. Notably, aggregating predictors into a factor enhances the performance of individual variables, especially in the case of trend-based information, where composite factors outperform their components. Trading exercises confirm that strategies built on these signals can generate economically meaningful gains compared to a buy-and-hold benchmark, with effectiveness varying across market regimes.

Our manuscript makes three main contributions. First, it provides the most comprehensive and systematic comparative evaluation of return predictors in the cryptocurrency literature within a unified methodological framework. Second, it shows that, although beating a random walk remains highly challenging (R. A. Meese & Rogoff, 1983; Welch & Goyal, 2008), a subset of technical variables consistently delivers robust predictive accuracy, while fundamental and macroeconomic predictors contribute primarily through improvements in economic value. Third, it extends existing evidence on the usefulness of technical rules for anticipating price movements (Svogun & Bazán-Palomino, 2022; Tan & Tao, 2023; Wei et al., 2024), thereby linking the literature on cryptocurrency predictability with the broader research on financial forecasting (Goyal et al., 2024; Rossi, 2013; Timmermann, 2008).

The remainder of the paper is organized as follows: Section 2 reviews the literature, Section 3 describes the data and methodology, Section 4 presents the results, and Section 5 concludes.

2. Literature review

The literature has attempted to forecast Bitcoin's price dynamics through a wide range of variables, including network metrics, technical patterns, sentiment indicators, and macro-financial factors. The versatility of Bitcoin suggests that some of these factors may help anticipate its movements, considering that although it was originally conceived as an innovative payment technology (Nakamoto, 2008), users have predominantly adopted it as a speculative instrument (Baur et al., 2018; A. D. Lee et al., 2020). This study contributes to this objective by constructing a comprehensive evaluation of the predictive power of these variables within a common methodological framework, identifying those that have delivered the greatest benefits for anticipating Bitcoin movements over the past decade.

A broad literature has sought to identify the economic fundamentals behind Bitcoin's valuation. Unlike traditional assets, whose prices are typically grounded in discounted cash flows, expected earnings, or book value, Bitcoin lacks physical backing and does not generate income on its own (Kogan et al., 2024). This initially led to the assertion that its fundamental value was null (Cheah & Fry, 2015). However, this judgment has been increasingly challenged by both theoretical and empirical research, which has proposed a reinterpretation of its foundations through the lens of digital asset logic. Models inspired by the monetary theory of overlapping generations (Biais et al., 2023) have demonstrated that Bitcoin can reach positive price equilibria as long as it fulfills useful roles such as a payment method, a safe haven, or a speculative asset (Feng & Zhang, 2023; Hayes, 2017; Xiong et al., 2020). Within this framework, it is argued that Bitcoin's price reflects not only its perceived utility and the security of its protocol, but also network effects, mining incentives, and adoption dynamics. On this basis, a set of "network fundamentals" has emerged, exploiting blockchain transparency to construct observable indicators of the protocol's internal functioning. Prominent examples include active addresses, adjusted transaction volume, and ratios such as Network Value to Transactions (NVT), an analogue to the price-to-earnings ratio in traditional markets. Other variables, such as hashrate, mining revenue, and exchange balances, provide complementary signals about network health and expectations regarding future supply (Guo et al., 2025). These indicators have shown predictive value in various market contexts, particularly during accumulation or distribution phases (Kubal & Kristoufek, 2022; Shen & Wu, 2025).

Another approach is technical analysis, whose graphical and quantitative tools reveal behavioral patterns in prices and volumes that guide decisions in speculative environments (Corbet et al., 2019). Numerous studies show that technical rules constructed using prices and volumes generate statistically significant predictive signals (Jamali & Yamani, 2019; Zarrabi et al., 2017). For Bitcoin, incorporating these indicators into econometric and machine learning models has been shown to improve forecasting accuracy relative to passive benchmarks (Bouri et al., 2021; Gerritsen et al., 2020; Gradojevic et al., 2023; Wei et al., 2024). Within this strand, moving average strategies stand out: by comparing recent trends with longer-term ones, they help identify when an asset may be starting a new trend or losing momentum, making them a practical and widely used tool for anticipating price movements (Detzel et al., 2021). For instance, Svogun and Bazán-Palomino (2022) demonstrate that moving average crossovers can outperform buy-and-hold during speculative bubbles, even after transaction costs, while Tan and Tao (2023) report that such strategies are more effective at short horizons, with volume-based signals gaining strength at longer ones.

Incorporating sentiment variables into asset price forecasting is a natural extension of technical analysis, particularly in markets highly sensitive to collective narratives. Building on insights from behavioral finance, a plausible explanation is that prices may respond not only to fundamentals but also to beliefs, emotions, and collective behavior (Barberis & Thaler, 2003). As previously noted, "*the question is no longer whether sentiment affects prices, but how to measure it and quantify its effects*" (Baker & Wurgler, 2007, p. 2). This is particularly relevant in the crypto ecosystem, where abundant digital data, rapid narrative diffusion, and the active participation of online communities enable sentiment to be operationalized with high frequency and granularity. Research in the cryptocurrency market has exploited platforms such as Twitter, Bitcointalk.org, and Thomson Reuters MarketPsych Analytics to construct indicators based on message content, frequency, and tone, documenting significant links with future Bitcoin returns (Aysan et al., 2019; Critien et al., 2022; Dias et al., 2022; Kraaijeveld & De Smedt, 2020). More structured sources, such as financial news headlines, have allowed for the development of polarity indices[3] using specialized dictionaries (Loughran & Mcdonald, 2011) and pre-trained artificial intelligence models, whose capabilities surpass traditional sentiment analysis methods in predicting and explaining returns (Huang et al., 2023). These approaches are complemented by attention-based proxies, such as Google Trends or Wikipedia visits (Bouri & Gupta, 2021; Ciaian et al., 2018; Nasir et al., 2019; Süssmuth, 2022), as well as composite measures such as the Fear and Greed Index, which synthesize these dynamics into signals of extreme sentiment (He et al., 2023). Taken together, this evidence shows that digital sentiment constitutes an essential complement to traditional fundamentals, capturing behavioral dimensions with the potential to forecast Bitcoin returns.

Although conceived as a decentralized alternative to the traditional financial system, Bitcoin has become increasingly sensitive to global macroeconomic conditions, especially in contexts of uncertainty or systemic stress (Ben Omrane et al., 2024; Corbet, Larkin, et al., 2020; Klein et al., 2018). This has spurred a growing literature examining how equities, bonds, currencies, and

[3] In this context, polarity refers to two opposite poles of sentiment. For instance, the Loughran and McDonald (2011) dictionary classifies words as positive or negative, while the *Fear and Greed Index* captures the sentiment dimension between greed and fear.

commodities contribute predictive value regarding the returns and volatility of cryptoassets (Salisu et al., 2023; J. Wang et al., 2023; Wu et al., 2023). Among the most common approaches is the use of international stock indices such as the S&P 500, Dow Jones Industrial Average, or Nasdaq Composite, employed as proxies for global risk appetite (Kim et al., 2025). Empirical evidence shows that during expansionary phases, Bitcoin tends to correlate positively with these indices, reflecting procyclical behavior (Jia et al., 2024; K. Q. Nguyen, 2022), although such correlations often intensify during sharp market downturns or financial shocks, revealing contagion effects and challenging its role as a safe-haven asset (Smales, 2019; Vuković et al., 2025; Wen et al., 2022). U.S. 10-year Treasury yields also exert a direct influence on major cryptocurrencies by altering the opportunity cost of holding non-yielding assets, an effect particularly visible during periods of monetary tightening (Ciner et al., 2022). At the international level, exchange rate fluctuations, especially in pairs such as EUR/USD, GBP/USD, or AUD/USD, have been used as indicators of macroeconomic tensions and shifts in monetary policy that affect the relative demand for Bitcoin (Ciaian et al., 2016).

3. Methodology

3.1. Data

Our dataset comprises logarithmic returns of Bitcoin at 1, 7, 14, and 28-day horizons, covering the period from September 2014 to April 2025[4]. These returns are merged with a set of 141 variables from four categories: fundamental, technical, sentiment-based, and macroeconomic. The number of available observations varies across categories due to the nature of each variable. Fundamental and technical variables, which are recorded seven days a week, yield a total of 3,854 observations. In contrast, data from traditional sources such as equity returns, commodities, or uncertainty indices are not available during weekends, so we restrict the sample to trading days only, resulting in 2,749 observations[5]. For sentiment-based variables, the main limitation is the historical availability required for their construction. Although weekend records are available, the sentiment dataset begins on 7 April 2018, leading to a total of 2,555 observations. A general summary of all variables is presented in Table 1.

[4]September 2014 marks the beginning of Bitcoin's mass commercialization, as trading volume surpassed 50 million dollars for the first time; between 2010 and early 2014, although prices existed, CoinMarketCap.com records show that on a significant share of days trading volume was zero.

[5]This detail is relevant because, for macroeconomic variables, the Monday forecast relies on Friday's data, whereas for technical, fundamental, and sentiment variables, the Monday forecast uses Sunday's data.

3.2. *Empirical strategy*

3.2.1. *In-Sample*

We begin by assessing the in-sample fit of the variables listed in Table 1 through a set of models, following the framework of Goyal et al. (2024) and Welch and Goyal (2008) for stock return predictability. Our objective is to forecast logarithmic Bitcoin returns at horizons $h \in \{1, 7, 14, 28\}$. Let r_t denote the daily logarithmic return of Bitcoin at time t. The h-step-ahead target return is defined as

$$r_{t,t+h} \equiv \begin{cases} r_{t+1}, & \text{if } h = 1, \\ \sum_{j=1}^{h} r_{t+j}, & \text{if } h \in \{7, 14, 28\}, \end{cases} \tag{1}$$

so that for $h = 1$ it corresponds to the next-day return, and for longer horizons it represents the cumulative return over the next h days. The forecasting model for our in-sample evaluation takes the form

$$r_{t,t+h} = \alpha + \rho\, r_{t-h,t} + \beta\, x_t + \varepsilon_{t+h}, \tag{2}$$

where $r_{t,t+h}$ denotes the cumulative return from t to $t + h$, x_t is the predictor of interest, and $\varepsilon_{t,t+h}$ is the error term. The coefficient ρ represents the autoregressive parameter in the AR(1) specification, while β measures the marginal predictive content of x_t. All regressions are estimated with HAC standard errors following Newey and West (1987, 1994). The null hypothesis in all cases is $H_0 : \beta = 0$, which tests whether x_t contains statistically significant information for forecasting Bitcoin returns, evaluated using a t-statistic.

3.2.2. *Out-Sample evaluation*

In-sample results should be interpreted with caution, as there is a risk of overfitting, meaning the model may capture patterns in the sample that do not persist in future data. Likewise, evaluating a large number of predictors increases the likelihood of finding statistically significant relationships by chance, a phenomenon known as *data snooping* (White, 2000). These considerations highlight the importance of conducting rigorous out-of-sample validation to assess predictive ability against observations not used in the initial estimation. We examine the out-of-sample predictive power of all variables that were significant at any horizon tested in the in-sample exercises. For this purpose, we compare the performance of nested forecasting models against two challenging benchmarks[6]: the random walk (RW) specification and an autoregressive model AR(1). Our core models (Eqs. 3 and 4) are derived from these benchmark specifications, to which an additional predictor x_t is

[6]We also considered the driftless random walk as a benchmark. However, this specification proved non-competitive in our exercises. On average, historical Bitcoin returns are positive over medium- to long-term horizons, implying that any model incorporating even minimal historical information systematically outperforms it.

incorporated.

$$r_{t,t+h} = \alpha + \beta x_t + \varepsilon_{t+h}, \tag{3}$$

$$r_{t,t+h} = \alpha + \rho r_{t-h,t} + \beta x_t + \varepsilon_{t+h}, \tag{4}$$

Forecasts are generated using both recursive and rolling estimation schemes, with the estimation window length defined as R, the prediction (evaluation) window length as P, and the total number of observations as $T = P + R$. We consider three splitting strategies for our datasets, in particular $P/R \in \{0.4, 1, 4\}$, corresponding to estimation/evaluation sample splits of 70/30, 50/50, and 30/70, respectively. Results are reported for the recursive scheme with $P/R = 1$[7]. The sample accuracy is measured using the out-of-sample R^2

$$R^2_{\text{oos}} = 1 - \frac{\text{MSPE}_{\text{forecast}}}{\text{MSPE}_{\text{benchmark}}}, \tag{5}$$

where $\text{MSPE}_{\text{forecast}}$ denotes the mean squared prediction error from either Eq. 3 or Eq. 4, and $\text{MSPE}_{\text{benchmark}}$ is the corresponding benchmark imposing $\beta = 0$. A value of $R^2_{\text{oos}} = 0$ indicates equal sample predictive accuracy between the model and its benchmark; negative values imply that the benchmark performs better, and positive values indicate that the model with x_t outperforms its benchmark. Alongside R^2_{oos}, we report the population predictability test of Clark and West (2006, 2007) for nested models[8]. This test adjusts the MSPE difference to account for the noise introduced when estimating additional parameters that are zero under the null, which can otherwise bias the comparison toward the parsimonious model. Intuitively, under the null hypothesis the larger model does not improve forecasts, but its extra parameters add estimation error that inflates its MSPE. The Clark and West adjustment corrects for this bias, enabling a valid test of whether the larger model truly delivers superior population predictive performance. The resulting statistic is one-sided and asymptotically normal, allowing for conventional inference.

3.3. Reducing the dimensionality: a PCA approach

To synthesize the most relevant predictive information within each category of variables, we construct category-specific indices using principal component analysis (PCA). This approach allows us to summarize a large set of potentially correlated predictors into a single factor that captures the maximum share of common variance, thereby reducing dimensionality while preserving the

[7] All results for the remaining window configurations and estimation schemes are available in an online appendix.

[8] An additional battery of tests was also conducted (available upon request), including the correlation-based predictability test (Brown & Hardy, 2024), the "wild Clark and West" test (Pincheira et al., 2021), and the ENCNEW test (Clark & McCracken, 2001).

core informational content (Bai & Ng, 2002; Stock & Watson, 2006). As argued by Baumeister et al. (2022), indices constructed from factors extracted from multiple series provide a more comprehensive representation of the system's underlying state than any single predictor.

In the in-sample stage, PCA is applied to all variables that exhibit statistically significant predictive power according to Equation 2[9], from which we construct one factor for each category of variables, using the entire available sample to estimate the first principal component. This component serves as the category index, condensing the most informative common variation across predictors. For the out-of-sample evaluation, we follow both recursive and rolling estimation schemes, reestimating the PCA within each estimation window to ensure that, at each forecast origin, the index is computed solely with information available up to that point. Formally, let $\mathbf{X}_t^{(c)}$ denote the $N_c \times 1$ vector of standardized predictors in category c at time t, where N_c is the number of significant variables in that category. The index for category c at forecast origin t is given by

$$\text{Index}_t^{(c)} = \hat{\mathbf{w}}_t^{(c)\prime}\mathbf{X}_t^{(c)}, \tag{6}$$

where $\hat{\mathbf{w}}_t^{(c)}$ denotes the vector of PCA loadings estimated by a recursive or rolling window from the sample $\{\mathbf{X}_s^{(c)}\}_s^t$, with $s = 1$ to t in the recursive scheme, and $s = t - r$ to t in the rolling scheme. This procedure constructs a synthetic index for each variable category, condensing the most relevant information into a compact form while preserving the temporal structure necessary for valid out-of-sample evaluation. The approach aligns with Farmer et al. (2023), Rossi (2013), and Timmermann (2008), who argue that predictors typically exhibit *pockets of predictability*, such that a single predictor rarely delivers consistent performance over time. Hence, a more effective strategy is to consider groups of predictors rather than relying on any one variable in isolation. By aggregating each category into a single factor, we retain these dispersed signals and mitigate the information loss that arises from overly selective models. This perspective contributes to the debate on the *illusion of sparsity* (Giannone et al., 2021), highlighting that indices can synthesize the information dispersed across many predictors and thereby generate more stable and robust forecasts.

[9] We also implemented this evaluation using Lasso regressions. These results yielded inferior performance and are available upon request.

Table 1: Set of predictors

Variable	Definition	Source Data
Panel A: Fundamentals		
Network Distribution	Measures the dispersion of Bitcoin holdings across addresses, indicating concentration or decentralization of supply.	CoinMetrics
NVT (Network Value to Transactions)	Ratio of market capitalization to transaction volume; analogous to a price-to-earnings ratio for blockchain activity.	CoinMetrics
Annual Inflation	Yearly change in Bitcoin circulating supply, driven by mining issuance.	CoinMetrics
Block Count	Number of blocks mined during a given period, reflecting network activity and security.	CoinMetrics
Exchange Withdrawals	Bitcoin flows leaving exchanges to external wallets; associated with accumulation and long-term holding.	CoinMetrics
Exchange Deposits	Bitcoin flows entering exchanges; proxy for potential selling pressure and market liquidity.	CoinMetrics
MVRV (Market Value to Realized Value)	Ratio of market value to realized value; indicates whether Bitcoin is overvalued or undervalued relative to historical purchase prices.	CoinMetrics
30-Day Active Supply	Amount of Bitcoin moved in the last 30 days; captures short-term liquidity and turnover.	CoinMetrics
1-Year Active Supply	Amount of Bitcoin moved in the last 365 days; reflects long-term liquidity and accumulation.	CoinMetrics
Active Addresses	Number of unique addresses active on the network (sending or receiving BTC); proxy for adoption and usage.	CoinMetrics
Difficulty	Mining difficulty level to validate a block; adjusted every ~2 weeks to maintain a stable block time.	CoinMetrics
Mean Difficulty	Average mining difficulty over a given period; smooths short-term fluctuations.	CoinMetrics
Total Fees	Sum of transaction fees paid to miners in a given period; reflects demand for block space.	CoinMetrics
Active Supply	Share of circulating Bitcoin supply that has moved recently; measures the proportion of active vs. inactive coins.	CoinMetrics
Miner Rev./Hash	Mining revenue per unit of computational power; proxy for miner profitability.	CoinMetrics
Mean Hash Rate	Average computational power securing the network; indicator of security and robustness.	CoinMetrics
1-Day Active Supply	Amount of Bitcoin moved within the last 24 hours; captures immediate liquidity.	CoinMetrics
Miner Rev./Hash/sec	Mining revenue per second of hash power; alternative normalization of mining profitability.	CoinMetrics
Blockchain Factor	Synthetic factor that summarizes the information from blockchain variables that are statistically significant in the in-sample exercises.	PCA
Panel B: Macroeconomics		
Euro (EUR)	Daily log return of the USD price of the euro (USD/EUR).	LSEG Datastream
Japanese Yen (JPY)	Daily log return of the USD price of the yen (USD/JPY).	LSEG Datastream
British Pound (GBP)	Daily log return of the USD price of the pound (USD/GBP).	LSEG Datastream
Swiss Franc (CHF)	Daily log return of the USD price of the franc (USD/CHF).	LSEG Datastream
Canadian Dollar (CAD)	Daily log return of the USD price of the Canadian dollar (USD/CAD).	LSEG Datastream
Australian Dollar (AUD)	Daily log return of the USD price of the Australian dollar (USD/AUD).	LSEG Datastream
New Zealand Dollar (NZD)	Daily log return of the USD price of the New Zealand dollar (USD/NZD).	LSEG Datastream
Chinese Yuan (CNY)	Daily log return of the USD price of the yuan (USD/CNY).	LSEG Datastream
Mexican Peso (MXN)	Daily log return of the USD price of the peso (USD/MXN).	LSEG Datastream
Hong Kong Dollar (HKD)	Daily log return of the USD price of the Hong Kong dollar (USD/HKD).	LSEG Datastream
Fiat Factor	Synthetic factor summarizing the information from fiat-currency variables that are statistically significant in the in-sample exercises.	PCA
Panel C: Equities and Global Indices		
Dow Jones	Daily log return of the Dow Jones Industrial Average (30 U.S. large-cap companies).	LSEG Datastream
Brent Crude	Daily log return of Brent crude oil price (global energy benchmark).	LSEG Datastream
Gold	Daily log return of gold price (safe-haven asset).	LSEG Datastream
Nasdaq Composite	Daily log return of the Nasdaq Composite Index (technology-oriented firms).	LSEG Datastream
S&P 500	Daily log return of the S&P 500 Index (broad U.S. equity market).	LSEG Datastream
VIX Index	Daily log return of the CBOE Volatility Index (market fear gauge).	LSEG Datastream
FTSE 100	Daily log return of the FTSE 100 Index (U.K. large-cap companies).	LSEG Datastream
DAX 40	Daily log return of the DAX 40 Index (German blue-chip firms).	LSEG Datastream
CAC 40	Daily log return of the CAC 40 Index (French large-cap firms).	LSEG Datastream

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Table 1 (continued)

Variable	Definition	Source Data
Euro Stoxx 50	Daily log return of the Euro Stoxx 50 Index (Eurozone blue-chip companies).	LSEG Datastream
Nikkei 225	Daily log return of the Nikkei 225 Index (Japanese equity market).	LSEG Datastream
Hang Seng	Daily log return of the Hang Seng Index (Hong Kong-listed firms).	LSEG Datastream
Shanghai Composite	Daily log return of the Shanghai Composite Index (mainland China equities).	LSEG Datastream
ASX 200	Daily log return of the ASX 200 Index (Australian equity market).	LSEG Datastream
BSE Sensex	Daily log return of the BSE Sensex Index (Indian equity market).	LSEG Datastream
IBOVESPA	Daily log return of the IBOVESPA Index (Brazilian equity market).	LSEG Datastream
Mexican IPC	Daily log return of the Mexican IPC Index (Mexican equity market).	LSEG Datastream
Kospi	Daily log return of the Kospi Index (South Korean equity market).	LSEG Datastream
EPU Index	Daily log return of the Economic Policy Uncertainty (EPU) Index.	Policy Uncertainty
Equities Factor	Synthetic factor summarizing the information from equity and global index variables that are statistically significant in the in-sample exercises.	PCA
Panel D: Fixed Income ETFs		
TLT	Daily log return of the iShares 20+ Year Treasury Bond ETF (long-term Treasuries, >20 years).	LSEG Datastream
IEF	Daily log return of the iShares 7–10 Year Treasury Bond ETF (intermediate-term Treasuries).	LSEG Datastream
IEI	Daily log return of the iShares 3–7 Year Treasury Bond ETF (short-to-intermediate Treasuries).	LSEG Datastream
VGSH	Daily log return of the Vanguard Short-Term Treasury ETF (1–3 year Treasuries).	LSEG Datastream
GOVT	Daily log return of the iShares U.S. Treasury Bond ETF (broad maturity spectrum).	LSEG Datastream
ZROZ	Daily log return of the PIMCO 25+ Year Zero Coupon U.S. Treasury Index ETF (long-duration exposure).	LSEG Datastream
IUSB	Daily log return of the iShares Core Total USD Bond Market ETF (Treasuries, MBS, corporates).	LSEG Datastream
TIP	Daily log return of the iShares TIPS Bond ETF (Treasury Inflation-Protected Securities).	LSEG Datastream
MBB	Daily log return of the iShares MBS ETF (agency mortgage-backed securities).	LSEG Datastream
Fixed Income Factor	Synthetic factor summarizing the information from fixed-income ETF variables that are statistically significant in the in-sample exercises.	PCA
Panel E: Sentiment Indicators		
Google Trends	Search intensity for Bitcoin-related terms on Google; proxy for public interest and retail attention.	Google Trends
Loughran & McDonald	Text-based sentiment measure constructed by the authors using the Loughran–McDonald financial dictionary, quantified from 17,051 financial news articles collected from specialized portals.	Bitcoin news
ChatGPT 4.0	Context-aware sentiment score constructed by the authors using ChatGPT 4.0, quantified from 17,051 financial news articles collected from specialized portals.	Bitcoin news
FinBERT	Sentiment classification constructed by the authors using the FinBERT model, quantified from 17,051 financial news articles collected from specialized portals.	Bitcoin news
BitcoinTalks	Sentiment extracted from BitcoinTalk forum posts; reflects opinions and mood of crypto community participants.	Bitcointalk
Fear and Greed Index	Composite index of crypto market sentiment; combines volatility, momentum, social media, and surveys into a greed–fear scale.	Fear and Greed Index
Wikipedia	Page views of Bitcoin-related Wikipedia articles; indicator of curiosity, learning, and retail awareness.	Wikipedia Pageviews
Sentiment Factor	Synthetic factor summarizing the information from sentiment-related variables that are statistically significant in the in-sample exercises.	PCA
Panel F: Volume Strategy		
Volume ADI	Accumulation/Distribution Index; measures the cumulative flow of money into and out of an asset. Signal = 1 when the slope is positive.	TA-Lib (Python)
Volume OBV	On-Balance Volume; cumulative total of volume adjusted for price direction. Signal = 1 when OBV increases.	TA-Lib (Python)
Volume CMF	Chaikin Money Flow; gauges buying and selling pressure based on price and volume. Signal = 1 when CMF crosses above 0.	TA-Lib (Python)

Continued on next page

Table 1 (continued)

Variable	Definition	Source Data
Volume FI	Force Index; combines price change and volume to capture the strength of market moves. Signal = 1 when FI crosses above 0.	TA-Lib (Python)
Volume EM	Ease of Movement; measures the relationship between price change and volume. Signal = 1 when EM > 0.	TA-Lib (Python)
Volume SMA EM	Smoothed Ease of Movement; EMV compared against its simple moving average. Signal = 1 when EM crosses above its SMA.	TA-Lib (Python)
Volume VPT	Volume Price Trend; cumulative indicator combining percentage price change and volume. Signal = 1 when the slope is positive.	TA-Lib (Python)
Volume VWAP	Volume-Weighted Average Price; average price weighted by traded volume. Signal = 1 when price > VWAP.	TA-Lib (Python)
Volume MFI	Money Flow Index; oscillator that uses price and volume to measure overbought or oversold conditions. Signal = 1 when MFI crosses above 20.	TA-Lib (Python)
Volume NVI	Negative Volume Index; assumes that smart money is active on low-volume days. Signal = 1 when the slope is positive.	TA-Lib (Python)
Volume Factor	Synthetic factor summarizing the information from volume-based indicators that are statistically significant in the in-sample exercises.	PCA
Panel G: Volatility Strategy		
Volatility BBM	Bollinger Band Middle; moving average of the price within Bollinger Bands. Signal = 1 when price crosses above BBM.	TA-Lib (Python)
Volatility BBH	Bollinger Band High; the upper band two standard deviations above the moving average. Signal = 1 when price crosses above BBH.	TA-Lib (Python)
Volatility BBL	Bollinger Band Low; the lower band two standard deviations below the moving average. Signal = 1 when price crosses above BBL.	TA-Lib (Python)
Volatility BBW	Bollinger Band Width; difference between the upper and lower bands, capturing volatility. Signal = 1 when BBW slope is positive.	TA-Lib (Python)
Volatility BBP	Bollinger Band %B; position of price within the bands. Signal = 1 when %B > 0.2.	TA-Lib (Python)
Volatility BBHI	Bollinger Band High Indicator; binary indicator of price relative to the upper band. Signal = 1 if value > 0.	TA-Lib (Python)
Volatility BBLI	Bollinger Band Low Indicator; binary indicator of price relative to the lower band. Signal = 1 if value > 0.	TA-Lib (Python)
Volatility KCC	Keltner Channel Center; central line of the Keltner Channel based on EMA. Signal = 1 when price crosses above KCC.	TA-Lib (Python)
Volatility KCH	Keltner Channel High; upper Keltner band. Signal = 1 when price crosses above KCH.	TA-Lib (Python)
Volatility KCL	Keltner Channel Low; lower Keltner band. Signal = 1 when price crosses above KCL.	TA-Lib (Python)
Volatility KCW	Keltner Channel Width; difference between upper and lower Keltner bands. Signal = 1 when KCW slope is positive.	TA-Lib (Python)
Volatility KCP	Keltner % Position; relative position of price within the Keltner Channel. Signal = 1 when KCP > 0.2.	TA-Lib (Python)
Volatility KCHI	Keltner High Indicator; binary indicator relative to the upper Keltner band. Signal = 1 if value > 0.	TA-Lib (Python)
Volatility KCLI	Keltner Low Indicator; binary indicator relative to the lower Keltner band. Signal = 1 if value > 0.	TA-Lib (Python)
Volatility DCL	Donchian Lower; minimum price over a defined lookback period. Signal = 1 when price crosses above DCL.	TA-Lib (Python)
Volatility DCH	Donchian Upper; maximum price over a defined lookback period. Signal = 1 when price crosses above DCH.	TA-Lib (Python)
Volatility DCP	Donchian % Position; relative position of price within the Donchian Channel. Signal = 1 when slope is positive.	TA-Lib (Python)
Volatility ATR	Average True Range; average range of price movement including gaps. Signal = 1 when ATR slope is positive.	TA-Lib (Python)
Volatility UI	Ulcer Index; measures downside risk and depth of price drawdowns. Signal = 1 when UI 3-day average is decreasing.	TA-Lib (Python)
Volatility Factor	Synthetic factor summarizing the information from volatility-based indicators that are statistically significant in the in-sample exercises.	PCA
Panel H: Trends Strategy		
Trend MACD	Moving Average Convergence Divergence line; difference between fast and slow EMAs. Signal = 1 when MACD crosses above the signal line.	TA-Lib (Python)
Trend MACD Signal	Signal line of MACD; EMA of the MACD line. Signal = 1 when MACD > Signal.	TA-Lib (Python)
Trend MACD Diff	MACD Histogram; difference between MACD line and Signal line. Signal = 1 when value > 0.	TA-Lib (Python)
Trend SMA Fast	Fast Simple Moving Average. Signal = 1 when it crosses above the slow SMA.	TA-Lib (Python)
Trend SMA Slow	Slow Simple Moving Average. Signal = 1 when fast SMA > slow SMA.	TA-Lib (Python)
Trend EMA Fast	Fast Exponential Moving Average. Signal = 1 when it crosses above the slow EMA.	TA-Lib (Python)
Trend EMA Slow	Slow Exponential Moving Average. Signal = 1 when fast EMA > slow EMA.	TA-Lib (Python)
Trend TRIX	Triple Exponential Average oscillator. Signal = 1 when value > 0.	TA-Lib (Python)
Trend Mass Index	Detects trend reversals using EMA ranges. Signal = 1 when Mass Index > 27.	TA-Lib (Python)
Trend DPO	Detrended Price Oscillator; removes long-term trend. Signal = 1 when slope is positive.	TA-Lib (Python)
Trend KST	Know Sure Thing momentum oscillator. Signal = 1 when KST crosses above its signal line.	TA-Lib (Python)

Continued on next page

Table 1 (continued)

Variable	Definition	Source Data
Trend KST Signal	Signal line of KST. Signal = 1 when KST > Signal.	TA-Lib (Python)
Trend KST Diff	Difference between KST and Signal. Signal = 1 when slope is positive.	TA-Lib (Python)
Trend Ichimoku Conversion	Tenkan-sen (conversion line). Signal = 1 when it crosses above the base line.	TA-Lib (Python)
Trend Ichimoku Base	Kijun-sen (base line). Signal = 1 when conversion line > base line.	TA-Lib (Python)
Trend Ichimoku A	Senkou Span A. Signal = 1 when price > Span A.	TA-Lib (Python)
Trend Ichimoku B	Senkou Span B. Signal = 1 when Span A > Span B and price > Span A.	TA-Lib (Python)
Trend STC	Schaff Trend Cycle; combines MACD and cycles. Signal = 1 when value > 25.	TA-Lib (Python)
Trend ADX	Average Directional Index; measures trend strength. Signal = 1 when ADX > 25 and DI+ > DI−.	TA-Lib (Python)
Trend ADX+	Positive directional indicator (DI+). Signal = 1 when DI+ > DI−.	TA-Lib (Python)
Trend CCI	Commodity Channel Index; measures deviation from mean price. Signal = 1 when crosses above −100.	TA-Lib (Python)
Trend Aroon Up	Aroon Up indicator; measures time since highest high. Signal = 1 when value > 70.	TA-Lib (Python)
Trend Aroon Down	Aroon Down indicator; measures time since lowest low. Signal = 1 when value < 30.	TA-Lib (Python)
Trend Aroon Oscillator	Difference between Aroon Up and Down. Signal = 1 when value > 50.	TA-Lib (Python)
Trend PSAR Up	Parabolic SAR in upward mode. Signal = 1 when PSAR < price.	TA-Lib (Python)
Trend PSAR Down	Parabolic SAR in downward mode. Signal = 1 when PSAR > price.	TA-Lib (Python)
Trends Factor	Synthetic factor summarizing the information from trend-based indicators that are statistically significant in the in-sample exercises.	PCA
Panel I: Momentum Strategy		
Momentum RSI	Relative Strength Index; measures speed and change of price movements. Signal = 1 when RSI > 30.	TA-Lib (Python)
Momentum Stoch RSI	Stochastic RSI; oscillator of RSI values. Signal = 1 when value > 0.2.	TA-Lib (Python)
Momentum TSI	True Strength Index; momentum indicator based on double smoothed price changes. Signal = 1 when value > 0.	TA-Lib (Python)
Momentum UO	Ultimate Oscillator; combines short, medium, and long-term price action. Signal = 1 when value > 30.	TA-Lib (Python)
Momentum Stochastic	Stochastic Oscillator; compares closing price to price range over a period. Signal = 1 when %K crosses above signal line.	TA-Lib (Python)
Momentum Stochastic Signal	Signal line of the Stochastic Oscillator. Signal = 1 when slope is positive.	TA-Lib (Python)
Momentum WR	Williams %R; measures overbought/oversold conditions. Signal = 1 when value > -80.	TA-Lib (Python)
Momentum AO	Awesome Oscillator; difference between two SMAs of median price. Signal = 1 when value > 0.	TA-Lib (Python)
Momentum ROC	Rate of Change; percentage change in price over a specified period. Signal = 1 when value > 0.	TA-Lib (Python)
Momentum PPO	Percentage Price Oscillator; measures difference between two EMAs as a percentage. Signal = 1 when it crosses above its signal line.	TA-Lib (Python)
Momentum PPO Signal	Signal line of PPO. Signal = 1 when PPO > signal line.	TA-Lib (Python)
Momentum PVO	Percentage Volume Oscillator; difference between two EMAs of volume. Signal = 1 when it crosses above its signal line.	TA-Lib (Python)
Momentum PVO Signal	Signal line of PVO. Signal = 1 when PVO > signal line.	TA-Lib (Python)
Momentum KAMA	Kaufman Adaptive Moving Average; adaptive trend-following indicator. Signal = 1 when price > KAMA.	TA-Lib (Python)
Momentum Factor	Synthetic factor that summarizes the information from momentum-based indicators that are statistically significant in the in-sample exercises.	PCA

Note: This table reports the definitions of the variables employed in the study. We classify as fundamental variables those in Panel A; as macroeconomic variables those in Panels B, C, and D; as sentiment variables those in Panel E; and as technical variables those in Panels F, G, H, and I. Each category is further disaggregated into segments of variables to improve the clarity and interpretation of our results. For the case of the sentiment measures Loughran & McDonald, ChatGPT 4.0, and FinBERT, we employed news from the following portals: *Cointelegraph*, *Cryptonews*, *Dailyhodl*, and *Coindesk*. A more detailed description of the procedure for measuring these variables is provided in the Appendix.

3.4. *Trading Strategies*

To evaluate the economic value of our forecasts, two trading exercises are conducted. First, we implement the seminal framework of Anatolyev and Gerko (2005), in which an investor takes a long position when the predicted return for the next period is positive and a short position otherwise. Let $\hat{r}_{t+1}$ denote the one-step-ahead forecast of the Bitcoin return. The trading signal is defined as

$$s_t = \begin{cases} 1, & \text{if } \hat{r}_{t+1} > 0, \\ -1, & \text{if } \hat{r}_{t+1} < 0, \end{cases} \tag{7}$$

so that the return of the strategy at $t + 1$ is

$$R_{t+1}^{\text{strat}} = s_t \cdot r_{t+1}, \tag{8}$$

where r_{t+1} is the realized Bitcoin return. We assess the statistical significance of the strategy's profitability using the Straightforward Excess Profitability (SEP) test proposed by Pincheira et al. (2022). This test evaluates the null hypothesis that r_{t+1} follows a driftless random walk (DRW), under which the trading rule has no predictive content. Compared with the traditional Excess Profitability (EP) test, the SEP test offers two advantages: (i) higher statistical power in finite samples, and (ii) a more direct formulation that avoids the need to estimate auxiliary parameters under the null. The SEP statistic is computed as a t-statistic with HAC standard errors.

Second, we consider a trading strategy based on portfolio allocation under mean–variance preferences, following Y. Wang et al. (2020). The investor allocates wealth between a risk-free asset and Bitcoin, with the optimal portfolio weight determined ex-ante by the forecasted mean and volatility of Bitcoin returns

$$U_t = \mathbb{E}\left[\omega_t r_{t+1} + r_f\right] - \frac{1}{2}\gamma \operatorname{Var}\left(\omega_t r_{t+1} + r_f\right), \tag{9}$$

where $\omega_t \in [0, 1]$ denotes the fraction of wealth invested in Bitcoin, r_{t+1} is the excess return of Bitcoin over the risk-free rate r_f (proxied by the 3-month U.S. Treasury bill rate), and γ is the coefficient of relative risk aversion. Maximizing (9) yields the optimal weight

$$\omega_t^* = \frac{\hat{r}_{t+1}}{\gamma\, \hat{\sigma}_{t+1}^2}, \tag{10}$$

where $\hat{r}_{t+1}$ and $\hat{\sigma}_{t+1}^2$ are the forecasted mean and variance of Bitcoin returns. For simplicity, we use a 28-day rolling window to generate the variance forecasts, and set $\gamma = 6$, consistent with Hardy et al. (2023). The weight is restricted to $[0, 1]$, allowing the investor to hold only the risk-free asset, only Bitcoin, or any convex combination of the two. The realized portfolio return is then

$$R^p_{t+1} = \omega^*_t r_{t+1} + r_{t+1,f} - \tau \left|\omega^*_{t+1} - \omega_t\right|, \tag{11}$$

where $r_{t+1,f}$ is the realized risk-free rate and $\tau = 0.01\%$[10] represents proportional transaction costs. For both trading exercises, we report the annualized returns and Sharpe ratios of each variable and compare them against a buy-and-hold strategy.

4. Results

This section summarizes the main findings. First, we report the in-sample exercises, where we identify the variables that are statistically significant in forecasting Bitcoin returns. Second, we examine the out-of-sample performance against benchmark models to assess their predictive power. Finally, we evaluate the economic value of the forecasts through trading exercises, testing whether they generate returns above passive strategies.

4.1. In-sample findings

The in-sample evidence reported in Table 2 highlights three main findings. First, out of 564 exercises[11], only 155 are statistically significant, corresponding to 27% of the total. Second, technical variables account for the largest share of significant results (37%), followed by fundamental (17.1%), macroeconomic (16.5%), and sentiment predictors (15.6%). Within the technical category, performance differs markedly across signal construction methods: trend-based and volume-based indicators yield significance rates of 49% and 45%, respectively, whereas momentum-based indicators are significant in only 12% of cases. A similar result is observed among macroeconomic variables: while 38% of fixed income exercises are statistically significant, only 15% of those based on global indices achieve significance. Third, as expected, the average R^2 rises with the forecasting horizon: 0.13% for 1 day, 0.2% for 7 days, 0.78% for 14 days, and 0.82% for 28 days. Consistently, trend-based technical predictors stand out once again, exhibiting average R^2 values approximately 40% higher than those of the other categories across forecasting horizons.

A category-level breakdown highlights the variables with the strongest fit. In the technical domain, the indicators *Volatility KCHI*, *Trend MACD Signal*, and *Trend Ichimoku B* present coefficients that are consistently significant at the 1% level across most forecasting horizons, reaching maximum R^2 values close to 2.21% (see Table 2, Panels G and H). In the fundamental dimension, the most relevant variable is *1-Year Active Supply* (Table 2, Panel A), with R^2 values of up to 1.98%.

[10] We adopt a conservative approach by applying the highest transaction costs reported for Bitcoin trading on Binance, the most widely used Bitcoin trading platform globally according to *CoinMarketCap.com*.

[11] We evaluate 141 predictors across forecasting windows of 1, 7, 14, and 28 days, yielding a total of 564 exercises.

Among macroeconomic indicators, the *Shanghai Composite* (Table 2, Panel C) stands out by delivering significant results at long-term horizons, reaching its highest explanatory power at 14 days (R^2 = 0.96%). Within sentiment predictors, the news tone measured by Loughran & McDonald reaches an R^2 = 1.91% at 28 days (Table 2, Panel E). Finally, regarding variables constructed from principal components, the most important benefits come from the technical segment: models incorporating the *Trends Factor* double the average R^2 of their category across all horizons, while the *Volatility Factor* shows similar performance, although restricted to the 1- and 7-day horizons.

Table 2: In-sample Findings

Variable	1 day		7 days		14 days		28 days	
	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)
Panel A: Blockchain metrics								
Network Dist.	−0.55	0.14	−0.93	0.13	−1.51	0.73	−3.67	0.81
NVT	0.00*	0.10	0.00	0.10	0.00	0.68	0.00	0.68
Annual Inflation	0.01**	0.16	0.02**	0.16	0.01	0.69	0.01	0.69
Block Count	0.00***	0.25	0.00	0.14	0.00	0.68	0.00	0.70
Exchange Withdrawals	0.00	0.07	0.00	0.10	0.00	0.68	0.00	0.68
Exchange Deposits	0.00	0.05	0.00	0.09	0.00	0.68	0.00	0.68
MVRV	−0.10	0.07	0.02	0.10	0.03	0.69	0.10	0.71
30-Day Active Supply	−0.05	0.16	0.14**	0.20	0.13*	0.73	0.15	0.71
1-Year Active Supply	0.08	0.05	2.94***	0.76	5.58***	1.85	8.66***	1.98
Active Addresses	0.01	0.07	0.02*	0.14	0.02	0.70	0.01	0.69
Difficulty	−0.01	0.05	−0.07	0.11	−0.07	0.69	−0.05	0.68
Mean Difficulty	−0.07	0.13	−0.12	0.13	−0.15	0.71	−0.08	0.69
Total Fees	0.00	0.06	0.00	0.09	0.00	0.68	−0.01	0.69
Active Supply	−1.84	0.05	−2.67	0.09	−8.04	0.69	−22.83	0.71
Miner Rev./Hash	−0.01	0.07	0.02	0.10	0.04	0.70	0.08*	0.72
Mean Hash Rate	0.01**	0.15	0.02**	0.16	0.01	0.69	0.01	0.69
1-Day Active Supply	0.00	0.12	0.00	0.09	0.00	0.68	0.00	0.68
Miner Rev./Hash/sec	−0.01	0.07	0.00	0.09	0.01	0.68	0.02	0.68
Blockchain Factor	0.00	0.06	0.01	0.12	0.01	0.70	0.01	0.71

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Table 2 (continued)

Variable	**1 day**		**7 days**		**14 days**		**28 days**	
	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)
Panel B: Fiat Moneys								
Euro (EUR)	–0.03	0.05	–0.13	0.06	0.26	0.81	0.49	0.65
Japanese Yen (JPY)	–0.07	0.06	0.13	0.06	0.08	0.80	–0.04	0.63
British Pound (GBP)	0.08	0.06	–0.11	0.06	0.33	0.82	0.57	0.66
Swiss Franc (CHF)	–0.12	0.07	–0.28	0.08	–0.13	0.81	–0.10	0.63
Canadian Dollar (CAD)	0.01	0.04	0.05	0.05	0.10	0.80	0.08	0.63
Australian Dollar (AUD)	0.08	0.06	–0.12	0.06	–0.07	0.80	–0.27	0.64
New Zealand Dollar (NZD)	0.12	0.08	–0.04	0.05	–0.01	0.80	–0.24	0.64
Chinese Yuan (CNY)	–0.24	0.08	–0.06	0.05	0.08	0.80	–0.59	0.64
Mexican Peso (MXN)	0.08	0.07	0.06	0.05	–0.12	0.81	–0.09	0.63
Hong Kong Dollar (HKD)	–1.44	0.06	–4.84	0.09	–1.70	0.80	–3.02	0.63
Fiat Factor	0.00	0.06	0.00	0.05	0.00	0.83	0.00	0.62
Panel C: Equities and Global Indices								
Dow Jones	–0.13	0.17	0.04	0.05	0.13	0.81	–0.07	0.63
Brent Crude	–0.01	0.05	0.07	0.09	0.02	0.81	0.13	0.66
Gold	–0.03	0.05	–0.24*	0.10	–0.22	0.82	–0.42	0.67
Nasdaq Composite	–0.10*	0.15	–0.03	0.05	0.05	0.81	0.07	0.63
S&P 500	–0.14*	0.20	–0.01	0.05	0.03	0.80	–0.08	0.63
VIX Index	0.01	0.06	0.01	0.05	0.01	0.81	0.02	0.64
FTSE 100	–0.09	0.10	0.01	0.05	0.17	0.82	–0.22	0.64
DAX 40	–0.12*	0.18	0.05	0.05	0.19	0.83	–0.18	0.64

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Table 2 (continued)

Variable	1 day		7 days		14 days		28 days	
	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)
CAC 40	−0.09	0.12	0.03	0.05	0.19	0.83	−0.27	0.66
Euro Stoxx 50	−0.12*	0.18	0.02	0.05	0.18	0.83	−0.17	0.64
Nikkei 225	0.04	0.06	0.03	0.05	0.10	0.81	0.07	0.63
Hang Seng	−0.05	0.07	−0.25**	0.17	−0.13*	0.82	0.08	0.63
Shanghai Composite	−0.02	0.05	−0.20**	0.12	−0.44***	0.96	−0.49**	0.72
ASX 200	−0.05	0.06	0.05	0.05	0.24	0.83	0.06	0.63
BSE Sensex	−0.09	0.10	−0.03	0.05	−0.14	0.81	−0.13	0.64
IBOVESPA	−0.10*	0.18	0.03	0.05	0.07	0.81	−0.02	0.63
Mexican IPC	−0.08	0.08	0.11	0.06	0.20	0.82	0.23	0.64
Kospi	0.08	0.09	−0.12	0.07	−0.04	0.80	0.00	0.63
EPU Index	0.00	0.05	0.00	0.05	0.00	0.81	0.00	0.63
Equities Factor	0.00*	0.17	0.00	0.05	0.00	0.81	0.00	0.64
Panel D: Fixed Income ETFs								
TLT	0.16*	0.20	0.27	0.12	0.21	0.82	0.26	0.65
IEF	0.35**	0.18	0.78*	0.17	0.40	0.82	0.81	0.66
IEI	0.48*	0.13	1.19*	0.14	0.49	0.81	1.49	0.66
VGSH	0.96	0.10	3.06*	0.14	1.56	0.81	4.41*	0.67
GOVT	0.33*	0.12	0.74	0.11	0.51	0.82	0.89	0.65
ZROZ	0.10*	0.16	0.14	0.09	0.12	0.82	0.12	0.64
IUSB	0.21	0.07	0.73	0.11	0.76	0.83	1.04	0.66
TIP	0.70**	0.47	1.29*	0.29	0.91	0.86	1.21*	0.68

Continued on next page

Table 2 (continued)

Variable	**1 day**		**7 days**		**14 days**		**28 days**	
	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)
MBB	0.02	0.04	0.99^{*}	0.15	0.67	0.83	1.23	0.67
Fixed Income Factor	0.00^{*}	0.15	0.00^{*}	0.16	0.00	0.83	0.00	0.67
Panel E: Sentiment Indicators								
Google Trends	0.00	0.30	0.00	0.09	0.01	0.20	0.01	1.52
Loughran & Mcdonald	0.05	0.32	−0.33	0.23	-0.58^{*}	0.41	-1.11^{***}	1.91
Chat GPT 4.o	0.07	0.42	−0.04	0.09	−0.26	0.29	-0.45^{*}	1.67
Finbert	−0.01	0.36	−0.02	0.23	-0.04^{**}	0.41	-0.07^{***}	1.86
Bitcoin Talks	0.00	0.30	0.01	0.09	0.01	0.19	0.02	1.54
Fear and Greed Index	0.00	0.33	0.00	0.09	0.01	0.20	0.00	1.52
Wikipedia	0.00	0.32	0.01	0.10	0.00	0.19	−0.01	1.52
Sentiment Factor	0.00	0.40	0.00	0.11	0.00	0.26	0.00	1.61
Panel F: Volume Strategy								
Volume ADI	0.04^{***}	0.28	0.07^{**}	0.23	0.08^{**}	0.77	0.21^{***}	0.94
Volume OBV	0.03^{*}	0.13	0.06^{**}	0.18	0.09^{**}	0.79	0.13^{**}	0.79
Volume CMF	−0.02	0.07	−0.15	0.20	−0.03	0.68	0.14	0.70
Volume FI	0.00	0.05	−0.04	0.10	−0.18	0.77	−0.18	0.72
Volume EM	0.01	0.05	0.02	0.10	−0.01	0.68	−0.01	0.68
Volume SMA EM	−0.01	0.07	0.04	0.11	0.04	0.69	0.02	0.68
Volume VPT	0.03^{*}	0.12	0.06^{**}	0.18	0.09^{**}	0.79	0.13	0.79
Volume VWAP	0.04^{***}	0.28	0.14^{***}	0.44	0.14^{**}	0.86	0.33^{***}	1.23

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Table 2 (continued)

Variable	1 day		7 days		14 days		28 days	
	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)
Volume MFI	−0.06	0.06	−0.36	0.16	−0.53	0.75	−1.02	0.80
Volume NVI	0.00	0.05	0.02	0.10	0.07*	0.73	0.09	0.72
Volume Factor	0.01**	0.18	0.02**	0.22	0.03***	0.83	0.05***	0.90
Panel G: Volatility Strategy								
Volatility BBM	−0.01	0.06	−0.07	0.12	−0.19	0.77	−0.20*	0.73
Volatility BBH	0.05*	0.12	0.24***	0.32	0.16	0.73	0.28*	0.75
Volatility BBL	−0.03	0.06	−0.02	0.09	−0.01	0.68	−0.11	0.69
Volatility BBW	0.01	0.08	0.12***	0.46	0.17***	1.06	0.20***	0.93
Volatility BBP	−0.06	0.15	−0.11	0.14	−0.17	0.74	−0.24	0.74
Volatility BBHI	0.04**	0.15	0.27***	0.66	0.32***	1.07	0.45***	1.06
Volatility BBLI	−0.06	0.16	−0.01	0.09	−0.06	0.69	−0.26	0.75
Volatility KCC	0.00	0.05	−0.05	0.11	−0.14	0.75	−0.20	0.75
Volatility KCH	0.07***	0.22	0.05	0.11	0.11	0.71	0.27**	0.78
Volatility KCL	−0.03	0.09	−0.04	0.10	−0.08	0.70	−0.06	0.69
Volatility KCW	0.01	0.06	0.07**	0.21	0.07*	0.74	0.02	0.68
Volatility KCP	−0.01	0.05	0.08	0.13	0.03	0.68	0.05	0.69
Volatility KCHI	0.07***	0.77	0.24***	0.94	0.32***	1.51	0.43***	1.49
Volatility KCLI	−0.01	0.05	0.01	0.09	0.05	0.70	−0.20	0.80
Volatility DCL	0.00	0.05	−0.21	0.11	−0.08	0.68	−0.38	0.69
Volatility DCH	0.00	0.05	0.00	0.09	0.00	0.68	0.00	0.68
Volatility DCP	0.03***	0.20	0.06**	0.18	0.08**	0.77	0.09*	0.73

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Table 2 (continued)

Variable	**1 day**		**7 days**		**14 days**		**28 days**	
	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)
Volatility ATR	0.01	0.07	0.09***	0.29	0.07*	0.74	0.06	0.70
Volatility UI	0.02**	0.14	0.02	0.10	−0.03	0.69	0.08	0.72
Volatility Factor	0.01***	0.44	0.06***	0.90	0.07***	1.21	0.09***	1.19
Panel H: Trends Strategy								
Trend MACD	−0.01	0.05	0.00	0.09	0.03	0.68	0.15	0.70
Trend MACD Signal	0.04***	0.30	0.19***	0.73	0.19***	1.02	0.30***	1.23
Trend MACD Diff	−0.01	0.05	0.00	0.09	0.03	0.68	0.15	0.70
Trend SMA Fast	−0.04	0.07	−0.02	0.09	−0.19	0.72	−0.12	0.69
Trend SMA Slow	0.02*	0.12	0.14***	0.58	0.23***	1.12	0.36***	1.16
Trend EMA Fast	0.03	0.06	0.02	0.09	0.01	0.68	0.16	0.69
Trend EMA Slow	0.03***	0.25	0.21***	1.04	0.31***	1.53	0.51***	1.49
Trend TRIX	0.08*	0.09	0.07	0.10	−0.02	0.68	0.21	0.69
Trend Mass Index	0.08	0.09	0.54***	0.36	0.41*	0.75	0.59***	0.75
Trend DPO	−0.01	0.06	0.01	0.09	−0.05	0.71	−0.03	0.69
Trend KST	0.05*	0.10	0.05	0.10	0.22*	0.74	0.17	0.70
Trend KST Signal	0.03***	0.19	0.14***	0.52	0.14**	0.86	0.22***	0.97
Trend KST Diff	0.01	0.06	−0.03	0.11	0.00	0.68	0.03	0.69
Trend Ichimoku Conversion	0.01	0.05	−0.11	0.12	−0.06	0.68	0.00	0.68
Trend Ichimoku Base	0.02**	0.15	0.13***	0.51	0.27***	1.27	0.31***	1.04
Trend Ichimoku A	0.04***	0.28	0.18***	0.67	0.20***	1.02	0.37***	1.30
Trend Ichimoku B	0.04***	0.39	0.25***	1.36	0.37***	1.87	0.66***	2.21

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Table 2 (continued)

Variable	1 day		7 days		14 days		28 days	
	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)
Trend STC	−0.03	0.07	0.01	0.09	−0.04	0.68	0.14	0.70
Trend ADX	0.03***	0.19	0.19***	0.81	0.21***	1.02	0.06	0.69
Trend ADX+	0.04***	0.28	0.22***	1.02	0.25***	1.17	0.29***	0.99
Trend CCI	−0.03	0.08	−0.02	0.09	−0.12	0.71	−0.15	0.70
Trend Aroon Up	0.04	0.08	0.04	0.10	0.06	0.68	0.23	0.71
Trend Aroon Down	0.05**	0.11	0.02	0.09	0.02	0.68	−0.02	0.68
Trend Aroon Oscillator	0.00	0.05	0.14*	0.13	0.32**	0.78	0.52***	0.80
Trend PSAR Up	0.02**	0.13	0.09**	0.21	0.11*	0.77	0.37***	1.27
Trend PSAR Down	−0.04	0.32	−0.15	0.49	−0.19	0.99	−0.43	1.58
Trends Factor	0.01***	0.39	0.06***	1.53	0.10***	2.13	0.14***	2.00
Panel I: Momentum Strategy								
Momentum RSI	0.01	0.05	0.06	0.10	0.15	0.69	0.18	0.69
Momentum Stoch RSI	−0.01	0.05	0.00	0.09	−0.05	0.69	−0.14	0.72
Momentum TSI	−0.01	0.05	−0.02	0.09	−0.09	0.69	0.04	0.68
Momentum UO	−0.11	0.10	0.27*	0.14	−0.06	0.68	−0.11	0.68
Momentum Stochastic	0.00	0.05	0.04*	0.13	0.03	0.69	0.06	0.70
Momentum Stochastic Signal	0.03**	0.17	−0.02	0.10	0.00	0.68	0.01	0.68
Momentum WR	0.01	0.05	−0.03	0.10	0.04	0.68	−0.02	0.68
Momentum AO	0.00	0.05	−0.10	0.11	−0.03	0.68	−0.01	0.68
Momentum ROC	0.01	0.05	−0.05	0.11	−0.09	0.70	−0.20	0.74

Continued on next page

Table 2 (continued)

Variable	**1 day**		**7 days**		**14 days**		**28 days**	
	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)	β	R^2 (%)
Momentum PPO	0.03	0.07	0.06	0.10	0.12	0.71	0.15	0.70
Momentum PPO Signal	0.04***	0.33	0.18***	0.67	0.17***	0.95	0.28***	1.15
Momentum PVO	−0.01	0.05	0.03	0.10	0.09	0.71	0.08	0.69
Momentum PVO Signal	0.01	0.09	0.03	0.12	−0.01	0.68	−0.07	0.71
Momentum KAMA	−0.01	0.06	−0.07	0.13	−0.12	0.73	−0.16	0.72
Momentum Factor	0.00	0.05	0.03**	0.17	0.03*	0.73	0.03	0.71

Note: Coefficient of determination (R^2) shown in percentage. Coefficients in Panels F, G, H, and I are multiplied by 10. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2. Out-of-sample performance

Given the risks of overfitting and *data snooping*, it is essential to rely on out-of-sample evaluation. Table 3 presents the out-of-sample results comparing our models with a random walk benchmark, assessing statistical significance with the Clark and West test. Although 67 variables exhibited in-sample predictive value, only 29 maintained significant out-of-sample benefits in at least one forecasting horizon, and just 4 outperformed the random walk across all horizons. In line with the in-sample analysis, performance differs substantially across predictor categories: 32.2% of the exercises based on technical indicators show predictive power at the population level and achieve R^2_{oos} values above the benchmark, compared to 16.7% for fundamentals, 18.8% for sentiment, and only 5.6% for macroeconomic variables.

Analyzing the results at a more disaggregated level reveals that trend-based technical indicators provide the strongest out-of-sample predictive power, with 48.4% of exercises being statistically significant. Within this group, the *Trend EMA Slow* and *Trend ADX+* stand out. These are followed by volatility strategies, with 29.5% of significant exercises, and volume strategies, with 16.7%. The construction of factors from these technical signals further strengthens the evidence: the *Trends Factor* achieves R^2_{oos} values of 0.13% (1 day), 0.37% (7 days), 0.52% (14 days), and 0.7% (28 days), all statistically significant (see Table 3, Panel G). This indicates that trend information is not only valuable at the individual predictor level but can also be more effectively exploited when aggregated into composite indices. Similarly, the *Volatility Factor* and *Volume Factor* deliver significant forecasting gains, though with stronger consistency at longer horizons. By contrast, no additional benefits are observed for the remaining categories when condensing information into a single factor.

Finally, we assess the robustness of these results by employing an alternative benchmark that incorporates greater memory of the series. Unlike what is typically observed in financial returns, Bitcoin returns exhibit noticeable persistence, as evidenced by consecutive periods of price increases, as evidenced by periods of consecutive price increases. For this reason, it is relevant to evaluate the results against a benchmark that captures this feature. Based on the autocorrelation function (ACF), we identify that an AR(4) specification constitutes an appropriate benchmark to represent such dynamics. When comparing the results against this benchmark, the magnitude of out-of-sample gains decreases on average. For instance, in the case of the *Volatility KCHI*, the average R^2_{oos} across horizons declines from 0.76 when contrasted with a random walk to 0.59 when evaluated against the AR(4) benchmark (see Table 3). However, this reduction in magnitude translates only into a slight decrease in the share of significant exercises, from 32.2% to 28.9% (see Table 6).

Table 3: R^2_{oos} at different forecast horizons

Variable	1 day	7 days	14 days	28 days
Panel A: Blockchain metrics				
NVT	−0.20	−0.06	−0.07	−0.07
Annual Inflation	0.09*	−0.01	−0.03	−0.04
Block Count	−0.02	−0.29	−0.19	−0.08
30-Day Active Supply	−0.10	0.10	−0.01	−0.12
1-Year Active Supply	−0.01	0.71***	1.03***	0.88***
Active Addresses	0.02	0.02	−0.02	−0.03
Miner Rev./Hash	0.08*	−0.12	−0.06	−0.06
Mean Hash Rate	0.11*	−0.01	−0.03	−0.04
Blockchain Factor	−0.12	−0.06	−0.05	−0.06
Panel B: Equities and Global Indices				
Gold	−0.10	0.02	−0.16	−0.01
Nasdaq Composite	−0.02	−0.30	−0.22	−0.13
S&P 500	−0.01	−0.40	−0.27	−0.14
DAX 40	0.21*	−0.20	−0.09	−0.08
Euro Stoxx 50	0.18*	−0.21	−0.08	−0.07
Hang Seng	−0.07	0.12*	−0.08	−0.09
Shanghai Composite	−0.02	0.08	0.13	0.01
IBOVESPA	−0.12	−0.31	−0.10	−0.10
Equities Factor	0.03	−0.36	−0.16	−0.11
Panel C: Fixed Income ETFs				
TLT	−0.09	−0.16	−0.11	−0.06
IEF	−0.04	0.05	−0.11	−0.04
IEI	−0.07	0.06	−0.13	−0.03
VGSH	−0.02	−0.05	−0.15	−0.03
GOVT	−0.03	−0.17	−0.14	−0.06
ZROZ	−0.03	−0.19	−0.11	−0.08
TIP	0.03*	0.14	−0.02	−0.03
MBB	−0.93	−0.08	−0.17	−0.13
Fixed Income Factor	−0.20	0.01	−0.10	−0.03

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Table 3 (continued)

Variable	**1 day**	**7 days**	**14 days**	**28 days**
Panel D: Sentiment Indicators				
Loughran & Mcdonald	–0.08	0.05	0.37	0.02
Chat GPT 4.o	–0.17	–0.08	–0.15	–0.60
Finbert	0.01	0.20*	0.26**	0.99***
Sentiment Factor	–0.12	–0.06	0.03	–0.27
Panel E: Volume Strategy				
Volume ADI	–0.21	0.13	0.16	0.38
Volume OBV	–0.18	–0.07	0.01	0.10
Volume VPT	–0.18	–0.07	0.01	0.10*
Volume VWAP	–0.14	–0.14	–0.29	0.27***
Volume NVI	–0.03	–0.02	–0.06	–0.03
Volume Factor	–0.22	0.01	0.07*	0.23**
Panel F: Volatility strategy				
Volatility BBM	0.00	–0.04	0.05	–0.04
Volatility BBH	–0.26	–0.10	–0.14	–0.02
Volatility BBW	0.02	0.44***	–0.18	0.27**
Volatility BBHI	–0.06	0.43***	0.18**	0.56***
Volatility KCH	–0.05	–0.12	–0.06	–0.02
Volatility KCW	–0.02	–0.08	–0.07	–0.07
Volatility KCHI	0.32***	0.75***	0.73***	1.27***
Volatility DCP	–0.36	–0.06	–0.01	0.00
Volatility ATR	0.00	–0.08	–0.18	–0.14
Volatility UI	0.12*	–0.03	–0.31	0.01
Volatility Factor	0.08*	0.37***	–0.15	0.55***
Panel G: Trends Strategy				
Trend MACD Signal	–0.03	–0.47	–0.24	1.02***
Trend SMA Slow	–0.05	–0.27	0.36***	0.33***
Trend EMA Slow	0.10*	0.70***	0.94***	0.14***
Trend TRIX	–0.04	–0.02	–0.04	0.00
Trend Mass Index	–0.27	0.05**	0.07**	0.00*
Trend KST	0.04	–0.05	0.03	–0.02

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Table 3 (continued)

Variable	**1 day**	**7 days**	**14 days**	**28 days**
Trend KST Signal	0.04	–0.16	–0.03	1.09***
Trend Ichimoku Base	0.08*	0.38**	0.82***	0.58***
Trend Ichimoku A	–0.11	0.00**	–0.21	–0.14
Trend Ichimoku B	–0.03	–0.07	–0.23	–1.16
Trend ADX	0.11*	0.26***	0.65***	0.22**
Trend ADX+	0.20**	0.71***	0.79***	0.57***
Trend Aroon Down	0.01	–0.08	–0.03	–0.06
Trend Aroon Oscillator	–0.20	0.06*	–0.14	0.04
Trend PSAR Up	–0.23	–0.42	0.05*	0.96***
Trends Factor	0.13**	0.37***	0.52***	0.70***
Panel H: Momentum Strategy				
Momentum UO	0.09	0.00	–0.07	–0.02
Momentum Stochastic	–0.02	–0.10	–0.08	–0.06
Momentum Stochastic Signal	–0.34	–0.09	–0.02	–0.06
Momentum PPO Signal	–0.08	–0.27	–0.28	1.03***
Momentum Factor	–0.02	–0.13	–0.04	–0.06

Note: Recursive window. P/R = 1. The benchmark model for this test is a random walk. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Evaluation of trading strategies

Forecast accuracy does not necessarily translate into economic value. For investors and traders, statistical precision measured by metrics such as MSPE represents only one dimension of forecast evaluation (Brown & Hardy, 2024). Equally important is the practical usefulness of a forecast for decision-making, for instance, its ability to correctly anticipate market direction or to generate economic gains through investment strategies. In this sense, accuracy and economic value represent two distinct yet complementary criteria for assessing predictive performance. To explore the latter, we simulate a laboratory trading exercise in which an agent opens a long (short) position in Bitcoin when the predicted return from Eq. 3 is positive (negative). Again, we only consider the 67 variables that displayed significant forecasting gains in the in-sample exercises.

The results show that variables from different categories can generate excess returns relative to the benchmarks[12]. Among fundamentals, *Block Count* is the strongest predictor, delivering an

[12]In our data, the buy-and-hold strategy is equivalent to a random walk, since the model intercept captures Bitcoin's positive historical average return, implying that the forecast is simply to maintain the position.

annual excess return of 27% and raising the Sharpe ratio by 0.38. In addition, variables associated with Bitcoin mining energy costs, such as *Miner Rev./Hash*, also improve performance, particularly in longer training windows, although the gains are smaller. Similar effects are observed among macroeconomic predictors, such as the *Nasdaq Composite* equity index and a medium-term U.S. Treasury bond ETF (*IEI*) (see Table 4, Panels C and D), which increase the Sharpe Ratio by about 0.2. In the technical group, most variables perform similarly, but those based on trend detection and moving average crossovers, such as *Trend ADX+* and *Trend EMA Slow*, consistently outperform both the buy-and-hold and the AR(1) benchmark in terms of returns and Sharpe ratio. The factor built from these technical indicators also raises annualized returns by more than 10% when longer training windows are used.

Table 4: Anatoliev and Gerko Trading Rule

Variable	P/R = 4		P/R = 1		P/R = 0.4	
	Profits (%)	**Sharpe**	**Profits (%)**	**Sharpe**	**Profits (%)**	**Sharpe**
Panel A: Blockchain metrics						
NVT	0.28	0.40	0.41*	0.64	0.35	0.64
Annual Inflation	0.06	0.08	0.14	0.22	0.13	0.23
Block Count	0.58**	0.83	0.66***	1.03	0.30	0.56
30-Day Active Supply	0.45*	0.65	0.45*	0.70	0.18	0.34
1-Year Active Supply	0.32	0.47	0.45*	0.69	0.20	0.38
Active Addresses	0.30	0.43	0.45*	0.70	0.20	0.37
Miner Rev./Hash	0.41*	0.59	0.60**	0.93	0.36	0.67
Mean Hash Rate	0.05	0.07	0.21	0.32	0.13	0.25
Blockchain Factor	0.17	0.25	0.32	0.50	0.10	0.18
AR1	0.33*	0.47	0.47*	0.73	0.27	0.50
Buy & Hold	0.31	0.45	0.45*	0.70	0.20	0.37
Panel B: Equities and Global Indices						
Gold	0.31	0.41	0.56*	0.79	0.30	0.50
Nasdaq Composite	0.51*	0.67	0.83**	1.17	0.55*	0.92
S&P 500	0.34	0.46	0.58*	0.81	0.52*	0.87
DAX 40	0.21	0.28	0.39	0.54	0.31	0.51
Euro Stoxx 50	0.30	0.40	0.52*	0.73	0.36	0.60
Hang Seng	0.28	0.37	0.54*	0.75	0.29	0.48
Shanghai Composite	0.37	0.49	0.60*	0.85	0.36	0.60

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Table 4 (continued)

Variable	P/R = 4		P/R = 1		P/R = 0.4	
	Profits (%)	**Sharpe**	**Profits (%)**	**Sharpe**	**Profits (%)**	**Sharpe**
IBOVESPA	0.27	0.36	0.52*	0.73	0.34	0.57
Equities Factor	0.28	0.37	0.48*	0.68	0.31	0.51
AR1	0.38	0.51	0.59*	0.83	0.43	0.71
Buy & Hold	0.35	0.46	0.58*	0.82	0.33	0.54
Panel C: Fixed Income ETFs						
TLT	0.30	0.40	0.58*	0.82	0.47	0.78
IEF	0.23	0.30	0.49*	0.69	0.26	0.43
IEI	0.56*	0.75	0.81**	1.13	0.42	0.70
VGSH	0.33	0.43	0.55*	0.77	0.07	0.12
GOVT	0.33	0.44	0.62*	0.87	0.60*	0.99
ZROZ	0.20	0.27	0.47	0.65	0.30	0.50
TIP	0.19	0.25	0.50*	0.70	0.04	0.07
MBB	0.44*	0.58	0.84**	1.18	0.44	0.74
Fixed Income Factor	0.38	0.50	0.64**	0.90	0.42	0.71
AR1	0.38	0.51	0.59*	0.83	0.43	0.71
Buy & Hold	0.35	0.46	0.58*	0.82	0.33	0.54
Panel D: Sentiment Indicators						
Loughran & Mcdonald	0.28	0.46	0.05	0.10	0.35	0.72
Chat GPT 4.o	0.22	0.36	−0.04	−0.07	0.47*	0.96
FinBERT	0.40*	0.66	0.08	0.16	0.58*	1.19

Continued on next page

Table 4 (continued)

Variable	**P/R = 4**		**P/R = 1**		**P/R = 0.4**	
	Profits (%)	**Sharpe**	**Profits (%)**	**Sharpe**	**Profits (%)**	**Sharpe**
Sentiment Factor	0.32	0.53	0.11	0.20	0.58*	1.19
AR1	0.32	0.53	0.30	0.55	0.59*	1.20
Buy & Hold	0.48**	0.80	0.16	0.29	0.61*	1.24
Panel E: Volume Strategy						
Volume ADI	0.24	0.34	0.15	0.24	0.08	0.15
Volume OBV	0.22	0.32	0.45*	0.70	0.20	0.37
Volume VPT	0.24	0.34	0.45*	0.70	0.20	0.37
Volume VWAP	0.37*	0.53	0.24	0.38	−0.04	−0.07
Volume NVI	0.31	0.45	0.45*	0.70	0.20	0.37
Volume Factor	0.30	0.44	0.33	0.51	0.20	0.37
AR1	0.33*	0.47	0.47*	0.73	0.27	0.50
Buy & Hold	0.31	0.45	0.45*	0.70	0.20	0.37
Panel F: Volatility Strategy						
Volatility BBM	0.32	0.46	0.46*	0.71	0.21	0.40
Volatility BBH	0.31	0.45	0.45*	0.70	0.20	0.37
Volatility BBW	0.31	0.45	0.45*	0.70	0.20	0.37
Volatility BBHI	0.31	0.45	0.45*	0.70	0.20	0.37
Volatility KCH	0.31	0.45	0.45*	0.70	0.20	0.37
Volatility KCW	0.31	0.45	0.45*	0.70	0.20	0.37
Volatility KCHI	0.41*	0.59	0.41*	0.64	0.30	0.56

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Table 4 (continued)

Variable	**P/R = 4**		**P/R = 1**		**P/R = 0.4**	
	Profits (%)	**Sharpe**	**Profits (%)**	**Sharpe**	**Profits (%)**	**Sharpe**
Volatility DCP	0.14	0.21	0.17	0.27	0.20	0.37
Volatility ATR	0.31	0.45	0.45*	0.70	0.20	0.37
Volatility UI	0.31	0.45	0.45*	0.70	0.20	0.37
Volatility Factor	0.23	0.33	0.39*	0.60	0.23	0.42
AR1	0.33*	0.47	0.47*	0.73	0.27	0.50
Buy & Hold	0.31	0.45	0.45*	0.70	0.20	0.37
Panel G: Trends Strategy						
Trend MACD Signal	0.48**	0.69	0.37*	0.57	0.11	0.20
Trend SMA Slow	−0.18	−0.26	0.04	0.07	0.01	0.02
Trend EMA Slow	0.29	0.41	0.52**	0.80	0.16	0.29
Trend TRIX	0.31	0.45	0.45*	0.70	0.20	0.37
Trend Mass Index	0.31	0.45	0.45*	0.70	0.20	0.37
Trend KST	0.27	0.38	0.45*	0.70	0.20	0.37
Trend KST Signal	0.10	0.14	0.18	0.29	0.04	0.08
Trend Ichimoku Base	0.07	0.11	0.12	0.18	−0.04	−0.08
Trend Ichimoku A	0.34*	0.49	0.30	0.47	0.12	0.22
Trend Ichimoku B	0.33*	0.47	0.33	0.51	0.07	0.13
Trend ADX	0.31	0.45	0.45*	0.70	0.20	0.37
Trend ADX+	0.37*	0.54	0.50**	0.78	0.11	0.20
Trend Aroon Down	0.31	0.45	0.45*	0.70	0.20	0.37
Trend Aroon Oscillator	0.26	0.37	0.31	0.48	0.05	0.10

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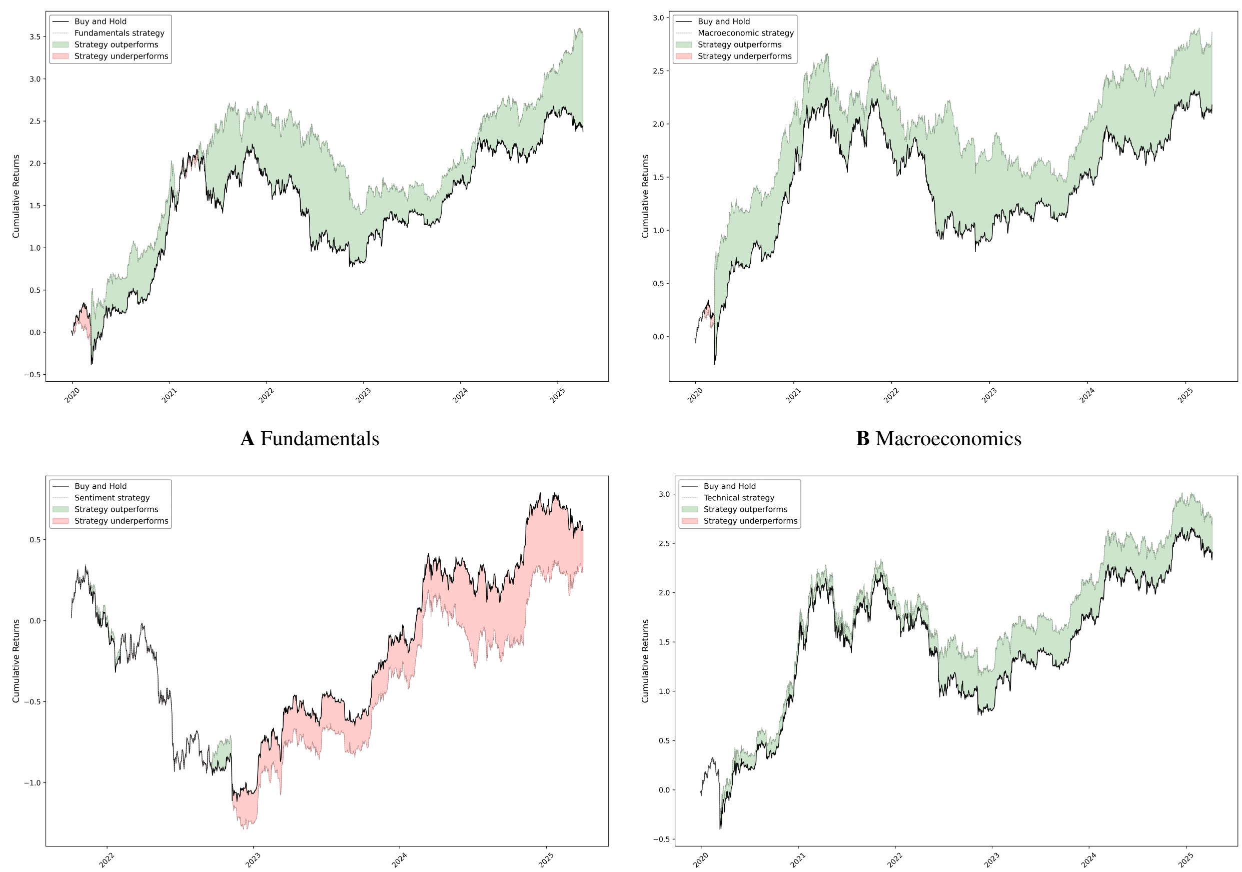
Table 4 (continued)

Variable	**P/R = 4**		**P/R = 1**		**P/R = 0.4**	
	Profits (%)	**Sharpe**	**Profits (%)**	**Sharpe**	**Profits (%)**	**Sharpe**
Trend PSAR Up	0.25	0.36	0.15	0.23	0.02	0.03
Trends Factor	0.46**	0.66	0.41*	0.64	0.11	0.21
AR1	0.33*	0.47	0.47*	0.73	0.27	0.50
Buy & Hold	0.31	0.45	0.45*	0.70	0.20	0.37
Panel H: Momentum Strategy						
Momentum UO	0.37*	0.54	0.52**	0.80	0.27	0.50
Momentum Stochastic	0.31	0.45	0.45*	0.70	0.20	0.37
Momentum Stochastic Signal	0.25	0.36	0.15	0.24	0.20	0.37
Momentum PPO Signal	0.44**	0.64	0.33	0.51	0.13	0.25
Momentum Factor	0.35*	0.50	0.46*	0.71	0.21	0.39
AR1	0.33*	0.47	0.47*	0.73	0.27	0.50
Buy & Hold	0.31	0.45	0.45*	0.70	0.20	0.37

Note: This table presents the annualized returns and Sharpe ratios derived from the Anatoliev and Gerko strategy across different estimation and forecasting windows, with the evaluation carried out within a recursive framework.

Figure 2 presents the four variables with the highest Sharpe ratio for each type of variable, showing that the relative benefits compared to the benchmark are concentrated in the contraction phases of the cryptocurrency market. However, as shown in Figure 2 (A and B), during expansive periods for Bitcoin these advantages tend to dissipate, and the passive strategy manages to match the cumulative returns obtained through the forecasting exercises. Taken together, these results confirm that, although the selected signals provide added value in adverse contexts, their effectiveness is sensitive to the market regime, which has relevant implications for the design of dynamic strategies.



A Fundamentals

B Macroeconomics

C Sentiment

D Technical

Figure 2: Trading exercises[a]

[a]The variable plotted in Panel A is *Block Count*; in Panel B, *Nasdaq Composite*; in Panel C, *FinBERT*; and in Panel D, *Trend EMA Slow*.

To incorporate the possibility of not investing in Bitcoin and instead holding liquidity with a risk-free return, we implement a strategy in which the investor determines, in each period, the proportion of wealth allocated to Bitcoin and to the risk-free asset. The results are consistent with the findings from both in-sample and out-of-sample exercises, reinforcing the evidence that technical variables offer superior predictive value. In particular, models that include this type of variable (Table 5, panels F, G, H, and I) consistently outperform the respective benchmarks. Strategies based on detecting trend changes, such as moving-average crossovers and momentum confirmations (*Volatility KCHI, Trend EMA Slow, and Trend Ichimoku A*) yield, on average, annualized returns 15% above the buy-and-hold benchmark. This pattern becomes more pronounced when focusing specifically on trend variables, where 72% of the forecasts exceed the performance of the reference strategies. More importantly, the factor that groups these variables achieves an annualized return 25% higher than the buy-and-hold and 34% higher than the AR(1), maintaining its advantage in both annualized return and Sharpe ratio.

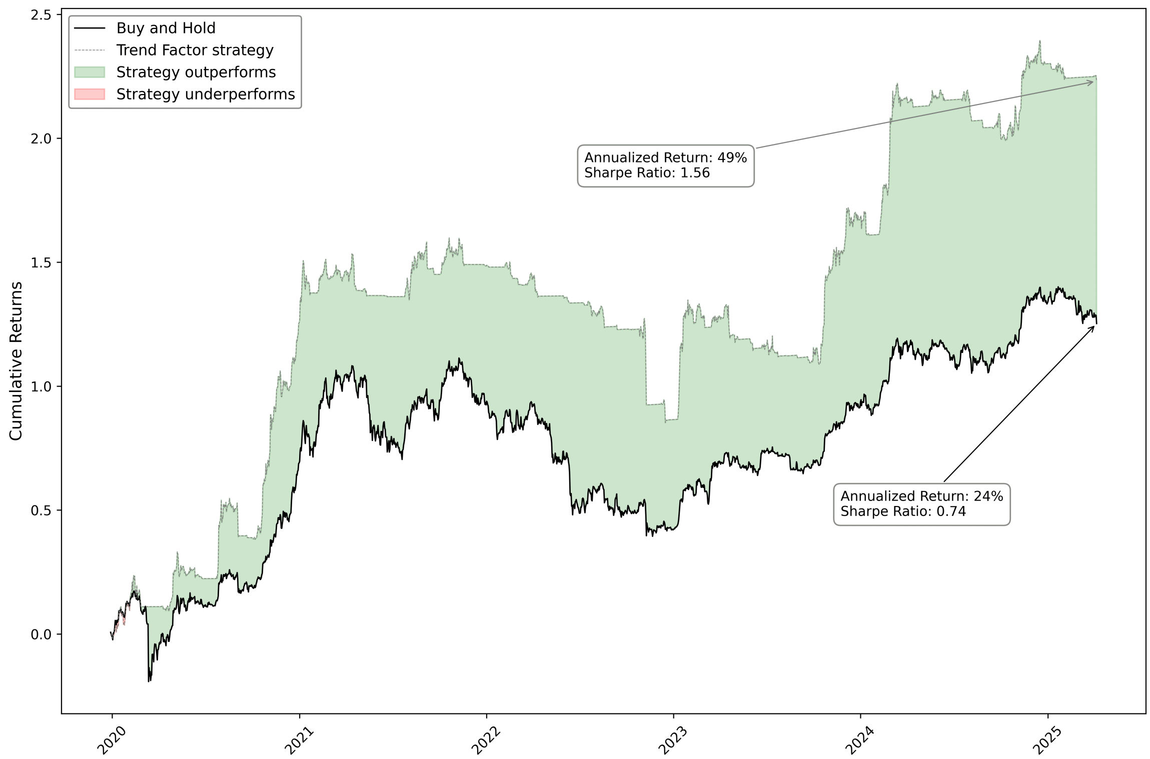


Figure 3: Trend Factor strategy vs buy-and-hold[a]

[a]The buy-and-hold strategy considers an equally-weighted portfolio.

Figure 3 presents the evolution of the cumulative returns of our *Trends Factor* in comparison with a buy-and-hold benchmark. A relevant aspect of our strategy is that the model correctly anticipates major downturns in the Bitcoin series. For instance, during the 55% correction between April and July 2021, our asset allocation rule indicates taking a short position in Bitcoin. Since we restrict the investment in the cryptocurrency to the range [0,1], the model simply reduces the position to zero and reallocates the entire investment to the risk-free asset. In the opposite direction, we also observe favorable results: the largest gains arise from the beginning of the bull market in January 2023, when the model accurately predicts Bitcoin's upward movements and progressively increases the exposure to the cryptocurrency. Overall, maintaining an active strategy based on the trend factor doubles the economic outcomes relative to the passive benchmark, both in terms of annualized return and Sharpe ratio. Finally, we emphasize that this is a laboratory experiment that relies on specific assumptions regarding risk aversion and a limited asset set. The reported annualized returns do not account for additional frictions such as taxes, alternative degrees of risk aversion, or higher transaction costs.

Table 5: Asset allocation Trading Rule

Variable	P/R = 4		P/R = 1		P/R = 0.4	
	Profits (%)	**Sharpe**	**Profits (%)**	**Sharpe**	**Profits (%)**	**Sharpe**
Panel A: Blockchain Metrics						
NVT	0.05	0.25	0.08	0.37	0.02	0.10
Annual Inflation	0.09	0.41	0.14*	0.65	0.07	0.28
Block Count	0.13*	0.54	0.11	0.47	0.07	0.30
30-Day Active Supply	0.07	0.32	0.10	0.40	−0.01	−0.02
1-Year Active Supply	0.14**	0.76	0.19***	1.01	0.11	0.59
Active Addresses	0.11*	0.55	0.17**	0.86	0.12	0.60
Miner Rev./Hash	0.10*	0.50	0.14*	0.71	0.07	0.37
Mean Hash Rate	0.09	0.40	0.14*	0.65	0.07	0.32
Blockchain Factor	0.06	0.30	0.10	0.47	0.01	0.05
AR1	0.10*	0.51	0.15**	0.75	0.07	0.36
Random Walk	0.14**	0.77	0.20***	1.08	0.13	0.67
Buy & Hold	0.17**	0.49	0.24***	0.74	0.12	0.45
Panel B: Equities and Global Indices						
Gold	0.05	0.25	0.11	0.57	0.00	−0.01
Nasdaq Composite	0.14*	0.65	0.26**	1.12	0.18	0.76
S&P 500	0.14*	0.63	0.26**	1.14	0.23*	0.94
DAX 40	0.13*	0.60	0.23**	0.97	0.14	0.57
Euro Stoxx 50	0.11	0.45	0.20*	0.77	0.10	0.38
Hang Seng	0.01	0.04	0.12	0.53	0.05	0.22

Continued on next page

Table 5 (continued)

Variable	P/R = 4		P/R = 1		P/R = 0.4	
	Profits (%)	**Sharpe**	**Profits (%)**	**Sharpe**	**Profits (%)**	**Sharpe**
Shanghai Composite	0.09	0.50	0.19**	0.97	0.11	0.58
IBOVESPA	0.04	0.19	0.18*	0.81	0.13	0.58
Equities Factor	0.06	0.27	0.17*	0.73	0.12	0.48
AR1	0.09	0.45	0.18**	0.92	0.12	0.62
Random Walk	0.12*	0.64	0.20**	1.07	0.14	0.73
Buy & Hold	0.18*	0.48	0.30**	0.85	0.19	0.62
Panel C: Fixed Income ETFs						
TLT	−0.01	−0.05	0.06	0.19	−0.06	−0.20
IEF	−0.02	−0.07	0.05	0.17	−0.04	−0.14
IEI	0.01	0.03	0.09	0.31	0.00	0.01
VGSH	0.06	0.24	0.14	0.50	0.03	0.10
GOVT	0.01	0.06	0.10	0.36	0.01	0.04
ZROZ	0.00	−0.02	0.07	0.23	−0.06	−0.22
TIP	0.01	0.04	0.12	0.34	0.01	0.04
MBB	0.05	0.24	0.13	0.64	0.04	0.21
Fixed Income Factor	−0.02	−0.07	0.05	0.16	−0.08	−0.24
AR1	0.09	0.45	0.18**	0.92	0.12	0.62
Random Walk	0.12*	0.64	0.20**	1.07	0.14	0.73
Buy & Hold	0.18*	0.48	0.30**	0.85	0.19	0.62
Panel D: Sentiment Indicators						

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Table 5 (continued)

Variable	**P/R = 4**		**P/R = 1**		**P/R = 0.4**	
	Profits (%)	**Sharpe**	**Profits (%)**	**Sharpe**	**Profits (%)**	**Sharpe**
Loughran & Mcdonald	0.05	0.38	−0.01	−0.10	0.05	0.35
Chat GPT 4.o	0.10	0.57	−0.01	−0.06	0.12	0.63
FinBERT	0.12	0.86	0.03	0.24	0.15*	1.10
Sentiment Factor	0.08	0.53	−0.01	−0.04	0.10	0.56
AR1	0.03	0.14	−0.09	−0.41	0.04	0.20
Random Walk	0.11	0.83	0.05	0.35	0.13*	0.93
Buy & Hold	0.25*	0.84	0.09	0.36	0.33**	1.34
Panel E: Volume Strategy						
Volume ADI	0.09	0.37	0.12	0.49	0.08	0.32
Volume OBV	0.12*	0.60	0.14*	0.71	0.11	0.57
Volume VPT	0.12*	0.61	0.14*	0.72	0.11	0.57
Volume VWAP	0.29***	1.07	0.29**	1.02	0.12	0.44
Volume NVI	0.09	0.46	0.14*	0.72	0.06	0.31
Volume Factor	0.11*	0.53	0.13*	0.62	0.10	0.50
AR1	0.10*	0.51	0.15**	0.75	0.07	0.36
Random Walk	0.14**	0.77	0.20***	1.08	0.13	0.67
Buy & Hold	0.17**	0.49	0.24***	0.74	0.12	0.45
Panel F: Volatility strategy						
Volatility BBM	0.14**	0.74	0.20***	1.06	0.15*	0.77
Volatility BBH	0.09	0.40	0.13*	0.58	0.08	0.34

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Table 5 (continued)

Variable	**P/R = 4**		**P/R = 1**		**P/R = 0.4**	
	Profits (%)	**Sharpe**	**Profits (%)**	**Sharpe**	**Profits (%)**	**Sharpe**
Volatility BBW	0.14**	0.74	0.20***	1.03	0.13	0.66
Volatility BBHI	0.18**	0.77	0.22**	0.95	0.19*	0.80
Volatility KCH	0.17**	0.79	0.20**	0.92	0.10	0.51
Volatility KCW	0.11**	0.60	0.17**	0.92	0.12	0.59
Volatility KCHI	0.48***	1.47	0.49***	1.49	0.38**	1.21
Volatility DCP	0.10	0.45	0.06	0.30	0.10	0.43
Volatility ATR	0.11*	0.55	0.17**	0.77	0.04	0.19
Volatility UI	0.17**	0.80	0.25***	1.16	0.19*	0.79
Volatility Factor	0.27**	0.95	0.30***	1.03	0.22*	0.76
AR1	0.10*	0.51	0.15**	0.75	0.07	0.36
Random Walk	0.14**	0.77	0.20***	1.08	0.13	0.67
Buy & Hold	0.17**	0.49	0.24***	0.74	0.12	0.45
Panel G: Trends strategy						
Trend MACD Signal	0.29**	0.99	0.34***	1.19	0.18	0.63
Trend SMA Slow	0.29***	1.22	0.34***	1.36	0.21*	0.87
Trend EMA Slow	0.36***	1.40	0.40***	1.42	0.28**	0.99
Trend TRIX	0.14**	0.75	0.19***	1.04	0.12	0.64
Trend Mass Index	0.15**	0.80	0.17**	0.92	0.12	0.65
Trend KST	0.16**	0.84	0.22***	1.16	0.16*	0.80
Trend KST Signal	0.22**	0.84	0.36***	1.35	0.20*	0.74
Trend Ichimoku Base	0.29***	1.22	0.36***	1.46	0.23*	0.92

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Table 5 (continued)

Variable	P/R = 4		P/R = 1		P/R = 0.4	
	Profits (%)	Sharpe	Profits (%)	Sharpe	Profits (%)	Sharpe
Trend Ichimoku A	0.38***	1.38	0.41***	1.39	0.29**	1.02
Trend Ichimoku B	0.46***	1.48	0.44***	1.31	0.27*	0.87
Trend ADX	0.25***	1.21	0.29***	1.35	0.20**	0.96
Trend ADX+	0.33***	1.31	0.39***	1.44	0.24*	0.85
Trend Aroon Down	0.15**	0.80	0.20***	1.07	0.13	0.68
Trend Aroon Oscillator	0.13**	0.67	0.18**	0.95	0.10	0.51
Trend PSAR Up	0.24***	1.00	0.24**	0.98	0.18*	0.72
Trends Factor	0.45***	1.54	0.49***	1.56	0.31**	1.04
AR1	0.10*	0.51	0.15**	0.75	0.07	0.36
Random Walk	0.14**	0.77	0.20***	1.08	0.13	0.67
Buy & Hold	0.17**	0.49	0.24***	0.74	0.12	0.45
Panel H: Momentum strategy						
Momentum UO	0.13**	0.65	0.21***	1.09	0.14	0.70
Momentum Stochastic	0.12**	0.62	0.18**	0.93	0.11	0.54
Momentum Stoch. Signal	0.15**	0.65	0.13*	0.55	0.08	0.34
Momentum PPO Signal	0.30**	0.99	0.34**	1.15	0.18	0.64
Momentum Factor	0.11*	0.56	0.18**	0.96	0.10	0.52
AR1	0.10*	0.51	0.15**	0.75	0.07	0.36
Random Walk	0.14**	0.77	0.20***	1.08	0.13	0.67
Buy & Hold	0.17**	0.49	0.24***	0.74	0.12	0.45

Note: This table presents the annualized returns and Sharpe ratios derived from the strategy of Wang et al. (2020) in different estimation and forecasting windows, with the evaluation carried out within a recursive framework.

5. Conclusions

This study provides a systematic and comparative evaluation of the predictive ability of a broad set of variables in forecasting Bitcoin returns. We analyze 141 predictors classified into technical, fundamental, macroeconomic, and sentiment categories, using daily data from 2014 to 2025. The methodology combines in-sample and out-of-sample exercises, accuracy metrics such as R^2_{oos} and the Clark and West test, along with trading exercises aimed at estimating the economic value of signals. In addition, principal component analysis (PCA) is employed to condense information and construct representative factors that synthesize the predictive contribution of each group of variables.

Four main conclusions emerge from the results. First, our evidence is consistent with the well documented difficulty of forecasting financial returns: starting from 141 candidate predictors, 67 exhibited in sample predictive value; however, only 29 maintained significant out of sample benefits in at least one forecasting horizon, and only 4 outperformed the random walk benchmark across all horizons. Second, technical indicators, particularly those related to trend, volume, and volatility, deliver the best forecasting results in both in-sample and out-of-sample settings. Factors constructed from these indicators amplify predictive gains, with the Trend Factor delivering statistically and economically significant improvements across all horizons analyzed. Third, macroeconomic and fundamental variables display episodic or horizon dependent predictive value, whereas sentiment measures are the weakest, showing limited robustness outside specific contexts. Fourth, the trading exercises confirm that signals derived from technical strategies generate excess returns and higher Sharpe ratios relative to a buy-and-hold strategy, especially during periods of contraction in the crypto market.

Our findings contribute to the literature on return predictability in cryptocurrencies, reinforcing and extending prior evidence that documents the usefulness of technical rules in anticipating price movements (Detzel et al., 2021; Svogun & Bazán-Palomino, 2022; Tan & Tao, 2023; Wei et al., 2024). Unlike these studies, we jointly and systematically evaluate a broad set of variables within a unified methodological framework, which enables an assessment of the relative robustness of alternative predictors and ensures fair comparisons within a common forecasting environment. Moreover, our work connects with the extensive literature on forecasting financial instruments (Goyal et al., 2024; R. Meese & Rogoff, 1988; R. A. Meese & Rogoff, 1983; Rossi, 2013; Timmermann, 2008; Welch & Goyal, 2008), showing that, although beating a random walk in return forecasting is extremely difficult, a subset of technical variables consistently performs well when evaluated by forecast accuracy, and that selected fundamental and macroeconomic variables also deliver benefits when performance is measured in terms of economic gains.

Finally, we suggest that the proposed technical factors can be employed by investors to complement their trading practices. Developing actionable indicators is critical in a market characterized by persistent volatility (Z. Zhang & Zhao, 2023), strong interconnectedness across assets (Yin et al., 2025), and exposure to systematic risk factors (Lan & Frömmel, 2025). Monitoring these factors has the potential to improve investors' performance and mitigate the impact of sharp downturns in the crypto ecosystem. Moreover, although we apply these factors to return forecasting, future work could (i) employ them to predict other key phenomena, such as volatility, financial contagion, and tail risk in Bitcoin returns, and (ii) incorporate them into high-dimensional multivariate frameworks to exploit complementary signals and pockets of predictability.

6. Appendix

To measure market sentiment regarding Bitcoin, we collected 17,051 news articles published by *Cointelegraph*, *Cryptonews*, *Dailyhodl*, and *Coindesk*, the four most widely read news outlets in this market. Each document was preprocessed by removing non-textual elements and matched to its publication date t. The classification of terms was carried out using the ChatGPT-4 lexicons, as proposed by Magner et al. (2025). Based on this input, we computed for each article i a net optimism index defined as

$$L_{i,t} = \frac{P_{i,t} - N_{i,t}}{W_{i,t}}, \tag{12}$$

where $P_{i,t}$ corresponds to the number of positive words, $N_{i,t}$ to the number of negative words, and $W_{i,t}$ to the total number of words in the article. We then aggregated these values at the daily level, constructing the average market tone as

$$\tau_t = \frac{1}{J_t} \sum_{j=1}^{J_t} L_{j,t}, \tag{13}$$

where J_t denotes the number of articles in period t. Additionally, we computed tone measures using the Loughran and Mcdonald (2011) lexicons as well as the FinBERT model by Huang et al. (2023).

Table 6: R^2_{oos} VS AR4

Variable	**1 day**	**7 days**	**14 days**	**28 days**
Panel A: Volume Strategy				
Volume ADI	0.12*	0.12*	0.15**	0.33***
Volume OBV	–0.07	–0.07	0.04	0.08*
Volume VPT	–0.07	–0.06	0.04	0.08*

Continued on next page

Table 6 (continued)

Variable	**1 day**	**7 days**	**14 days**	**28 days**
Volume VWAP	–0.26	–0.26	–0.35	–0.53
Volume NVI	–0.05	–0.02	–0.03	–0.02
Volume Factor	–0.05	0.00	0.08*	0.15**
Panel B: Volatility strategy				
Volatility BBM	–0.02	–0.05	0.04	–0.07
Volatility BBH	–0.22	–0.09	–0.11	–0.06
Volatility BBW	0.02	0.46***	–0.15	0.38**
Volatility BBHI	–0.06	0.45***	0.12*	0.30**
Volatility KCH	0.08*	–0.12	–0.06	–0.03
Volatility KCW	–0.02	–0.07	–0.05	–0.07
Volatility KCHI	0.37***	0.82***	0.51***	0.67***
Volatility DCP	–0.12	–0.06	0.04	0.07*
Volatility ATR	0.00	–0.09	–0.12	–0.16
Volatility UI	0.10*	–0.04	–0.14	0.04
Volatility Factor	0.18**	0.34***	–0.17	0.28**
Panel C: Trends Strategy				
Trend MACD Signal	–0.16	–0.73	–0.30	0.87***
Trend SMA Slow	–0.08	–0.41	0.29**	–1.05
Trend EMA Slow	0.05*	0.57***	0.80***	–2.04
Trend TRIX	–0.07	–0.05	–0.06	0.00
Trend Mass Index	–0.29	0.03**	0.05**	–0.03
Trend KST	0.04	–0.06	0.03	0.00
Trend KST Signal	–0.02	–0.31	–0.10	0.72***
Trend Ichimoku Base	0.05	0.23**	0.65***	–0.60
Trend Ichimoku A	–0.19	–0.11	–0.32	–1.37
Trend Ichimoku B	–0.08	–0.22	–0.34	–3.73
Trend ADX	0.08*	0.12**	0.40**	–0.30
Trend ADX+	0.16**	0.65***	0.53**	–0.53
Trend Aroon Down	–0.01	–0.07	–0.03	–0.05
Trend Aroon Oscillator	–0.20	0.05	–0.13	0.05
Trend PSAR Up	–0.36	–0.46	–0.04	0.29**
Trends Factor	0.06**	0.19***	0.49***	–1.80

Continued on next page

Table 6 (continued)

Variable	**1 day**	**7 days**	**14 days**	**28 days**
Panel D: Momentum Strategy				
Momentum UO	0.04	0.01	–0.04	–0.03
Momentum Stochastic	–0.03	–0.12	–0.09	–0.07
Momentum Stochastic Signal	–0.19	–0.17	–0.12	–0.08
Momentum PPO Signal	–0.22	–0.47	–0.33	0.88***
Momentum Factor	–0.04	–0.18	–0.06	–0.06

Note: Recursive window. P/R = 1. The benchmark model in this test is an AR(4). Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 2

Gold vs. Bitcoin as Safe Havens Across U.S. Sectors: Evidence from the Latest Equity Market Crashes

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Abstract

This article examines, with sector-level disaggregation, the defensive capacity of gold and Bitcoin against the returns of the eleven U.S. GICS sectors. Although Bitcoin has gained prominence under the "digital gold" narrative, there is no conclusive evidence that this implies safe-haven behavior comparable to gold, whose protective role is well documented. To compare both assets, the study estimates conditional and dynamic comovement using a DCC–GARCH model, incorporates directional connectedness measures based on R^2, and analyzes left-tail behavior during the largest sectoral drawdowns, assessing whether the asset–sector relationship turns negative under severe stress. The results show that gold displays better countercyclical performance than Bitcoin during the five largest U.S. equity market crashes over the last decade; however, rather than a strict safe haven, gold mainly exhibits hedging properties. Bitcoin provides no defensive benefits for any sector, except Utilities, where it can serve as an alternative diversification vehicle. These findings are relevant for portfolio managers seeking to strengthen hedging strategies and manage risk exposure during crisis episodes.

Keywords: Safe-haven, Gold, Bitcoin, DCC–GARCH.

1. Introduction

Gold has long been the preferred asset when discussing safe havens, and a broad literature has documented it as a benchmark during episodes of financial stress (Anas et al., 2025). However, in recent years its usefulness as a safe haven has been questioned once one looks inside the market: sector-level evidence for the U.S. shows that gold does not deliver consistent hedging in industries such as Energy, Basic Materials, and Utilities, and that its defensive role has weakened in more recent subperiods (Baumöhl & Lyócsa, 2017; K. Chen & Wang, 2019; Kinateder et al., 2024). In parallel, the literature has turned to Bitcoin as a potential refuge due to intrinsic features of the asset: it is a non-sovereign instrument whose issuance and transfer do not rely on central banks, governments, or the banking infrastructure, so its defensive potential may become relevant when stress originates precisely from banking fragility, doubts about the credibility of monetary policy, capital controls, or disruptions to payment infrastructure (Abd Rabbo & Disli, 2025; Aysan et al., 2019; Kang et al., 2025; Luther & Salter, 2017). Can Bitcoin outperform gold as a safe haven for U.S. industries? This study examines, across the 11 U.S. sectors, how the usefulness of gold and Bitcoin varies during episodes of extreme stress, and assesses whether "digital gold" can act as a sectoral alternative when the traditional refuge fails to hedge.

A safe haven is defined as an instrument that preserves value during episodes of financial stress, in the sense that its returns become independent of, or offsetting to, the returns of risky assets precisely when risk materializes and prices fall (Baur & McDermott, 2016). Operationally, safe-haven status is assessed conditionally on stress: during turbulent periods, co-movement with another asset should be zero or negative, thereby mitigating portfolio losses (Feder-Sempach et al., 2024). This definition distinguishes a weak safe haven, where correlation under stress is approximately zero, from a strong safe haven, where correlation is negative and hedging is more effective because the asset tends to appreciate when risk increases (Baur & Lucey, 2010). Accordingly, the safe-haven effect is not treated as an unconditional or permanent property, but rather as a state-contingent behavior that emerges only in sufficiently severe stress episodes, such as systemic banking crises, abrupt equity market crashes, or large geopolitical shocks (P. Liu & Yuan, 2024; P. Wang et al., 2021).

From this perspective, the evidence on gold's and Bitcoin's safe-haven roles has been repeatedly reshaped as stress episodes evolve and as both markets mature. In the aftermath of the Global Financial Crisis, a substantial strand of the literature reinforced gold's status as a comparatively robust hedge against equity drawdowns, with particularly favorable results in developed markets and in windows tied to systemic shocks (Burdekin & Tao, 2021; Junttila et al., 2018). Following the rapid expansion of crypto markets after 2017, attention shifted to whether Bitcoin could replicate these properties. Early studies often emphasized Bitcoin's low correlation with traditional assets and its potential to provide hedging or diversification benefits, but also cautioned that its use requires care given its high volatility and its ability to amplify losses during stress episodes (Atree & Tripathy, 2025; Burdekin & Tao, 2021; Junttila et al., 2018).

The COVID-19 shock strained this narrative. For gold, the evidence suggests that its safe-haven performance was most pronounced during the initial phase of the pandemic and weakened thereafter, partly because hedging costs increased and protection became more transitory, concentrating at shorter horizons (Akhtaruzzaman et al., 2021). For Bitcoin, findings during COVID-19 are even more heterogeneous. In some settings, it appears to exhibit safe-haven behavior over narrow windows or relative to specific benchmarks (Corbet, Hou, et al., 2020; Kumar & Padakandla, 2022); in others, it acts as a conduit for contagion, with co-movement with equities rising precisely as turbulence intensifies (Conlon & McGee, 2020). In the post-pandemic period, the evidence increasingly points to deeper integration between cryptocurrencies and traditional markets, which weakens the notion of a stable safe haven and suggests that, when it exists, Bitcoin's contribution is better understood as time-varying diversification rather than reliable crisis insurance (Shahrour et al., 2024).

Still, these properties have been evaluated primarily in the aggregate, even though risk and financial stress do not materialize homogeneously across the market. In this context, a sector-level perspective is warranted for three complementary reasons: (i) industries differ in their exposure and sensitivity to macro-financial shocks, so safe-haven behavior may be sectoral and therefore obscured by market-level averages (Ouyang et al., 2024); (ii) because asset allocation and risk control are often implemented at the sector level, disaggregated evidence is directly informative for hedging and portfolio design, particularly for investors who actively manage drawdowns (Nystrup et al., 2019); and (iii) since 2024, Bitcoin has been institutionally accessible via regulated spot ETFs, yet its safe-haven role has not been systematically evaluated in recent episodes of heightened uncertainty, such as the "Liberation Day" tariff announcements that coincided with a 21% decline in the S&P 500[13], a natural setting to observe whether its defensive behavior activates under stress.

This article is the first to compare, at the sector level, the safe-haven performance of Bitcoin and gold during the five most severe equity market downturn episodes in the recent history of the U.S. stock market. The analysis uses the full available history of Bitcoin since it has been traded as a capital-market instrument and benchmarks it against gold across the 11 U.S. GICS sectors. Methodologically, the paper combines time-varying conditional-correlation estimates from a DCC–GARCH model (Engle, 2002), measures of directional interdependence based on an R^2-connectedness framework (Cocca et al., 2024) and a left-tail robustness exercise that isolates the worst drawdown episodes to assess whether, under extreme stress, each asset satisfies the defining safe-haven condition (Baur & Lucey, 2010).

Three results stand out. First, the DCC–GARCH estimates document a clear asymmetry in conditional comovement: Bitcoin is, on average, positively related to all 11 U.S. GICS sectors and its correlations increase sharply from 2020 onward, whereas gold correlations are systematically lower, often close to zero, and turn negative in key cyclical sectors, most notably Financials. Second, the divergence widens in stress episodes: Bitcoin's sectoral correlations rise and remain positive, while gold, despite weaker refuge performance in recent events such as "Liberation Day," stays less correlated than Bitcoin across many sectors, especially Communication Services, Consumer

[13] An interesting analysis of this episode was published by J.P. Morgan in its column *'Liberation Day' in retrospect: 6 things that surprised investors* (October 10, 2025).

Discretionary, Financials, Industrials, and Information Technology. Third, left-tail evidence shows that gold's safe-haven properties are state dependent: conditioning on the worst 5% of sectoral outcomes, gold deepens its decoupling in a manner consistent with flight-to-quality behavior, but at the most extreme 1% tail this effect attenuates and can partially reverse in some sectors; by contrast, Bitcoin displays no safe-haven behavior, as comovement remains positive and tends to strengthen with uncertainty. Overall, gold exhibits a more stable degree of sectoral decoupling under stress than Bitcoin, whereas Bitcoin behaves predominantly as a procyclical risk asset, closer to time-varying diversification than to reliable crisis insurance.

This article contributes to the safe-haven literature by reframing the gold–Bitcoin comparison as a phenomenon conditioned by economic sectors. Prior evidence shows that gold's refuge role is state-dependent and can weaken in specific U.S. industries (K. Chen & Wang, 2019; Kinateder et al., 2024); by contrast, empirical work on Bitcoin has often relied on aggregate benchmarks (Jin & Tian, 2024; Pastén-Henríquez et al., 2025), which blurs mechanism identification under stress and reduces practical value for managers who control drawdowns and make decisions at the sector level. The contribution of this study is to close this gap by testing a core theoretical hypothesis about Bitcoin: that, due to its institutional and technological features, it could decouple from risk assets when stress arises in episodes of heightened geopolitical and trade uncertainty. In practice, however, the results suggest that markets treat Bitcoin mainly as a procyclical portfolio complement, using it to enhance returns in bullish phases rather than as insurance that activates when risk materializes. As a result, its behavior under stress is more consistent with selective, time-varying diversification than with the notion of "digital gold".

The remainder of the paper is organized as follows. Section 2 reviews the related literature, Section 3 describes the data and empirical methodology, Section 4 presents the main results, and Section 5 concludes.

2. Literature review

The safe haven condition should be understood as an empirical, state-dependent property rather than a stable label attached to an asset (Baur & Lucey, 2010). Its economic meaning becomes apparent when financial stress reaches a threshold at which conventional diversification is no longer sufficient, particularly because co-movement across assets tends to intensify in crises and correlations estimated in normal times lose informational value for risk management (Hartmann et al., 2004; Konstantakis et al., 2023). In that setting, a safe haven is an asset that preserves value or exhibits zero or negative co-movement precisely when risky assets experience sharp losses (Bouri et al., 2017). This definition requires testing safe-haven behavior in episodes of severe stress and distinguishing it clearly from related notions such as hedging and diversification. The standard taxonomy in the literature defines a hedge as protection on average, a diversifier as low dependence in normal states, and a safe haven as protection conditional on stress episodes, when the marginal value of protection is highest (Baur & Lucey, 2010).

2.1. *Gold*

Gold has been proposed as a natural candidate for this role based on mechanisms that combine economic fundamentals with institutional features. First, its value does not rest on an issuer's promise to pay and therefore does not embed counterparty risk in the usual sense associated with debt-based financial instruments (Selmi et al., 2022). Second, during phases of heightened risk aversion, investors tend to reallocate portfolios toward assets perceived as safer, a pattern consistent with the flight-to-safety hypothesis (Li & Lucey, 2017). Because gold supply is relatively inelastic in the short run, demand shocks in these episodes can translate into larger price adjustments than would be expected for assets with more flexible supply (Li & Liu, 2026). Finally, in an environment of geopolitical fragmentation, sanctions, and tensions over payment infrastructure, gold retains appeal as a store of value given its lower reliance on financial intermediaries and on international settlement channels (Ngo et al., 2024). Taken together, these mechanisms support the view that, under stress, gold should decouple from equities and improve portfolio risk performance precisely when protection is most valuable.

The empirical evidence, however, supports this idea only in a conditional sense. Findings depend on the nature of the shock, the market under study, and the metric used to operationalize the safe-haven concept (Beckmann et al., 2015; Ryan et al., 2024). In systemic crises, the literature documents stronger safe-haven properties for gold, particularly in developed economies; in emerging markets, protection tends to be less robust, suggesting that liquidity, market depth, and institutional quality shape the transmission mechanism (Feder-Sempach et al., 2024; Gürgün & Ünalmış, 2014; Tarchella et al., 2024). Moreover, even within a given crisis, gold's refuge role can vary as conditions evolve. For example, during the recent COVID-19 crisis, the evidence is often phase-dependent: gold may provide protection early on, but its effectiveness can weaken when liquidity demand dominates and investors liquidate positions to raise cash (Akhtaruzzaman et al., 2021). This pattern reinforces a central methodological point: the gold–equity relationship is not stable and calls for identification strategies that capture time variation and tail behavior. This consideration has motivated a shift from static tests toward dynamic models and extreme-risk approaches, including GARCH/DCC families, quantile dependence, and stress-based risk measures, which are better suited to evaluate the safe-haven condition as a regime-contingent phenomenon (Bouri et al., 2020; Dammak et al., 2025; Mejri et al., 2025).

2.2. *Bitcoin*

Bitcoin enters the safe-haven debate through a theoretical channel that differs from gold. Its original proposition is that of a non-sovereign asset: its issuance and transfer do not rely on central banks, governments, or the balance sheets of financial intermediaries (Kang et al., 2025). Under this logic, its defensive potential should become relevant when stress originates from doubts about the credibility of monetary policy, banking fragility, capital controls, or disruptions to payment infrastructure (Abd Rabbo & Disli, 2025; Aysan et al., 2019; Luther & Salter, 2017). The intuition is that a decentralized system could remain relatively insulated from these points of failure. The literature typically frames this argument around three core ideas: (i) Bitcoin as an alternative settlement technology, (ii) its programmatic scarcity as the basis for a store-of-value narrative, and (iii) its potential role as an alternative monetary asset in portfolio decisions (Anas et al., 2025). Still, this view has clear limits. Bitcoin's price is highly sensitive to marginal demand, which is often driven by risk appetite, leverage, and liquidity conditions (Ahmad et al., 2025; Joebges et al., 2025). As a result, during deleveraging episodes it may behave like a high-beta asset (Julaiti et al., 2026). Moreover, as crypto markets become more integrated with traditional finance through institutional access, derivatives, and shared funding channels, transmission mechanisms such as margin-driven selling and liquidity-motivated liquidations become stronger (Akyildirim et al., 2020, 2025).

The empirical evidence on Bitcoin broadly supports a conditional interpretation of its safe-haven role. On average, it is more often classified as a diversifier and, in narrow windows, as a tactical hedge, rather than as a robust safe haven (B. K. Q. Nguyen & Pham, 2025). Early studies document diversification benefits and episodic hedging properties (Stensås et al., 2019; Urquhart & Zhang, 2019), but subsequent evidence suggests that when safe-haven-type behavior arises, it is typically partial, market- and horizon-dependent, and less stable relative to developed equity markets (Feder-Sempach et al., 2024; Julaiti et al., 2026). During global crises such as COVID-19, a substantial body of findings shows that its dependence with equities intensifies, which is consistent with a regime dominated by liquidity demand and deleveraging (Frikha et al., 2023; K. Q. Nguyen, 2022). In more recent episodes, the literature again reports defensive signals when the shock is linked to tensions in the financial system or to periods of political uncertainty (Jin & Tian, 2024; Pastén-Henríquez et al., 2025). Overall, this evidence keeps the asset within the safe-haven debate, but its usefulness across market conditions remains an open question.

3. Methodology

This study compares the safe-haven properties of gold and Bitcoin relative to the 11 U.S. GICS sector using three complementary empirical approaches. First, it estimates time-varying conditional correlations for each asset–sector pair using the Dynamic Conditional Correlation GARCH model (DCC-GARCH) of Engle (2002). Second, it characterizes directional interdependence through an R^2-based connectedness framework that follows the connectedness logic of Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014) and decomposes equation-level explanatory power into individual-variable contributions using the R^2 contribution decomposition of Genizi (1993). Third, it implements a sector-level crisis-shock test following Baur and McDermott (2016), assessing whether each asset's comovement with sector proxies weakens or turns negative precisely on days of extremely adverse sector returns.

3.1. Data

All empirical analyses in this article use daily data from September 2014 to December 2025, obtained from LSEG Datastream, for a total of 2,833 observations[14]. The sample includes the SPDR Gold Shares ETF (GLD)[15] as a proxy for gold and the Bitcoin spot price. These series are combined with the 11 U.S. GICS sector proxies and a standard set of control variables commonly used in the safe-haven literature. Descriptive statistics for the full sample are reported in Table 1.

3.2. DCC-GARCH

Let $P_{i,t}$ denote the price of series i at time t. Returns are computed as log differences, $r_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1})$. For each sector s and each asset $a \in \{\text{Gold}, \text{Bitcoin}\}$, the study estimates a bivariate DCC-GARCH model for the return vector $(r_{a,t}, r_{s,t})'$. Following Engle (2002), the conditional covariance matrix is factorized as

$$\mathbf{H}_{a,s,t} = \mathbf{D}_{a,s,t}\, \mathbf{R}_{a,s,t}\, \mathbf{D}_{a,s,t}, \tag{1}$$

where $\mathbf{D}_{a,s,t}$ collects the conditional standard deviations from the univariate GARCH components and $\mathbf{R}_{a,s,t}$ is the 2×2 time-varying conditional correlation matrix. Let $\mathbf{u}_{a,s,t}$ denote standardized residuals. The DCC(1,1) dynamics are defined through the auxiliary matrix $\mathbf{Q}_{a,s,t}$,

$$\mathbf{Q}_{a,s,t} = (1-\alpha-\beta)\,\bar{\mathbf{Q}}_{a,s} + \alpha\, \mathbf{u}_{a,s,t-1}\mathbf{u}'_{a,s,t-1} + \beta\, \mathbf{Q}_{a,s,t-1}, \qquad \alpha \geq 0,\ \beta \geq 0,\ \alpha+\beta < 1, \tag{2}$$

which is normalized to obtain the conditional correlation matrix,

$$\mathbf{R}_{a,s,t} = \operatorname{diag}(\mathbf{Q}_{a,s,t})^{-1/2}\, \mathbf{Q}_{a,s,t}\, \operatorname{diag}(\mathbf{Q}_{a,s,t})^{-1/2}, \tag{3}$$

where $\operatorname{diag}(\mathbf{Q}_{a,s,t})$ denotes the diagonal matrix formed from the diagonal of $\mathbf{Q}_{a,s,t}$. For each day t, the conditional correlation of interest, $\rho_{a,s,t}$, corresponds to the off-diagonal element of $\mathbf{R}_{a,s,t}$. For interpretability over time, the study reports calendar-year summaries obtained by averaging $\rho_{a,s,t}$

[14] An important feature of the data is that Bitcoin trades on weekends, whereas the remaining instruments do not. Given this limitation, the empirical exercises exclude weekend observations

[15] GLD is the largest gold-focused exchange-traded product by total assets under management (AUM). According to State Street Global Advisors (SSGA), as of January 16, 2026, SPDR® Gold Shares (GLD) managed approximately US$160.9 billion in AUM.

Table 1: Descriptive statistics

	Ticker	Mean	Std.Dev	Skewn	Kurtosis	ARCH(20)	ADF
Panel A: Variables of interest							
Gold	GLD	0.0004	0.009	−0.225	6.262	172.758 ***	−53.642 ***
Bitcoin	BTC	0.0020	0.042	−0.602	12.588	92.531 ***	−29.181 ***
Panel B: U.S. economic sectors							
Comm. Services	IYZ	0.0001	0.012	−0.331	7.752	777.488 ***	−17.402 ***
Cons. Discr.	XLY	0.0005	0.014	−0.586	12.180	643.260 ***	−16.910 ***
Cons. Staples	XLP	0.0003	0.009	−0.466	17.764	1204.612 ***	−16.863 ***
Energy	XLE	0.0002	0.019	−0.876	18.639	796.579 ***	−17.863 ***
Financials	XLF	0.0004	0.014	−0.571	18.304	983.624 ***	−16.736 ***
Health Care	XLV	0.0004	0.011	−0.415	11.870	1016.538 ***	−12.844 ***
Info. Tech.	XLK	0.0007	0.015	−0.305	12.919	671.681 ***	−17.785 ***
Materials	XLB	0.0003	0.013	−0.404	12.428	859.895 ***	−17.825 ***
Real Estate	VNQ	0.0002	0.013	−1.510	28.333	898.262 ***	−17.156 ***
Utilities	XLU	0.0004	0.012	−0.313	18.150	1245.793 ***	−15.990 ***
Industrials	XLI	0.0004	0.012	−0.531	16.930	999.020 ***	−16.728 ***
Panel C: U.S. Control variables							
Silver	SLV	0.0005	0.017	−0.339	8.942	297.928 ***	−35.260 ***
Commodity Index	DBC	0.0001	0.011	−0.674	7.154	281.841 ***	−51.914 ***
US Dollar Index	UUP	0.0001	0.005	−0.068	7.054	445.754 ***	−23.150 ***
Swiss Franc	FXF	0.0000	0.006	7.074	186.488	4.743	−19.615 ***
0–1Y U.S. Treasury Bonds	SHV	0.0001	0.000	0.633	6.244	363.000 ***	−3.707 ***
3–7Y U.S. Treasury Bonds	IEI	0.0001	0.002	0.251	6.152	392.218 ***	−39.261 ***
7–10Y U.S. Treasury Bonds	IEF	0.0001	0.004	0.119	5.942	447.794 ***	−39.887 ***
Panel D: Uncertainty variables							
CBOE Volatility Index	VIX	−0.0002	0.080	1.254	10.695	143.975 ***	−22.242 ***
US EPU Index	EPU	−0.0697	0.535	0.126	7.223	320.965 ***	−32.574 ***

Notes: Ticker reports the mnemonic used for each series. ARCH(20) reports the Engle ARCH LM test statistic with 20 lags. ADF reports the Augmented Dickey–Fuller test statistic. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

over all trading days within each year for every asset–sector pair. These annual averages are presented in Table 2 for gold–sector and Bitcoin–sector relationships. To compare gold and Bitcoin against the same sector s, the analysis constructs the daily correlation differential $d_{s,t} \equiv \rho_{\text{Gold},s,t} - \rho_{\text{Bitcoin},s,t}$. Statistical significance is assessed within each calendar year y by estimating, separately for each year, the mean regression

$$d_{s,t} = \delta_{s,y} + e_{s,t}, \tag{4}$$

and testing $H_0 : \delta_{s,y} = 0$ using HAC standard errors (Newey & West, 1987). The significance markers in Table 2 correspond to this test. A positive (negative) estimate indicates that, in year y, gold exhibited a higher (lower) conditional correlation with sector proxy s than Bitcoin, which is directly informative about their relative safe-haven performance in that period[16]. This correlation-differential exercise is also replicated for high-uncertainty subsamples. Following the stress-identification criterion in J. Wang et al. (2009), the sample is restricted to episodes in which the S&P 500 records either a daily decline of at least 5% or a drawdown of at least 20% from its most recent peak; the S&P 500 is used as the benchmark to detect these events because it aggregates the 11 GICS sectors[17].

3.3. R^2-based connectedness measures

To complement conditional correlations with a directional measure of dependence, the study adopts an R^2-based connectedness framework following Cocca et al. (2024). This approach preserves the interpretation of connectedness as explained variation in a multivariate system (Diebold & Yilmaz, 2012; Diebold & Yılmaz, 2014), while replacing forecast-error variance shares with nonnegative contributions obtained from an R^2 decomposition (Genizi, 1993). The implementation uses one lag and is computed on a rolling window indexed by its endpoint t. In each equation, the dependent variable is regressed on the remaining contemporaneous variables and their first lag, and the resulting R^2 is decomposed into variable-specific contributions. Let $R^2_{i\leftarrow j,t}$ denote the time-t contribution of variable j to the R^2 of the equation for variable i. Directional connectedness is summarized by the TO and FROM measures,

$$\mathrm{FROM}_{i,t} = \sum_{j\neq i} R^2_{i\leftarrow j,t}, \qquad \mathrm{TO}_{i,t} = \sum_{j\neq i} R^2_{j\leftarrow i,t}. \tag{5}$$

To further characterize bilateral imbalances in directional dependence, the study computes the Net Pairwise Directional Connectedness (NPDC). The NPDC between variables i and j is defined as the difference between the two opposite directional contributions,

$$\mathrm{NPDC}_{ij,t} \;=\; R^2_{i\leftarrow j,t} \;-\; R^2_{j\leftarrow i,t}. \tag{6}$$

The value $\mathrm{NPDC}_{ij,t}$ is antisymmetric by construction ($\mathrm{NPDC}_{ij,t} = -\mathrm{NPDC}_{ji,t}$) and provides a pairwise analogue to the system-level NET measure. A positive value indicates that, at time t, variable j accounts for a larger share of the explained variation in i than i accounts for in j, consistent with a net directional influence from j to i. Conversely, negative values point to a net influence

[16] Stationarity for all series is assessed using the Augmented Dickey–Fuller test and the Phillips–Perron test. In all cases, the tests reject the unit-root null hypothesis. The corresponding outputs are available upon request.

[17] The high-uncertainty windows considered are: (i) Brexit referendum (June 23, 2016–October 15, 2016), (ii) U.S.–China trade war (September 1, 2018–January 15, 2019), (iii) COVID-19 crisis (February 10, 2020–May 20, 2020), (iv) 2022 bear market (January 1, 2022–October 12, 2022), and (v) "Liberation Day" tariff announcements (February 19, 2025–May 10, 2025).

from i to j. Values close to zero suggest a broadly balanced relationship, in which the explanatory contributions are similar in both directions.

3.4. Safe-haven behavior under extreme negative sector shocks

A key requirement for a safe haven is that the asset remains weakly correlated with (or becomes negatively correlated with) risky assets precisely during severe downturns. Following the crisis-shock approach of Baur and McDermott (2016), this study assesses whether gold and Bitcoin display safe-haven behavior when U.S. equity sector proxies experience extreme negative returns, while allowing sector exposure to vary with aggregate market stress and policy-related stress.

For each sector s, let $q_s(p)$ denote the p-quantile of sector returns $r_{s,t}$ computed over the full sample, with $p \in \{0.10, 0.05, 0.01\}$. The extreme-shock indicator is defined as

$$D^{p}_{s,t} = \mathbb{I}\big(r_{s,t} \leq q_s(p)\big), \qquad p \in \{0.10, 0.05, 0.01\}. \tag{7}$$

To capture broader stress conditions beyond sector-specific crashes, the analysis also incorporates measures of market and economic policy uncertainty, both computed as daily log changes. Specifically, it uses the daily change in the VIX and the daily change in the U.S. Economic Policy Uncertainty index, interacting each of them with sector returns so that asset–sector exposure can vary across stress states. For each asset $a \in \{\text{Gold}, \text{Bitcoin}\}$ and each sector s, the following specification is estimated:

$$r_{a,t} = \alpha_{a,s} + \boldsymbol{\beta}'_{a,s}\mathbf{X}_t + \gamma_{a,s} r_{s,t} + \sum_{p \in \mathcal{P}^-} \delta_{p,a,s}\left(r_{s,t} D^{p}_{s,t}\right) + \eta_{a,s}\left(r_{s,t}\mathrm{VIX}_t\right) + \theta_{a,s}\left(r_{s,t}\mathrm{EPU}_t\right) + \varepsilon_{a,s,t}, \tag{8}$$

where $\mathcal{P}^- = \{0.10, 0.05, 0.01\}$. Here, $r_{s,t}$ denotes the return on sector proxy s, and $\mathbf{X}_t$ is a vector of controls including daily U.S. Treasury bond returns (0–1 year, 3–7 years, and 7–10 years), silver, a broad commodity proxy, the Swiss franc, and the U.S. dollar index. All tests are conducted using HAC standard errors. The baseline exposure of asset a to sector s is captured by $\gamma_{a,s}$. The interaction terms $r_{s,t}D^{p}_{s,t}$ quantify the incremental comovement between asset a and sector s on days of extreme negative sector returns. Thus, a negative and statistically significant $\delta_{p,a,s}$ indicates that the asset's exposure to the sector decreases (or becomes more negative) precisely during severe sector downturns, consistent with stronger safe-haven behavior. Finally, $\eta_{a,s}$ and $\theta_{a,s}$ measure how contemporaneous sector exposure varies with changes in market uncertainty and policy uncertainty, respectively: a negative coefficient implies that higher stress is associated with weaker comovement (greater decoupling) between the asset and the sector.

4. Results

This section evaluates the relative safe-haven performance of gold and Bitcoin from a sectoral perspective. First, it examines how each asset co-moves with GICS sector returns using time-varying conditional correlations, reported both as annual averages and over selected high-uncertainty windows, with the Gold–Bitcoin differential providing a direct measure of relative decoupling. Next, the evidence on contemporaneous co-movement is complemented with a regime-dependent analysis of directional dependence based on R^2 connectedness, aimed at assessing whether sector returns become more informative for explaining each asset precisely when financial stress intensifies. Finally, regression-based results incorporate tail-state conditioning and proxies for uncertainty (VIX and EPU), allowing the assessment of how sector exposures change across severe downside states and across volatility regimes.

4.1. Sectoral evidence on relative safe-haven performance: Gold vs. Bitcoin

Table 2 documents a systematic contrast in the dynamics of conditional correlations between gold and Bitcoin across the GICS sectors. On average, gold exhibits persistently lower correlations, including negative values in sectors such as Financials and Industrials (Panel A), whereas Bitcoin displays predominantly positive and larger co-movements with virtually all sectors, with a particularly pronounced increase from 2020 onward (Panel B). This pattern is mirrored in the Gold–Bitcoin differential, which is predominantly negative and statistically significant for most sectors and years, with especially large gaps for Financials, Consumer Discretionary, Information Technology, Industrials, and Communication Services (Panel C). Taken together, the evidence indicates that gold maintains a more stable degree of conditional decoupling from sectoral equity risk than Bitcoin, a feature more consistent with safe-haven behavior.

Two episodes are particularly informative: in 2020 and 2022, Bitcoin's sector correlations rise broadly, widening the differential in favor of gold (Panel C), which is consistent with the view that Bitcoin tends to behave as a risk asset during periods of heightened stress and shifts in financial conditions. The main exception is Utilities, where the differential is uniformly positive and significant, implying that for this defensive sector Bitcoin maintains a lower conditional correlation than gold (Panel C). More broadly, the results suggest that gold's relative safe-haven performance is not homogeneous across sectors: in Materials and Utilities, gold does not display the expected pattern of conditional decoupling under stress, which weakens its interpretation as a safe haven (K. Chen and Wang (2019) reports a similar result over 1996–2017). Moreover, in interest-rate- and real-factor-sensitive sectors such as Real Estate and, in some years, Consumer Staples, the differentials are close to zero and occasionally turn positive, suggesting that gold's hedging advantage is not systematic and that, in these segments, Bitcoin can deliver comparable hedging performance.

Table 3 reports time-varying asset–sector correlations during selected episodes of heightened uncertainty. It shows that, during severe stress events such as the COVID–19 crisis (Panel C) and the tariffs episode (Panel E), the Gold–Bitcoin differential is negative and statistically significant for a broad set of sectors, consistent with superior relative performance of gold as a hedging asset against sectoral equity risk in those windows. In particular, during COVID–19 (Panel C), gold exhibits lower conditional correlations than Bitcoin in 9 out of 11 sectors, while Bitcoin remains strongly and uniformly positively correlated across sectors, reinforcing the interpretation that it behaves as a risk asset at the peak of uncertainty. In the tariffs episode (Panel E), gold's relative advantage is concentrated in Communication Services, Consumer Discretionary, Financials, Industrials, and Information Technology, whereas the only case in which Bitcoin is significantly less correlated than gold is Utilities, where the differential is positive and highly significant.

Moreover, there is a temporally distinctive feature in gold's behavior: across most major equity drawdowns over the last decade (with the exception of the U.S.–China trade-war window), Figure 1 suggests that gold's defensive benefits are most pronounced in the early stages of the sell-off and tend to fade as the drawdown progresses. In particular, the minimum sector correlation turns negative at the onset and then converges toward less negative values as the episode unfolds. This feature of gold was previously documented by Akhtaruzzaman et al. (2021) during the COVID-19 crisis, and our results indicate that the same pattern extends to other extreme market downturns. For Bitcoin, conditional co-movement remains positive across all industries in every event window, implying that even for Utilities, despite being the comparatively less correlated sector in differential terms, the correlation remains in the positive domain and therefore does not meet the canonical safe-haven criterion.

4.2. Regime-dependent directional connectedness

The R^2-based connectedness results indicate clear, regime-dependent directional imbalances between GICS sectors and each asset (see Figure 2). During high-uncertainty periods, gold exhibits deeper and more persistent departures from balance across most sectors, suggesting that sector returns become more informative for explaining gold dynamics precisely when the equity system is under stress. Combined with the evidence of lower and, in several episodes, negative conditional correlations between gold and sectors, a plausible interpretation is a flight-to-quality mechanism: adverse equity shocks trigger portfolio reallocation toward defensive assets, strengthening directional dependence toward gold even when contemporaneous co-movement is weak or of opposite sign (Baur et al., 2021). By contrast, Bitcoin displays a more episodic pattern, remaining closer to balance for much of the sample but showing spikes in directional imbalance during uncertainty phases, in

Table 2: Dynamic correlations by year

	Comm. Services	Cons. Discr.	Cons. Staples	Energy	Financials	Health Care	Industrials	Info. Tech.	Materials	Real Estate	Utilities
Panel A: Gold											
2014	−0.01	−0.09	−0.07	0.09	−0.14	−0.07	−0.05	−0.04	0.09	0.08	0.10
2015	0.05	−0.06	0.04	0.10	−0.09	−0.01	−0.01	0.00	0.11	0.14	0.17
2016	−0.05	−0.15	−0.02	−0.02	−0.22	−0.11	−0.12	−0.10	0.01	0.05	0.16
2017	0.04	−0.08	0.07	0.01	−0.22	0.00	−0.11	−0.05	0.00	0.13	0.20
2018	0.06	0.03	0.02	0.12	−0.03	0.02	0.04	0.03	0.15	0.08	0.07
2019	−0.06	−0.11	0.01	−0.07	−0.15	−0.03	−0.12	−0.09	0.01	0.11	0.17
2020	0.05	0.01	0.10	−0.01	−0.08	0.04	−0.01	0.05	0.08	0.12	0.17
2021	0.09	0.04	0.11	0.07	−0.01	0.08	0.06	0.09	0.16	0.16	0.15
2022	0.09	0.04	0.12	0.20	0.02	0.09	0.10	0.06	0.21	0.19	0.24
2023	0.07	0.02	0.11	0.06	0.00	0.08	0.04	0.04	0.15	0.14	0.20
2024	0.14	0.09	0.12	0.13	0.04	0.11	0.11	0.08	0.25	0.24	0.23
2025	0.06	−0.03	0.06	0.06	−0.07	0.06	0.01	0.03	0.14	0.13	0.22
Mean	0.04	−0.02	0.06	0.06	−0.08	0.02	−0.01	0.01	0.11	0.13	0.17
Panel B: Bitcoin											
2014	0.11	0.14	0.05	0.01	0.12	0.07	0.09	0.14	0.10	0.07	0.02
2015	0.10	0.13	0.07	0.06	0.11	0.06	0.08	0.11	0.10	0.06	0.02
2016	0.07	0.07	0.00	0.05	0.06	0.04	0.05	0.07	0.07	0.06	0.02
2017	0.11	0.07	0.07	0.05	0.10	0.10	0.06	0.10	0.09	0.08	0.03
2018	0.10	0.14	0.04	0.06	0.16	0.09	0.13	0.15	0.13	0.06	0.03
2019	0.03	0.05	−0.04	0.03	0.03	0.00	0.03	0.05	0.05	0.03	−0.01
2020	0.22	0.22	0.16	0.17	0.18	0.16	0.19	0.22	0.23	0.20	0.13
2021	0.16	0.21	0.10	0.10	0.18	0.12	0.14	0.21	0.20	0.14	0.08
2022	0.31	0.38	0.16	0.19	0.31	0.26	0.28	0.36	0.30	0.26	0.13
2023	0.17	0.21	0.11	0.06	0.17	0.13	0.16	0.18	0.16	0.16	0.07
2024	0.19	0.22	0.06	0.10	0.24	0.13	0.19	0.18	0.17	0.16	0.07
2025	0.22	0.31	0.07	0.11	0.22	0.12	0.24	0.28	0.22	0.15	0.10
Mean	0.15	0.18	0.07	0.08	0.16	0.11	0.14	0.17	0.15	0.12	0.06
Panel C: Raw Differential (Gold–Bitcoin)											
2014	−0.12*	−0.23*	−0.12*	0.08*	−0.26*	−0.13*	−0.14*	−0.18*	−0.01	0.00	0.08*
2015	−0.05*	−0.19*	−0.03	0.04*	−0.19*	−0.06*	−0.09*	−0.11*	0.01	0.09*	0.15*
2016	−0.12*	−0.21*	−0.01	−0.07*	−0.28*	−0.15*	−0.16*	−0.17*	−0.05*	−0.01	0.14*
2017	−0.06*	−0.15*	0.00	−0.03*	−0.31*	−0.10*	−0.17*	−0.16*	−0.08*	0.06*	0.17*
2018	−0.04*	−0.11*	−0.02	0.06*	−0.19*	−0.07*	−0.09*	−0.12*	0.03	0.02	0.05*
2019	−0.10*	−0.16*	0.06*	−0.10*	−0.19*	−0.03	−0.15*	−0.14*	−0.05	0.09*	0.18*
2020	−0.17*	−0.21*	−0.06*	−0.18*	−0.26*	−0.11*	−0.21*	−0.18*	−0.15*	−0.08*	0.04*
2021	−0.07*	−0.17*	0.00	−0.03	−0.19*	−0.04*	−0.08*	−0.12*	−0.04*	0.02	0.06*
2022	−0.23*	−0.33*	−0.04*	0.01	−0.29*	−0.16*	−0.19*	−0.30*	−0.09*	−0.07*	0.11*
2023	−0.10*	−0.19*	−0.01	−0.01	−0.16*	−0.05*	−0.12*	−0.15*	−0.01	−0.01	0.13*
2024	−0.05*	−0.14*	0.07*	0.04	−0.19*	−0.02	−0.08*	−0.09*	0.08*	0.08*	0.16*
2025	−0.16*	−0.33*	0.00	−0.05*	−0.29*	−0.05*	−0.24*	−0.25*	−0.08*	−0.02*	0.12*

Notes: Panel A (Panel B) reports Gold (Bitcoin) sector values. Panel C reports the raw differential as Gold minus Bitcoin. * denotes statistical significance for the differential, based on tests of the null hypothesis $\alpha = 0$ in a constant-only regression of the differentials using HAC standard errors. A positive value indicates that Gold is higher, while a negative value indicates that Bitcoin is higher.

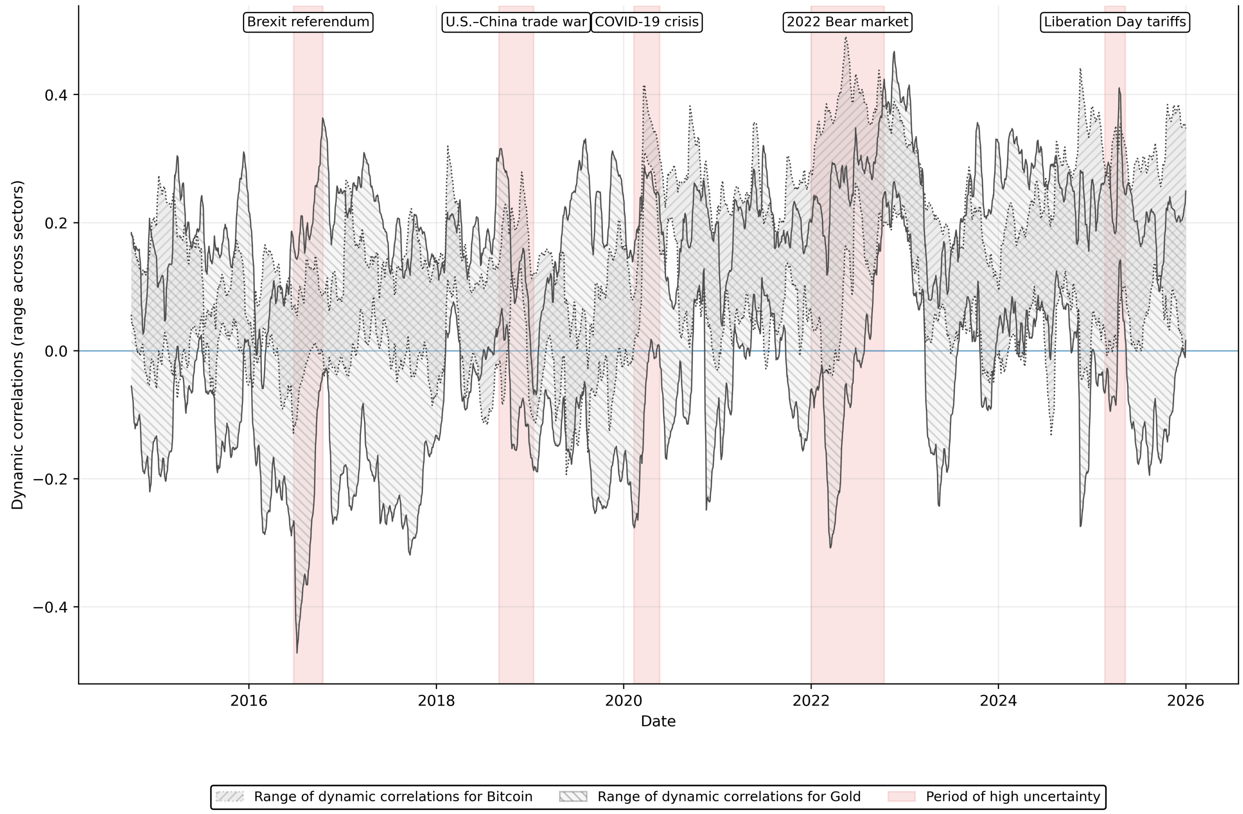

Figure 1: Range of dynamic correlations by sector: Gold and Bitcoin

line with a more procyclical linkage and risk-asset behavior. Table 5 summarizes this evidence by showing that aggregate FROM spillovers into gold (27.51) exceed those into Bitcoin (17.67) and that connectedness is largely contemporaneous, pointing to rapid stress-driven adjustments rather than gradual transmission through lagged channels.

4.3. Tail-risk results across sectors

Table 4 highlights three core findings. First, baseline sector exposure differs sharply across assets. Gold exhibits, in most cases, a negative and statistically significant average sensitivity to sector returns, suggesting weak or offsetting co-movement under normal conditions; by contrast, Bitcoin shows a positive, large, and highly significant baseline sensitivity across all sectors, reflecting a more procyclical pattern. Second, when conditioning on severe downturns, gold's safe-haven behavior is concentrated in episodes located in the 5% left tail. When sector returns fall into that percentile, the gold–sector relationship becomes more negative in Health Care and Industrials, and more modestly in Materials, pointing to stronger decoupling on pronounced downside days. However, when shocks shift into the 1% left tail, this benefit attenuates and the incremental exposure turns positive in Industrials, Information Technology, and also in Energy, indicating that gold does not sustain systematic decoupling under the most extreme sector downturns. For Bitcoin, tail-state

Table 3: Dynamic correlations by event: Gold, Bitcoin, and differentials

	Comm. Services	Cons. Discr.	Cons. Staples	Energy	Financials	Health Care	Industrials	Info. Tech.	Materials	Real Estate	Utilities
Panel A: Brexit referendum											
Gold	−0.10	−0.20	−0.04	−0.06	−0.27	−0.11	−0.17	−0.17	−0.04	0.07	0.22
Bitcoin	0.09	0.08	−0.03	0.07	0.06	0.02	0.04	0.05	0.05	0.10	0.08
Diff	-0.19***	-0.27***	-0.01	-0.13***	-0.33***	-0.13***	-0.20***	-0.22***	-0.08**	-0.03	0.14***
Panel B: U.S.–China trade war											
Gold	−0.01	−0.03	−0.04	0.03	−0.08	−0.03	−0.02	0.00	0.14	0.01	0.03
Bitcoin	0.14	0.19	0.06	0.08	0.17	0.12	0.14	0.18	0.12	0.07	0.03
Diff	-0.15***	-0.22***	-0.10**	-0.05	-0.25***	-0.15***	-0.17***	-0.18***	0.02	-0.06	0.00
Panel C: COVID–19 crisis											
Gold	0.01	−0.05	0.07	−0.01	−0.07	−0.01	−0.02	−0.05	0.04	0.13	0.24
Bitcoin	0.27	0.24	0.22	0.28	0.25	0.22	0.25	0.22	0.27	0.29	0.25
Diff	-0.26***	-0.30***	-0.15***	-0.29***	-0.33***	-0.23***	-0.27***	-0.27***	-0.23***	-0.17***	-0.01
Panel D: 2022 Bear market											
Gold	0.04	−0.02	0.08	0.18	−0.04	0.05	0.05	0.01	0.15	0.15	0.23
Bitcoin	0.31	0.38	0.13	0.17	0.31	0.25	0.28	0.37	0.29	0.25	0.11
Diff	-0.27***	-0.40***	-0.05**	0.01	-0.35***	-0.20***	-0.24***	-0.36***	-0.14***	-0.10***	0.12***
Panel E: Liberation Day tariffs											
Gold	0.10	0.04	0.09	0.11	−0.01	0.12	0.07	0.14	0.18	0.15	0.27
Bitcoin	0.20	0.31	0.05	0.09	0.20	0.11	0.22	0.27	0.19	0.15	0.07
Diff	-0.09***	-0.27***	0.04	0.02	-0.21***	0.01	-0.14***	-0.13***	-0.02	-0.00	0.20***

Notes: Each panel corresponds to one high-uncertainty event window. Rows report Gold and Bitcoin sector correlations and their raw differential (Gold minus Bitcoin). * denotes statistical significance for the differential, based on tests of the null hypothesis $\alpha = 0$ in a constant-only regression of the daily differentials using HAC standard errors. A positive value indicates that Gold is higher, while a negative value indicates that Bitcoin is higher.

adjustments are more limited and concentrate in Information Technology, where the relationship strengthens in the positive direction; this result is particularly striking, as it contrasts with the evidence reported by Umar et al. (2021) of a disconnect between Bitcoin and the technology sector over 2014–2018. Third, the VIX interactions reinforce the asymmetry between assets. For gold, higher market uncertainty is associated with a more negative sector sensitivity in several cases, whereas for Bitcoin higher uncertainty is more often linked to a more positive sector sensitivity. In economic terms, when uncertainty rises, gold tends to move in the opposite direction to a meaningful share of sector equity returns, while Bitcoin tends to move in the same direction, moving away from a canonical safe-haven pattern.

Table 4: Benchmark interaction and stress-sensitivity effects for Bitcoin and Gold across sectors

	Comm. Services	Cons. Discr.	Cons. Staples	Energy	Financials	Health Care	Industrials	Info. Tech.	Materials	Real Estate	Utilities
Panel A: Gold											
Industry_i	−0.05**	−0.08***	−0.04	−0.05***	−0.08***	−0.03	−0.07***	−0.06***	−0.05**	−0.04**	0.02
	−2.29	−4.25	−1.13	−4.40	−3.31	−0.98	−2.78	−3.06	−2.21	−1.99	0.74
$\text{Industry} \cdot \text{D}_{q10}$	−0.02	−0.02	0.05	0.03	−0.01	0.02	0.04	0.03	0.02	−0.02	−0.02
	−0.42	−0.56	0.79	1.02	−0.16	0.34	0.88	1.16	0.48	−0.40	−0.38
$\text{Industry} \cdot \text{D}_{q05}$	0.01	0.05	−0.02	−0.04	0.00	−0.11**	−0.09**	−0.03	−0.06*	0.02	−0.01
	0.22	1.45	−0.40	−1.55	0.04	−2.38	−2.08	−0.92	−1.72	0.51	−0.14
$\text{Industry} \cdot \text{D}_{q01}$	0.07	0.03	0.05	0.05*	0.03	0.08	0.09**	0.09***	0.05	0.02	0.03
	1.59	0.76	0.88	1.94	0.64	1.35	2.21	2.80	1.20	0.36	0.77
Industry · VIX	−0.31**	−0.27*	−0.34**	−0.13	−0.18	−0.17	−0.21	−0.33***	−0.20	−0.20*	−0.24**
	−2.48	−1.86	−2.34	−1.50	−1.44	−1.19	−1.36	−3.25	−1.40	−1.67	−2.33
Industry · EPU	0.02	0.02	0.02	0.01	0.04	0.04	0.03	0.02	0.01	0.01	0.01
	1.02	1.17	0.56	0.40	1.35	1.43	1.18	1.13	0.53	0.29	0.29
Panel B: Bitcoin											
Industry_i	0.56***	0.55***	0.49**	0.25***	0.57***	0.45***	0.53***	0.55***	0.49***	0.41***	0.37***
	5.01	4.87	2.56	2.64	4.87	3.40	4.20	5.79	4.08	3.91	3.26
$\text{Industry} \cdot \text{D}_{q10}$	−0.06	0.19	−0.67*	−0.06	−0.10	−0.26	−0.11	−0.46**	−0.01	−0.27	−0.67**
	−0.20	0.78	−1.52	−0.36	−0.37	−0.86	−0.37	−2.08	−0.03	−1.23	−2.38
$\text{Industry} \cdot \text{D}_{q05}$	−0.44	−0.04	0.17	−0.01	−0.02	−0.13	−0.01	0.53**	0.02	0.22	0.20
	−1.51	−0.18	0.35	−0.05	−0.07	−0.38	−0.03	2.26	0.07	0.88	0.69
$\text{Industry} \cdot \text{D}_{q01}$	0.79	0.45	0.64	0.28	0.08	0.66	0.33	0.45	0.47	0.05	0.16
	1.54	1.16	1.14	1.15	0.23	1.29	0.88	1.27	1.20	0.15	0.48
Industry · VIX	2.44**	0.76	3.43***	1.41*	1.26	2.26**	1.40	0.48	1.13	2.08**	4.19***
	2.10	0.81	2.60	1.65	1.46	2.00	1.30	0.68	1.13	2.27	3.92
Industry · EPU	−0.14	−0.10	0.06	−0.01	−0.03	−0.21	−0.07	−0.10	−0.02	0.07	0.14
	−0.88	−0.64	0.27	−0.06	−0.14	−1.10	−0.39	−0.76	−0.14	0.38	0.89

Notes: This table reports estimates from Equation (8) with HAC standard errors. Coefficients are reported on the first line and t-statistics on the second line. Control variables are omitted from the table for brevity and are available upon request. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ (based on two-sided normal/t critical values).

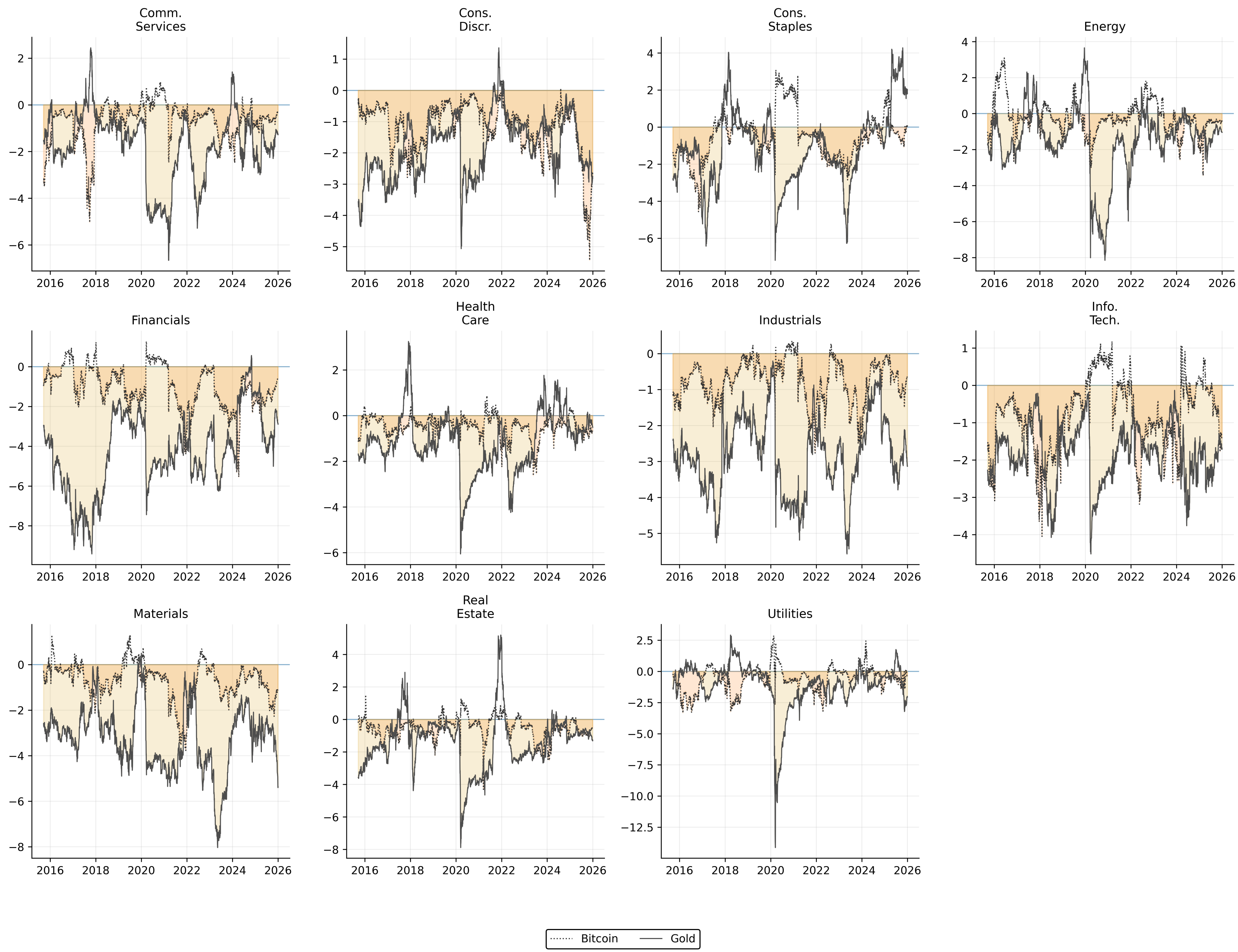

Figure 2: Net pairwise directional connectedness.

5. Conclusions

This article compares, at the sector level, the defensive role of gold and Bitcoin against the returns of the eleven GICS sectors of the U.S. equity market, with the aim of assessing whether either asset can serve as a safe-haven alternative for portfolio managers. Prior evidence indicates that gold does not provide consistent protection in certain sectors, such as Energy, Materials, and Utilities (Baumöhl & Lyócsa, 2017; K. Chen & Wang, 2019; Kinateder et al., 2024), which challenges its safe-haven status in a disaggregated setting. At the same time, it suggests that Bitcoin could represent an alternative, since, in theory, it may decouple from traditional assets in episodes where stress is associated with banking fragility, doubts about the credibility of monetary policy, or disruptions in payment infrastructure. To evaluate this hypothesis, the study estimates dynamic and conditional comovements between each asset and sectoral returns using a DCC–GARCH model (Engle, 2002), incorporates measures of directional interdependence based on an R^2-connectedness framework (Cocca et al., 2024), and complements the analysis with a left-tail approach conditioned on the worst sectoral drawdowns, testing whether, under severe stress, the relationship becomes zero or negative, which is the standard operational condition for identifying a safe haven.

The results reveal a systematic contrast between the two assets. On an annual average basis, gold exhibits persistently lower sectoral correlations and, in some cases, negative correlations, particularly in Financials and Industrials, whereas Bitcoin displays predominantly positive correlations of larger magnitude with virtually all sectors, with a particularly pronounced increase since 2020. Consistent with this, the Gold–Bitcoin differential is mostly negative and statistically significant, with large gaps in Financials, Consumer Discretionary, Information Technology, Industrials, and Communication Services, indicating stronger relative decoupling of gold from sectoral equity risk. This pattern intensifies during high-uncertainty episodes, such as COVID-19 and the 2022 bear market, when Bitcoin correlations rise broadly and remain positive, widening the differential in favor of gold. Similarly, during events such as Brexit and, to a large extent, the U.S.–China trade war, gold maintains low and often negative comovements, while Bitcoin preserves positive comovement, reinforcing its procyclical character. The main exception is Utilities, where Bitcoin is systematically less correlated than gold; however, correlations do not become negative, so it does not satisfy the operational safe-haven criterion.

Left-tail evidence further supports the state-dependent nature of gold's safe-haven properties. Conditioning on the worst 5% of sectoral performance, gold deepens its decoupling, becoming more negative in Health Care and Industrials and, more moderately, in Materials, which is consistent with a flight-to-quality mechanism and a weak safe-haven role. However, at the most extreme 1% tail, this property attenuates, as gold's incremental exposure turns positive in Industrials, Information Technology, and Energy, suggesting that its value-preservation capacity weakens under black-swan-type shocks (Taleb, 2010). By contrast, Bitcoin shows no evidence of safe-haven behavior, as its comovement remains positive across the episodes considered and tends to strengthen with uncertainty. Under the standard taxonomy, gold therefore resembles a partial hedge with weak safe-haven features under severe stress, whereas Bitcoin behaves predominantly as a risk asset, with benefits closer to time-varying diversification and, at the margin, concentrated in Utilities.

This article contributes to the safe-haven debate by providing the first systematic comparison between gold and Bitcoin at a disaggregated level across U.S. equity sectors. Although recent literature has suggested that Bitcoin could function as "digital gold," the evidence shows that, in practice, the two assets play different roles within portfolios: Bitcoin has not replaced gold as a safe haven during the major U.S. stock market downturns of the last decade, while gold tends to perform better as a hedging instrument than as a cross-sector safe haven. This result is particularly useful for institutional portfolio managers, who must design protection strategies when risk increases, as it calls for caution in the use of Bitcoin and supports assigning it a role closer to that proposed by Platanakis and Urquhart (2020), namely as a complement to improve the portfolio's risk-adjusted returns rather than as crisis insurance. Regarding gold, the results indicate greater usefulness than Bitcoin across U.S. sectors and show that it tends to be more effective as a hedge in the initial phase of a crisis; however, as the shock evolves, its effectiveness tends to weaken and its comovement with risk assets tends to increase.

6. Appendix

Table 5: Sector spillovers *to* and *from Gold* and *Bitcoin* by connectedness component (DCC-GARCH R^2)

	Gold						*Bitcoin*					
	Overall		Contemp.		Lagged		Overall		Contemp.		Lagged	
	To	From	To	From	To	From	To	From	To	From	To	From
Financials	2.55	4.71	2.38	4.29	0.17	0.41	1.43	1.94	1.18	1.46	0.25	0.48
Health Care	0.90	1.47	0.56	1.07	0.34	0.40	0.89	1.13	0.68	0.84	0.21	0.29
Comm. Services	0.79	1.67	0.56	1.15	0.23	0.52	1.24	1.58	1.03	1.19	0.21	0.40
Real Estate	1.62	2.33	1.20	1.85	0.42	0.47	1.09	1.35	0.83	1.01	0.26	0.34
Materials	1.98	3.60	1.65	3.19	0.33	0.41	1.22	1.57	1.01	1.26	0.20	0.30
Energy	1.84	2.59	1.48	2.04	0.35	0.54	1.07	1.18	0.74	0.85	0.33	0.33
Industrials	1.00	2.43	0.82	2.00	0.18	0.42	1.02	1.40	0.85	1.09	0.17	0.31
Info. Tech.	1.01	1.93	0.84	1.46	0.17	0.47	2.03	2.43	1.79	2.04	0.24	0.38
Cons. Staples	1.19	1.76	0.70	1.17	0.49	0.59	0.97	1.23	0.59	0.76	0.37	0.47
Utilities	2.53	3.09	2.17	2.75	0.36	0.34	0.66	0.98	0.37	0.44	0.29	0.54
Cons. Discr.	1.05	1.96	0.82	1.54	0.23	0.42	2.28	2.88	2.16	2.53	0.13	0.35
TO/FROM	16.46	27.51	13.19	22.51	3.28	5.01	13.90	17.67	11.23	13.48	2.67	4.20

Notes: For each sector, *To* reports the contribution from *Gold*/*Bitcoin* to the sector's connectedness; *From* reports the contribution from the sector to *Gold*/*Bitcoin*. The columns decompose the R^2-based connectedness into Overall, Contemp. (same-period comovement), and Lagged (spillovers through lags, with $nlag = 1$).

Chapter 3

The Moby Dick effect: Contagious Bitcoin Whales in the Crypto Market

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Abstract

This study examines the *Bitcoin Whale* contagion on the cryptocurrency market. We built a whale signal considering transfers from wallets to exchanges and vice versa, reported on the "Whale Alert" Telegram group. We then measured whale contagion on the returns of the 15 cryptocurrencies with the largest market capitalization using time-varying parameters VAR at 1, 6, and 24 hours after the transfer. The results indicated a significant contagion of Bitcoin whales, mainly after 6 and 24 hours. These results provide a new perspective on the factors influencing contagion in the cryptocurrency market and its impact on financial stability.

Keywords: Bitcoin Whales, Cryptocurrency, Financial Contagion.

1. Introduction

This study examines the "Bitcoin Whales" contagion on the largest cryptocurrencies by market capitalization, contributing to the extensive financial literature on contagion and its implications for risk and financial stability. While research has traditionally focused on contagion in conventional assets such as commodities, equities, and bonds (Bouteska et al., 2024; Yonghui & Wenlong, 2025), recent studies have extended this analysis to cryptocurrencies (Akyildirim et al., 2024; Chowdhury et al., 2024), which are highly interconnected during media turbulence (Conlon et al., 2024; Galati et al., 2024), speculative bubbles (Ben Osman et al., 2024), cyberattacks (Cheraghali et al., 2024), and financial crises (Soltani et al., 2023; F. Zhou, 2024).

Institutional adoption has rapidly fueled the growth in the market capitalization of major crypto assets (Babalos et al., 2025; Hasavari et al., 2025), increasing interconnectedness and increasing the risk of financial contagion. In this tightly linked environment, shocks to one asset can quickly spill over to others, amplifying systemic instability. The decentralized structure of the cryptocurrency market, combined with high volatility and a lack of regulatory oversight, further reinforces this fragility. Bitcoin plays a central role in transmitting volatility across digital assets, mainly due to disparities in market capitalization (Balcilar & Ozdemir, 2023; Moratis, 2021). Under these conditions, localized events, such as forced liquidations or the collapse of major exchanges, can trigger cascading effects that extend beyond the crypto ecosystem (Bouri et al., 2023; Galati et al., 2024; S. Lee et al., 2023).

This spillover has already reached traditional financial markets. F. Zhou (2024) identifies transmission channels from crypto assets to stocks, bonds, and commodities, especially during periods of high volatility. Pacelli (2025) emphasizes that systemic risk stems not just from isolated events but from the dense network of links among market participants, which accelerates the spread of financial stress through shared exposures and herd behavior. As digital and traditional markets become increasingly integrated, the risk of cross-market contagion rises, posing a threat to global financial stability. To counteract this, Aliano and Ragni (2026) highlights the importance of cooperation between platforms, investors, and regulators. Their findings show that coordinated efforts enhance the resilience of the crypto-financial system and help mitigate long-term contagion effects.

Given that financial contagion poses a threat to market stability (Yu et al., 2024; Y. Zhang et al., 2024), academic research has increasingly focused on identifying the underlying drivers of this phenomenon. Among these, behavioral factors, such as market sentiment and herd behavior, have emerged as key catalysts in the transmission of financial shocks, especially in markets dominated by irrational investors (Akyildirim et al., 2024; Chowdhury et al., 2024; J. Liu et al., 2024; Mbarek & Msolli, 2025; Mensi et al., 2024). Building on this literature, our study argues that Bitcoin whale transactions should not be interpreted merely as technical events but rather as behavioral signals that, when collectively perceived, can trigger synchronized responses and generate contagion across crypto assets. These whales, defined as large holders that control 500 or more units of Bitcoin, possess a considerable capacity to influence prices for two main reasons. First, due to the absence of fundamental valuation anchors (e.g., dividends or interest rates), crypto investors rely heavily on price and volume dynamics, making them primarily reactive to large-scale movements (Azamjon et al., 2023; Long et al., 2025; Saggu, 2022; Scaillet et al., 2020). Second, blockchain transparency enables these transactions to be tracked and disseminated in real time across public platforms. In crypto markets, where noise traders play a significant role, such visibility often catalyzes herd behavior, amplifying correlated responses and intensifying systemic risk (Inuduka et al., 2024; Karaa et al., 2024).

To the best of our knowledge, this is the first study to empirically examine how Bitcoin whale activity triggers contagion effects on the returns of major cryptocurrencies. We add to the financial contagion literature by demonstrating that these effects are not uniform but depend critically on the perceived signal behind each transaction, becoming more pronounced when the market interprets them as strategic liquidations or accumulations. To capture this dynamic, we introduce a novel classification framework that considers both the direction of the transaction and the type of wallet involved, enabling a more precise identification of market expectations. Furthermore, our findings show that the magnitude of the contagion increases over time, particularly at 6- and 24-h intervals, underscoring the need to incorporate temporal dimensions into models of systemic risk.

2. Methodology

We evaluated the contagion effect of Bitcoin whale movements on the 15 largest cryptocurrencies by market capitalization. To build our database of Bitcoin whales, we use the blockchain monitoring platform *Whale Alert*, covering the period from April 22, 2022, to May 7, 2025, and then, using a Min-Max method, normalized the whale transactions to scale values between 0 and 1 (Lima & Souza, 2023). Finally, this information was then merged with the hourly returns of Bitcoin, Ethereum, XRP, BNB, Solana, Cardano, Dogecoin, TRON, Hedera, Chainlink, Avalanche, Stellar, Litecoin, UNI, and Bitcoin Cash, resulting in a total of 26,616 observations. We perform stationarity tests and reject the null hypothesis of a unit root at the 1% significance level for all series. Furthermore, the Ljung and Box (1978) test revealed significant serial correlation in all variables (see Table 1).

Table 1: Whale transaction types and market signals

Option	Sending wallet	Receiving wallet	Movement made	Market signal	ADF	Ljung-Box
1	Known wallet	Known wallet	Exchange to exchange	Neutral	-16.72***	2635.65***
2	Known wallet	Unknown wallet	Exchange withdrawal	Hold position	-30.72***	6429.99***
3	Unknown wallet	Unknown wallet	Unknown to unknown	Neutral	-31.90***	1987.38***
4	Unknown wallet	Known wallet	Transfer to exchange	Strong sell	-16.69***	904.23***

Note: This table summarizes the four whale transaction types and their market interpretations. The ADF Statistic refers to the Augmented Dickey and Fuller (1979) test for stationarity; Ljung-Box column reports the test statistic for autocorrelation (Ljung & Box, 1978). *** indicates rejection of the null hypothesis at the 1% significance level.

Table 1 classifies the signals generated by Bitcoin whale movements into four categories based on the types of wallets involved as origin and destination. A user creates an *unknown wallet* without completing the Know Your Customer (KYC) verification process. These wallets allow investors to store their cryptocurrencies anonymously without the intention of selling them. Instead, a user creates a *known wallet* within an exchange platform after completing the KYC process. Depending on the investor's decision, these wallets are associated with a potential sale because they can often be used to store cryptocurrency to sell or convert it.

The crypto community widely understands the distinction between *known* and *unknown wallets*. The transfer of Bitcoin from a *known wallet* to an *unknown wallet* typically signals medium- or long-term storage intentions because there are no regulated channels that allow the conversion of crypto assets into fiat money while maintaining anonymity (Table 1, option 2). If such channels existed, their use would imply illegality by evading records and taxes. In contrast, when a whale transfers Bitcoin from an *unknown wallet* to a *known wallet*, the market interprets this as an imminent sell signal since exchanges are the primary means of converting Bitcoin into fiat money (Table 1, option 4).

In the results presented below, we analyze the contagion effects of Bitcoin whales on cryptocurrency returns, focusing on the *Exchange withdrawal* and *Transfer to exchange* movements (Table 1, options 2 and 4, respectively). We consider these two types of transactions as holding and selling signals, respectively, which may influence investor decisions and, in turn, transmit information to prices. To further investigate the effects of these signals, we conduct statistical tests comparing their average contagion levels with those generated by the *Exchange to exchange* and *Unknown to unknown* movements (Table 1, options 1 and 3, respectively), which are treated as neutral signals. We use these latter options as *"placebo experiments"* because they do not convey meaningful information to the market and exhibit weaker contagion effects. Finally, we emphasize that the main objective of this study is to understand how Bitcoin whale activity contributes to contagion within the cryptocurrency market. Although we do not aim to assess the predictive power of these signals, we include predictive tests for completeness; results are available upon request.

2.1. Spillover effect of Bitcoin whales

To analyze the effect of contagion of the movements of Bitcoin whales on the 15 largest cryptocurrencies, we use the autoregressive vector model with time-varying parameters (TVP-VAR) (Antonakakis et al., 2020). This model captures the dynamic evolution of spillover effects over time, incorporating structural changes in the relationship between assets and variations in the variance-covariance matrix. The model reflects the dynamic evolution of parameters in a multivariate time series, allowing us to model the changing relationships among variables. It is expressed as

$$\mathbf{y}_k = \mathbf{A}_k \mathbf{z}_{k-1} + \boldsymbol{\epsilon}_k, \quad \boldsymbol{\epsilon}_k \sim \mathbf{N}(\mathbf{0}, \boldsymbol{\Sigma}_k), \tag{1}$$

where $\mathbf{y}_k$ is the $m \times 1$ vector of endogenous variables observed at hour k, comprising the log-returns of the 15 largest cryptocurrencies and a variable capturing whale activity, so that $m = 16$; $\mathbf{z}_{k-1}$ is the $mp \times 1$ vector of regressors formed by stacking the first lag of all endogenous variables, with $p = 1$; $\mathbf{A}_k$ is the $m \times mp$ matrix of time-varying coefficients; and $\boldsymbol{\epsilon}_k$ is the $m \times 1$ vector of residuals, with corresponding time-varying variance-covariance matrix $\boldsymbol{\Sigma}_k$.

To assess dynamic connectedness among cryptocurrencies, we use the generalized forecast error variance decomposition (GFEVD), which allows us to measure how much of the uncertainty in a given variable can be explained by shocks from other variables over a specified forecast horizon. Following (Antonakakis et al., 2020), the GFEVD is

$$\phi_{ij,k}(H) = \frac{\sum_{h=0}^{H-1} \Psi_{ij,k}(h)^2}{\sum_{j=1}^{N} \sum_{h=0}^{H-1} \Psi_{ij,k}(h)^2}, \tag{2}$$

where $\phi_{ij,k}(H)$ denotes the proportion of the H-step-ahead forecast error variance of variable i that is attributable to shocks from variable j at time k. The term $\Psi_{ij,k}(h)$ refers to the impulse response of variable i to a one-standard deviation shock in variable j at horizon h. In our analysis, we set the forecast horizon H to 1, 6, and 24 hours and the system includes $N = 16$ variables. This decomposition enables us to quantify not only the direct impact of whale movements on other assets but also how these effects evolve across different time horizons. Finally, we construct a *Whale Hit* ratio to assess the frequency with which Bitcoin whale movements generate stronger spillovers than other cryptocurrencies. The ratio is

$$W_{\text{hit}} = \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}\left(C_{\text{whale}\to i} > C_{j\to i}\right), \tag{3}$$

where $C_{j\to i}$ represents the share of forecast error variance in asset i that is attributable to shocks from asset j, based on the GFEVD matrix. The indicator function $\mathbb{I}(\cdot)$ takes the value 1 when the spillover from the whale to asset i is greater than that from cryptocurrency j, and 0 otherwise. The final value of W_{hit} reflects the percentage of cases in which Bitcoin whale movements are the most influential source of variance among all cryptocurrencies.

3. Results

3.1. Whale withdrawals from exchanges

We find evidence of moderate contagion associated with Bitcoin whale withdrawals from exchanges to unknown wallets. This effect intensifies over time: it is limited to 1-h after the transfer but becomes significant after 24-h. Table 2 reports the magnitude of the contagion in three horizons: 1-h, 6-h, and 24-h. On average, the spillover increases from 2.78% at the 1-h mark to 4.68% after 24-h, indicating that these whale movements explain a growing share of return variance in the broader market. Specifically, 24-h after the transfer, whale activity accounts for an average of 4.68% of the return variance across the 15 cryptocurrencies analyzed. In relative terms, contagion also becomes more prominent: the *Whale Hit* ratio rises from 2.38% at 1-h to 17.62% at 24-h, showing that, at 1-h, the whale is more contagious than only 2.38% of the cryptocurrencies, but after 24-h, it surpasses 17.62% of them (see Table 2).

Table 2: Contagion effects after a whale withdrawal from an exchange

	1 Hour			6 Hours			24 Hours		
	1 Whale	2 From	3 W_{hit}	4 Whale	5 From	6 W_{hit}	7 Whale	8 From	9 W_{hit}
Bitcoin	2.85	83.58	0.00	5.89	88.50	42.86	6.41	88.76	71.43
Ethereum	2.17	83.90	0.00	4.67	88.07	14.29	5.03	88.24	14.29
XRP	2.91	81.43	0.00	5.11	88.30	14.29	5.45	88.47	28.57
BNB	2.39	82.81	0.00	4.26	88.15	7.14	4.40	88.22	7.14
Solana	2.54	83.35	0.00	4.02	88.20	0.00	4.16	88.28	0.00
Cardano	2.59	84.14	0.00	3.99	88.69	0.00	4.08	88.74	0.00
Dogecoin	2.62	80.20	0.00	3.55	84.87	7.14	3.64	84.94	7.14
TRON	3.92	73.55	21.43	4.91	90.30	0.00	5.31	90.44	21.43
Hedera	2.92	80.95	0.00	4.68	86.84	7.14	4.89	86.97	14.29
Chainlink	2.52	81.06	0.00	3.67	85.64	0.00	3.96	85.84	0.00
Avalanche	2.08	84.52	0.00	3.74	89.11	0.00	3.89	89.18	0.00
Stellar	2.37	82.11	0.00	2.89	86.31	0.00	2.92	86.35	0.00
Litecoin	3.19	80.69	0.00	6.82	85.31	85.71	7.33	85.66	100.00
Uniswap	2.67	81.80	0.00	3.77	87.09	0.00	3.84	87.16	0.00
Bitcoin Cash	4.01	75.65	14.29	4.77	87.09	0.00	4.94	87.21	0.00
Whale	37.15	62.85	–	25.11	74.89	–	24.37	75.63	–
Average	2.78	81.32	2.38	4.45	87.50	11.90	4.68	87.63	17.62
To	41.76	1282.57	–	66.74	1387.36	–	70.25	1390.10	–

Note: This table shows the contagion effect measured by TVP-VAR at 1, 6 and 24-h after the transfer from a known wallet to an unknown wallet. All values are percentages. The *Whale* column indicates how much of a variable's forecast error variance is explained by the whale. The *From* column shows the share explained by all other variables in the system. The *To* row shows the sum of forecast error variance that each variable explains in the rest of the system. W_{hit} represents the extent to which the whale contributes more to contagion than the rest of the crypto assets.

3.2. *Whales transfer to exchange*

We find similar evidence when analyzing the contagion triggered by whale transfers to exchanges. The effect remains low in the short term, but increases in magnitude and relevance at the 6-h and 24-h horizons. Table 3 shows that, on average, the spillover rises from 2.51% after 1-h to 6.30% after 24-h. In relative terms, contagion also becomes more significant: the *Whale Hit* ratio increases from 1.90% to 50.00%, indicating that initially, the whale is more contagious than only 1.90% of the cryptocurrencies analyzed, but after 24-h, it surpasses half of the market in terms of impact (see Table 3).

Table 3: Contagion effects after a whale transfer to an exchange

	1 Hour			6 Hours			24 Hours		
	1 Whale	2 From	3 W_{hit}	4 Whale	5 From	6 W_{hit}	7 Whale	8 From	9 W_{hit}
Bitcoin	2.15	84.86	0.00	3.67	87.88	0.00	5.54	88.61	35.71
Ethereum	1.86	86.35	0.00	3.01	88.45	0.00	5.00	88.52	14.29
XRP	2.73	83.62	0.00	4.72	88.19	14.29	6.34	88.97	57.14
BNB	2.14	83.69	0.00	3.10	86.80	0.00	7.47	87.35	92.86
Solana	2.22	85.17	0.00	5.06	88.70	14.29	8.20	88.30	92.86
Cardano	1.98	85.86	0.00	3.30	88.24	0.00	6.63	87.88	85.71
Dogecoin	2.20	82.84	0.00	5.42	86.71	35.71	9.57	85.78	100.00
TRON	3.97	71.22	21.43	6.18	87.13	85.71	9.59	91.07	100.00
Hedera	3.19	80.29	7.14	8.13	86.88	100.00	6.03	88.38	57.14
Chainlink	2.49	84.17	0.00	3.06	86.50	0.00	4.54	87.82	7.14
Avalanche	2.23	85.86	0.00	2.99	88.30	0.00	5.49	89.96	21.43
Stellar	2.25	83.50	0.00	4.12	87.29	7.14	4.82	88.09	7.14
Litecoin	2.72	81.52	0.00	3.20	84.61	0.00	4.34	86.30	0.00
Uniswap	2.15	85.03	0.00	3.38	87.63	0.00	4.68	88.10	7.14
Bitcoin Cash	3.36	77.32	0.00	5.02	86.14	7.14	6.25	87.77	71.43
Whale	37.46	62.54	–	25.73	74.27	–	24.11	75.89	–
Average	2.51	82.75	1.90	4.29	87.30	17.62	6.30	88.19	50.00
To	37.64	1303.85	–	64.35	1383.73	–	94.48	1398.80	–

Note: This table shows the contagion effect measured by TVP-VAR at 1, 6, and 24 hours after a transfer from an unknown wallet to an exchange. All values are percentages. The *Whale* column indicates how much of a variable's forecast error variance is explained by the whale. The *From* column shows the share explained by all other variables in the system. The *To* row shows the sum of forecast error variance that each variable explains in the rest of the system. W_{hit} represents the extent to which the whale contributes more to contagion than the rest of the crypto assets.

3.3. The 4 whales: Comparison between signals

The previous analysis focused on two types of whale movements with the greatest potential to generate contagion: *Exchange withdrawal* and *Transfer to exchange* (Table 1, options 2 and 4), both of which are associated with changes in large holders' selling intentions. To test this hypothesis, we compared the average contagion effects across all four types of movements, including *Exchange to exchange* and *Unknown to unknown*, by examining differences in the mean values of the GFEVD matrix over 1-, 6-, and 24-h horizons. Results for the neutral movements are available upon request.

The findings reveal significant differences. At all horizons, *exchange withdrawal* and *transfers to exchanges* exhibit more substantial contagion effects than neutral movements. At the 1-h horizon, *exchange withdrawal* exceeds *exchange to exchange* by 1.20% and *unknown to unknown* by 0.75%, both statistically significant. *Transfer to exchange* also shows more potent effects than both comparisons. At 6-h, *exchange withdrawal* remains dominant, although the difference with *transfer* *to exchange* becomes statistically insignificant. At 24-h, the pattern reverses: *transfer to exchange* becomes the most contagious movement, significantly surpassing the others. In contrast, differences between the neutral movements are never statistically significant (see Table 4).

These results confirm that large-holder movements tied to strategic decisions have greater explanatory power in propagating shocks, evidencing the role of key indicators in systemic risk models within the cryptocurrency market. Moreover, they show that not all whale flows carry the same informational weight: their impact depends on the type of wallet involved and varies in magnitude and timing.

Table 4: Comparison of contagion effects across whale signals by horizon

Horizon (h)	**Comparison**		**Diff**
	Signal a	**Signal b**	
1-h	Exchange withdrawal	Exchange to exchange	1.20^{***}
	Unknown to unknown	Exchange to exchange	0.45
	Transfer to exchange	Exchange to exchange	0.93^{***}
	Unknown to unknown	Exchange withdrawal	-0.75^{***}
	Transfer to exchange	Exchange withdrawal	-0.27
	Transfer to exchange	Unknown to unknown	0.48^{*}
6-h	Exchange withdrawal	Exchange to exchange	1.67^{***}
	Unknown to unknown	Exchange to exchange	0.67
	Transfer to exchange	Exchange to exchange	1.52^{***}
	Unknown to unknown	Exchange withdrawal	-1.01^{**}
	Transfer to exchange	Exchange withdrawal	-0.16
	Transfer to exchange	Unknown to unknown	0.85^{*}
24-h	Exchange withdrawal	Exchange to exchange	1.89^{***}
	Unknown to unknown	Exchange to exchange	0.92
	Transfer to exchange	Exchange to exchange	3.51^{***}
	Unknown to unknown	Exchange withdrawal	-0.97^{*}
	Transfer to exchange	Exchange withdrawal	1.62^{***}
	Transfer to exchange	Unknown to unknown	2.59^{***}

Note: This table reports pairwise differences (Diff) in contagion effects across whale signals, estimated from paired t-tests at three time horizons. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4. Conclusions

Using a TVP-VAR model, this study examines the contagion effects of Bitcoin whale activity on the returns of major cryptocurrencies. The results show that large-scale transfers, commonly referred to as whale movements, play an important role in the transmission of shocks across crypto assets.

Although the immediate impact is relatively low, the contagion intensifies over time, eventually exceeding the average spillover effects observed between individual cryptocurrencies. These findings contribute to the financial contagion literature in crypto markets (Akyildirim et al., 2024; Chowdhury et al., 2024; P. Liu & Yuan, 2024; Mbarek & Msolli, 2025; Mensi et al., 2024) by revealing a novel mechanism through which behavioral signals, such as exchange deposits and withdrawals by large holders, can generate synchronized responses in decentralized markets. Unlike traditional contagion channels based on institutional exposure or macroeconomic links, the mechanism uncovered here is based on real-time visibility of blockchain transactions and the way investors interpret these actions. Specifically, transfers to exchanges are perceived as signals of selling pressure, while withdrawals are interpreted as signs of accumulation and long-term holding. These perceptions amplify herd behavior and increase systemic volatility.

From a practical standpoint, the results suggest that market participants should not dismiss whale transactions as irrelevant background noise. Instead, they should treat them as meaningful signals with the power to influence short-term volatility and cross-asset connectedness. Real-time whale monitoring enhances market surveillance by anticipating periods of heightened stress and guiding dynamic risk management strategies. Institutional investors and algorithmic trading systems could benefit from integrating these behavioral signals into their models. Likewise, regulators and exchanges could harness this information to design early warning systems or implement safeguard mechanisms that help contain panic-driven contagion. As crypto markets increasingly intertwine with traditional financial systems, ignoring these dynamics may undermine efforts to build resilient financial markets.

5. Appendix

Table 5: Whale effects on crypto returns (Option 2 and Option 4)

Asset	1 hour		6 hours		24 hours	
	Whale effect	R^2	Whale effect	R^2	Whale effect	R^2
Panel a: Option 2, table 1						
Bitcoin	0.00015 (0.00017)	0.00070	-0.00010 (0.00016)	0.00070	-0.00008 (0.00015)	0.00070
Ethereum	0.00020 (0.00022)	0.00200	-0.00012 (0.00021)	0.00190	-0.00015 (0.00020)	0.00190
XRP	0.00049** (0.00028)	0.00200	0.00012 (0.00028)	0.00180	0.00001 (0.00025)	0.00180
BNB	0.00001 (0.00019)	0.00070	0.00010 (0.00020)	0.00070	0.00004 (0.00019)	0.00070
Solana	0.00091*** (0.00036)	0.00130	0.00036 (0.00032)	0.00090	0.00002 (0.00032)	0.00090
Cardano	0.00026 (0.00028)	0.00230	-0.00012 (0.00028)	0.00230	0.00000 (0.00026)	0.00230
Dogecoin	0.00004 (0.00029)	0.00090	0.00034 (0.00031)	0.00080	-0.00025 (0.00028)	0.00080
TRON	0.00023 (0.00020)	0.01110	-0.00002 (0.00019)	0.01110	-0.00002 (0.00017)	0.01110
Hedera	0.00022 (0.00032)	0.00030	-0.00014 (0.00030)	0.00030	-0.00012 (0.00031)	0.00030
Chainlink	0.00022 (0.00029)	0.00230	0.00004 (0.00027)	0.00220	-0.00021 (0.00026)	0.00220
Avalanche	0.00063** (0.00033)	0.00080	-0.00035 (0.00030)	0.00060	-0.00013 (0.00030)	0.00060
Stellar	0.00061** (0.00029)	0.00280	-0.00003 (0.00026)	0.00250	-0.00012 (0.00027)	0.00250
Litecoin	0.00045** (0.00027)	0.00170	0.00008 (0.00026)	0.00150	-0.00013 (0.00022)	0.00150
Uniswap	0.00003 (0.00027)	0.00060	0.00035 (0.00034)	0.00060	-0.00011 (0.00028)	0.00060
Bitcoin Cash	0.00007 (0.00025)	0.00050	0.00008 (0.00024)	0.00050	-0.00030 (0.00023)	0.00050
Panel b: Option 4, table 1						
Bitcoin	-0.00016 (0.00018)	0.00060	-0.000213* (0.00016)	0.00070	-0.00008 (0.00019)	0.00060
Ethereum	-0.00010 (0.00023)	0.00150	-0.00018 (0.00022)	0.00150	-0.00003 (0.00023)	0.00140
XRP	-0.00007 (0.00028)	0.00080	-0.00051** (0.00026)	0.00100	0.00004 (0.00025)	0.00080
BNB	-0.00013 (0.00021)	0.00050	0.00006 (0.00020)	0.00040	0.00015 (0.00021)	0.00050
Solana	-0.00017 (0.00039)	0.00050	0.00004 (0.00034)	0.00050	0.00003 (0.00036)	0.00050
Dogecoin	-0.00038 (0.00032)	0.00050	-0.00011 (0.00029)	0.00050	-0.00015 (0.00031)	0.00050
TRON	0.00019 (0.00018)	0.01130	-0.00004 (0.00019)	0.01120	-0.00003 (0.00020)	0.01120
Cardano	0.00023 (0.00031)	0.00190	-0.00043* (0.00027)	0.00200	0.00020 (0.00028)	0.00190
Chainlink	-0.00004 (0.00032)	0.00180	-0.00021 (0.00029)	0.00180	0.00012 (0.00031)	0.00180
Avalanche	-0.00009 (0.00038)	0.00040	-0.00026 (0.00033)	0.00040	0.00037 (0.00035)	0.00050
Stellar	0.00004 (0.00028)	0.00140	-0.00042* (0.00025)	0.00150	0.00019 (0.00029)	0.00140
Litecoin	0.00001 (0.00027)	0.00120	-0.00026 (0.00025)	0.00130	0.00006 (0.00025)	0.00120
Uniswap	-0.00024 (0.00033)	0.00060	-0.00014 (0.00030)	0.00050	0.00014 (0.00033)	0.00050
Hedera	0.00032 (0.00035)	0.00040	0.00013 (0.00034)	0.00040	-0.00001 (0.00030)	0.00040
Bitcoin Cash	-0.00029 (0.00024)	0.00030	-0.00013 (0.00024)	0.00020	-0.00026 (0.00024)	0.00020

Note: All results are based on HAC models. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, In Panel a, the null hypothesis is rejected in the right tail; in Panel b, it is rejected in the left tail. The sample includes 26,616 hourly observations.

Table 6: Whale effects on crypto returns (Option 1 and Option 3)

Asset	1 hour		6 hours		24 hours	
	Whale effect	R^2	Whale effect	R^2	Whale effect	R^2
Panel a: Option 1, table 1						
Bitcoin	-0.00051 (0.00033)	0.00060	-0.00033 (0.00033)	0.00050	-0.00023 (0.00034)	0.00040
Ethereum	-0.00048 (0.00045)	0.00200	-0.00010 (0.00044)	0.00180	-0.00045 (0.00048)	0.00190
XRP	0.00058 (0.00061)	0.00260	0.00021 (0.00045)	0.00250	-0.00033 (0.00057)	0.00250
BNB	-0.00018 (0.00042)	0.00140	-0.00024 (0.00038)	0.00140	-0.00035 (0.00046)	0.00140
Solana	-0.00080 (0.00066)	0.00110	-0.00007 (0.00062)	0.00100	-0.00051 (0.00074)	0.00110
Dogecoin	-0.00015 (0.00064)	0.00200	0.00052 (0.00067)	0.00200	-0.00086 (0.00079)	0.00210
TRON	-0.00029 (0.00041)	0.01250	0.00028 (0.00037)	0.01250	-0.00057 (0.00036)	0.01270
Cardano	-0.00060 (0.00063)	0.00470	0.00010 (0.00056)	0.00460	-0.00083 (0.00074)	0.00480
Chainlink	-0.00039 (0.00062)	0.00320	-0.00012 (0.00055)	0.00320	-0.00010 (0.00068)	0.00320
Avalanche	-0.00065 (0.00071)	0.00110	-0.00012 (0.00067)	0.00100	-0.00032 (0.00076)	0.00100
Stellar	0.00002 (0.00054)	0.00320	-0.00004 (0.00047)	0.00320	-0.00055 (0.00060)	0.00330
Uniswap	0.00008 (0.00077)	0.00180	0.00107 (0.00083)	0.00210	-0.00060 (0.00073)	0.00190
Hedera	-0.00040 (0.00061)	0.00020	0.00025 (0.00058)	0.00020	-0.00022 (0.00071)	0.00020
Litecoin	-0.00033 (0.00051)	0.00220	-0.00016 (0.00046)	0.00220	-0.00038 (0.00054)	0.00220
Bitcoin Cash	-0.00098* (0.00051)	0.00070	-0.00013 (0.00055)	0.00070	-0.00098** (0.00046)	0.00070
Panel b: Option 3, table 1						
Bitcoin	-0.00006 (0.00022)	0.00060	0.00007 (0.00016)	0.00060	-0.00021 (0.00017)	0.00060
Ethereum	0.00018 (0.00030)	0.00220	0.00028 (0.00021)	0.00220	-0.00032 (0.00023)	0.00220
XRP	0.00041 (0.00038)	0.00160	0.00032 (0.00033)	0.00160	-0.00009 (0.00032)	0.00150
BNB	-0.00001 (0.00025)	0.00090	0.00017 (0.00020)	0.00100	-0.00010 (0.00020)	0.00090
Solana	-0.00005 (0.00040)	0.00080	-0.00015 (0.00031)	0.00080	-0.00010 (0.00032)	0.00080
Dogecoin	-0.00011 (0.00050)	0.00220	0.00050 (0.00039)	0.00230	0.00001 (0.00037)	0.00220
TRON	-0.00010 (0.00023)	0.01070	-0.00010 (0.00019)	0.01070	-0.00001 (0.00022)	0.01070
Cardano	0.00029 (0.00043)	0.00350	0.00013 (0.00032)	0.00350	-0.00022 (0.00034)	0.00350
Chainlink	0.00020 (0.00042)	0.00290	-0.00021 (0.00032)	0.00290	-0.00032 (0.00031)	0.00300
Avalanche	0.00003 (0.00041)	0.00070	-0.00006 (0.00034)	0.00070	-0.00031 (0.00034)	0.00070
Stellar	0.00008 (0.00040)	0.00300	0.00059 (0.00038)	0.00320	0.00011 (0.00039)	0.00310
Uniswap	-0.00005 (0.00059)	0.00310	-0.00022 (0.00043)	0.00310	-0.00003 (0.00036)	0.00310
Hedera	0.00079* (0.00047)	0.00040	0.00000 (0.00039)	0.00020	0.00045 (0.00046)	0.00020
Litecoin	-0.00007 (0.00038)	0.00230	-0.00009 (0.00029)	0.00230	-0.00003 (0.00030)	0.00230
Bitcoin Cash	-0.00022 (0.00031)	0.00030	-0.00016 (0.00028)	0.00030	-0.00019 (0.00026)	0.00030

Note: All results are based on HAC models. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample includes 26,616 hourly observations.

Table 7: Contagion effects: Option 1, “exchange to exchange", table 1

	1 Hour			6 Hours			24 Hours		
	1 Whale	2 From	3 W_{hit}	4 Whale	5 From	6 W_{hit}	7 Whale	8 From	9 W_{hit}
Bitcoin	1.29	85.86	0.00	2.67	87.04	0.00	2.69	87.05	0.00
Ethereum	1.32	86.85	0.00	2.38	87.57	0.00	2.39	87.58	0.00
XRP	1.93	80.07	0.00	3.22	83.92	0.00	3.23	83.93	0.00
BNB	1.53	83.65	0.00	2.96	85.49	0.00	2.99	85.51	0.00
Solana	1.33	84.87	0.00	2.45	85.60	0.00	2.48	85.62	0.00
Cardano	1.37	85.32	0.00	2.54	86.85	0.00	2.55	86.86	0.00
Dogecoin	1.37	85.08	0.00	2.23	85.18	0.00	2.24	85.19	0.00
TRON	2.76	72.76	0.00	4.28	84.79	0.00	4.29	84.86	0.00
Hedera	1.59	82.04	0.00	2.88	84.36	0.00	2.90	84.37	0.00
Chainlink	1.47	85.08	0.00	2.61	86.39	0.00	2.63	86.40	0.00
Avalanche	1.31	85.24	0.00	2.38	86.02	0.00	2.39	86.04	0.00
Stellar	1.50	83.91	0.00	2.56	85.16	0.00	2.58	85.17	0.00
Litecoin	1.53	83.15	0.00	2.43	83.93	0.00	2.44	83.94	0.00
Uniswap	1.55	83.63	0.00	2.77	85.57	0.00	2.79	85.59	0.00
Bitcoin Cash	1.86	79.76	0.00	3.27	84.51	0.00	3.28	84.54	0.00
Whale	51.25	48.75	–	27.34	72.66	–	27.16	72.84	–
Average	1.58	83.15	0.00	2.78	85.49	0.00	2.79	85.51	0.00
To	23.70	1296.01	–	41.64	1355.03	–	41.86	1355.49	–

Note: This table shows the contagion effect measured by TVP-VAR at 1, 6 and 24 hours after the transfer from one known wallet to another known wallet. All values are percentages. The *Whale* column indicates how much of a variable's forecast error variance is explained by the whale. The *From* column shows the share explained by all other variables in the system. The *To* row shows the sum of forecast error variance that each variable explains in the rest of the system. W_{hit} represents the extent to which the whale contributes more to contagion than the rest of the crypto assets.

Table 8: Contagion effects: Option 3, “unknown to unknown", table 1

	1 Hour			6 Hours			24 Hours		
	1	2	3	4	5	6	7	8	9
	Whale	From	W_{hit}	Whale	From	W_{hit}	Whale	From	W_{hit}
Bitcoin	1.67	86.53	0.00	3.20	88.51	7.14	3.48	88.95	7.14
Ethereum	1.48	87.15	0.00	2.54	88.30	0.00	2.77	88.58	0.00
XRP	2.18	83.38	0.00	3.79	86.71	7.14	4.10	87.39	7.14
BNB	1.80	84.06	0.00	2.99	86.17	0.00	3.25	86.70	7.14
Solana	1.84	85.51	0.00	3.31	87.84	7.14	3.62	88.46	7.14
Cardano	1.92	86.39	0.00	3.41	88.22	7.14	3.75	88.69	7.14
Dogecoin	1.53	84.32	0.00	2.74	85.72	0.00	3.01	86.01	7.14
TRON	3.84	71.33	0.00	5.56	85.21	50.00	5.78	86.33	71.43
Hedera	2.19	83.64	0.00	3.43	86.26	7.14	3.76	86.89	7.14
Chainlink	1.57	85.15	0.00	2.96	87.14	7.14	3.19	87.59	7.14
Avalanche	1.96	86.09	0.00	3.48	88.59	7.14	3.79	89.14	7.14
Stellar	1.79	84.12	0.00	3.07	86.40	7.14	3.29	86.95	7.14
Litecoin	1.94	83.60	0.00	2.95	85.49	0.00	3.19	86.07	7.14
Uniswap	2.24	84.62	0.00	3.65	87.38	7.14	3.94	88.03	7.14
Bitcoin Cash	2.55	80.55	0.00	4.53	86.56	7.14	4.77	87.19	7.14
Whale	42.68	57.32	–	16.52	83.48	–	14.70	85.30	–
Average	2.03	83.76	0.00	3.44	86.97	8.10	3.71	87.53	10.95
To	30.52	1313.75	–	51.60	1387.99	–	55.70	1398.28	–

Note: This table shows the contagion effect measured by TVP-VAR at 1, 6 and 24 hours after the transfer from one unknown wallet to another unknown wallet. All values are percentages. The *Whale* column indicates how much of a variable's forecast error variance is explained by the whale. The *From* column shows the share explained by all other variables in the system. The *To* row shows the sum of forecast error variance that each variable explains in the rest of the system. W_{hit} represents the extent to which the whale contributes more to contagion than the rest of the crypto assets.

Concluding Remarks

Academic research on cryptocurrencies takes place in a relatively young market that is still undergoing consolidation, both in its technological dimension and in its institutional and regulatory architecture. Unlike traditional asset classes, cryptoassets have experienced simultaneous changes in their underlying infrastructure, in the composition of market participants, and in their degree of integration with global financial markets. This combination of transformations weakens the stability of historical regularities and reduces the reliability of extrapolating patterns identified in short-horizon samples. In this context, empirical evidence must contribute to identifying more precisely the intrinsic characteristics of these assets and to delineating the functions they may perform within diversified portfolios, hedging strategies, and risk management frameworks. With this objective, this thesis contributes to the literature through three articles with complementary aims, each seeking to characterize more precisely the risk–return profile of cryptoassets in an environment in which their economic role remains in evolution. The following sections detail the objectives, evidence, and main results of each article.

The first article conducts a systematic and comparable evaluation of the return predictors for Bitcoin proposed in the literature and translates this evaluation into a tool suitable for real-time use. Specifically, the analysis examines 141 variables commonly employed to forecast returns, using daily data from September 2014 to April 2025, and subjects each signal to a demanding set of out-of-sample validation procedures. These tests encompass multiple estimation schemes, different training window specifications, and a range of forecast horizons, including multi-step predictions. While in-sample analysis provides an informative starting point, economic relevance lies in identifying signals capable of anticipating price movements using exclusively the information available at the time investment decisions are made. For this reason, all variables are evaluated out of sample and benchmarked against standard, difficult-to-beat references in the literature, such as random walk processes and autoregressive models. The results indicate that trend-based technical indicators exhibit, on average, greater consistency. In addition, the thesis constructs composite indices using principal component analysis to summarize the informational content within each family of signals and to facilitate operational scalability. This contribution culminates in the implementation of a replicable indicator that is publicly available on GitHub[18], explicitly linking academic evidence with practical needs in monitoring, allocation, and decision-making in crypto markets.

The second article focuses on the risk management dimension and evaluates the defensive role

[18] Replication instructions are available at https://github.com/AliroJoel/Technical-analysis.

of Bitcoin by incorporating a sectoral disaggregation that is directly relevant for applied analysis. The study compares Bitcoin with gold, the conventional benchmark for protection, and shows that even during severe episodes of stress in the U.S. equity market, Bitcoin does not display behavior consistent with that of a sector-level safe haven. Gold, by contrast, exhibits a more defensive profile, although its benefits are more accurately characterized as hedging properties rather than strict safe-haven qualities. These findings suggest that the narrative portraying Bitcoin as "digital gold" may lead to misleading conclusions if protection is not assessed in economically relevant contexts, particularly during extreme losses and under sectoral heterogeneity. Accordingly, the disaggregated evidence provided by the thesis offers portfolio managers and market participants a more realistic empirical basis for calibrating hedges and managing exposure during crises, positioning Bitcoin, with limited exceptions, closer to a procyclical asset than to a financial insurance instrument.

Finally, the third article addresses the internal dynamics of the crypto ecosystem and develops an operational conceptualization of "whale" activity and its implications for financial contagion. Based on a classification derived from observable blockchain movements, the thesis distinguishes between signals associated with potential accumulation, signals linked to potential selling pressure, and movements with limited informational content. Using this typology, the analysis demonstrates that these actions are not equivalent and that their effects differ systematically in magnitude, direction, and speed of transmission. The central argument is that such movements function as differentiated signals that coordinate expectations, amplify shocks, and reshape intramarket financial connectivity at high frequency. Consequently, their interpretation is critical for monitoring systemic risk. This evidence is particularly relevant for regulators and for the process of institutional integration of cryptoassets, as it reveals endogenous channels of risk propagation that are not easily captured by traditional price-based metrics.

Despite these contributions, the research agenda remains open. First, future work should examine in greater detail the contagion mechanisms associated with stablecoin de-pegging events, given that stablecoins represent the primary operational link between the traditional financial system and the crypto ecosystem. Second, additional analysis is required to characterize how volatility dynamics and co-movements have evolved in the context of increasing institutional participation, explicitly incorporating regime changes associated with milestones such as the approval of Bitcoin exchange-traded funds (ETFs) in 2024. Finally, a systematic evaluation is needed of the macroeconomic and fiscal implications of treating Bitcoin as a strategic reserve or sovereign asset. If, as the evidence presented in this thesis suggests, Bitcoin behaves predominantly as a risk-bearing instrument within portfolios, it becomes essential to understand the vulnerabilities it may introduce for economies that seek to incorporate it as a reserve asset or even as legal tender. Taken together, these research directions would complement the findings presented here and deepen the understanding of a market that, despite its relatively short history, already operates with potentially systemic effects.

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