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The role of gold in bubble formation in the U.S. equity market and bitcoin

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Abstract
This study examines bubble dynamics in the S&P 500 Index and Bitcoin, with particular emphasis on the role of gold as a proxy for market-wide stress. We apply the GSADF bubble test, time-varying Granger causality, and multifractal detrended fluctuation analysis to both original and gold-filtered price series. The results reveal a pronounced asymmetry between equity and cryptocurrency markets. Bitcoin exhibits statistically significant and persistent bubble behavior in both raw and filtered data, accompanied by multifractal persistence consistent with self-reinforcing speculative dynamics. In contrast, the S&P 500 shows no consistent evidence of sustained bubble behavior, and its multifractal properties remain aligned with short memory and rapid information absorption. The causality analysis indicates a stable, state-dependent predictive relationship from gold to equity prices, suggesting sensitivity to global risk sentiment, while no comparable persistent linkage is observed for Bitcoin. Overall, the findings suggest that equity price dynamics remain connected to market-wide stress conditions, whereas Bitcoin's behavior appears to be driven primarily by asset-specific speculative forces.

Keywords Financial bubbles · Time-varying Granger causality · Bitcoin · Flight-to-quality · Gold

1 Introduction

Asset prices are shaped by supply–demand dynamics, yet financial markets do not always reflect fundamental values. A wide range of forces—some beyond regulatory control—can distort equilibrium and drive prices away from intrinsic value. In particular, behavioral fac-

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tors and informational cascades may induce departures from fully rational decision-making, especially during periods of heightened uncertainty and volatility. Under such conditions, investors often exhibit herd behavior rather than relying on fundamentals, leading to pronounced mispricing and, in some cases, the formation of bubbles that are inherently unstable and prone to collapse.

Building on this perspective, the literature documents extensive evidence that asset bubbles are influenced by behavioral forces, including departures from fully rational investor behavior (Kahneman and Tversky 1979, 2013; De Bondt and Thaler 1985; Barberis et al. 1998; Hirshleifer et al. 2006), herd behavior (Scharfstein and Stein 1990; Cont and Bouchaud 2000; Lux 1995; Choijil et al. 2022; Vieito et al. 2024), and psychological mechanisms such as fear of missing out (FOMO) (Wang et al. 2023; Gupta and Shrivastava 2022; Ivantchev and Ivantcheva 2023; Bonaparte and Fabozzi 2025) and social influence (Bianchi et al. 2024; Han and Yang 2013; Halim et al. 2019). Advances in technology and communication have intensified the speed and reach of sentiment-driven information diffusion, amplifying fear- and hype-based trading. Comparable dynamics also appear in consumer behavior, where social trends shape decision-making beyond fundamentals (Zhang 2023; Saboo et al. 2016; Schivinski et al. 2016). In financial markets, however, these mechanisms can have particularly severe consequences, as bubble collapses generate broad economic, psychological, and social costs, often prompting regulatory intervention aimed at restoring stability (Miao and Wang 2015; Shim 2025; Wegner 2024). Taken together, this evidence underscores the importance of identifying and understanding bubble dynamics.

Against this background, this study examines bubble formation in the S&P 500 Index and Bitcoin while explicitly accounting for gold price dynamics. The core objective is to assess whether gold—widely viewed as a barometer of market-wide risk sentiment—shapes the emergence and persistence of asset price bubbles. During speculative expansions, capital typically reallocates toward rapidly appreciating assets, reducing demand for gold, whereas periods of market stress and bubble collapses are associated with increased flight-to-gold behavior (Vayanos 2004; Baur and Lucey 2010; Miyazaki and Hamori 2013). Beyond crisis episodes, gold also serves diversification and hedging roles due to its limited supply, inflation-hedging properties, and reserve status among central banks (Batten et al. 2014; Lucey et al. 2017; Lean and Wong 2015; Bouri et al. 2020; Cui et al. 2023). A broad literature documents causal linkages between gold and multiple asset classes, including equities and cryptocurrencies, though with no consensus on direction or stability (Baur and Lucey 2010; Miyazaki and Hamori 2013; Ciner et al. 2013; Coronado et al. 2018; Hong et al. 2022; Papadamou et al. 2021; Fasanya et al. 2023; Zhang et al. 2025). Motivated by these considerations, we filter asset prices through gold to obtain a stress-reduced representation of valuation. Bubble dynamics are examined in two stages—using original and gold-filtered series—to distinguish explosiveness associated with aggregate risk sentiment from asset-specific speculative behavior. By abstracting from common stress reallocations, this approach facilitates a clearer empirical assessment of whether detected explosiveness reflects intrinsic bubble dynamics or broader macro-financial conditions. Although gold prices may also respond to forces beyond risk sentiment, the filtered series are used to sharpen interpretation rather than to replace original price dynamics, enabling transparent comparison with existing empirical evidence (Oldani et al. 2025; Yao and Li 2021).

In light of this evidence, existing empirical research on asset price bubbles remains segmented across distinct strands. A substantial group of studies focuses on identifying and dating speculative bubbles using price-based empirical frameworks, documenting explosive or regime-dependent episodes in equities and cryptocurrencies with limited or no explicit conditioning on broader market-wide stress factors or cross-asset filtering mechanisms (Hong and Sraer 2013; Anderson et al. 2010; Jahan-Parvar and Waters 2009; Geuder et al. 2019; Assaf et al. 2024). Another strand emphasizes behavioral interaction, investor sentiment, or nonlinear market dynamics, examining bubbles through interacting-agent models, sentiment-driven mispricing, or econophysics-based bubble and crash dynamics (Kaizoji et al. 2002; Berger and Turtle 2015; Fry and Cheah 2016), while a related line develops econometric refinements such as volatility-adjusted recursive bubble tests (Hafner 2018). A third group provides conceptual or theoretical definitions of bubbles based on deviations from fundamentals or expected returns, without offering an empirical framework that jointly links explosive behavior to market efficiency, persistence, or common stress components (Flood and Hodrick 1990; Siegel 2003). Taken together, most existing studies do not systematically distinguish asset-specific speculative dynamics from market-wide stress effects, nor do they jointly evaluate bubble formation, efficiency departures, and persistence within a unified empirical setting. Practically, this limits the ability to assess whether detected bubbles reflect asset-specific speculation or broader stress-driven mispricing, while theoretically it highlights the absence of an empirical framework consistent with valuation theory, efficiency, and persistence. This motivates an empirical design that disentangles common stress-driven price movements from asset-specific speculative dynamics while remaining consistent with valuation theory and policy interpretation.

In response to these considerations, this study contributes along three complementary dimensions. Empirically, the gold-filtering procedure allows us to separate price movements associated with market-wide fear and greed from asset-specific hype that may induce bubble formation. By removing gold-related price components, we isolate valuation dynamics more closely linked to asset-specific expectations—such as technological developments or growth opportunities—rather than to broad shifts in risk sentiment. This facilitates a clearer assessment of whether detected explosiveness reflects intrinsic speculative dynamics or is more likely driven by temporary reactions to global stress. From a theoretical perspective, the framework sharpens the interpretation of asset valuation under speculative conditions. While standard finance theory links prices to discounted expected future cash flows, bubble episodes may embed implausible cash-flow expectations driven by sentiment amplification rather than fundamentals. Filtering reduces the valuation "foam" associated with aggregate fear and greed, revealing residual price inflation that can be attributed more closely to market-specific dynamics. In policy terms, explicitly characterizing the role of gold in bubble formation yields asset-dependent insights. Assets exhibiting limited sensitivity to gold tend to reflect dynamics driven primarily by internal market forces, whereas stronger gold linkages signal stress-driven valuation pressures. This distinction can support conditional early-warning interpretation and inform more targeted policy responses to mitigate the costs of persistent explosive price behavior.

From a methodological standpoint, we combine the Generalized Supremum Augmented Dickey–Fuller (GSADF) bubble detection framework, time-varying Granger causality (TVGC), and multifractal detrended fluctuation analysis (MFDFA) with a structured data transformation inspired by the Fisher equation (Fisher 1907), whereby gold returns are removed from the gross daily returns of the S&P 500 Index and Bitcoin to reconstruct stress-adjusted price series. This design allows bubble and causality analyses to be conducted on both original and gold-filtered data, thereby facilitating identification of explosive dynamics and their sensitivity to market-wide stress. Relative to earlier approaches such as the Supremum Augmented Dickey–Fuller (SADF) test, the GSADF framework accommodates multiple bubble episodes through a double-sup procedure over flexible start points and window sizes, which enhances discriminatory power and supports reliable date-stamping of recurring bubbles (Phillips et al. 2011 2015). Similarly, the TVGC framework of Shi, Hurn, and Phillips departs from static causality methods by employing recursive Wald tests in a lag-augmented VAR setting that is robust to integration and cointegration without requiring prior detrending or differencing. Taken together, these time-varying frameworks are well suited to capturing structural breaks, regime shifts, and evolving predictive relationships. Finally, MFDFA complements the analysis by characterizing persistence and scale-dependent dependence in potentially nonstationary series, providing additional insight into the heterogeneous dynamics underlying bubble formation.

The remainder of the paper is structured as follows. Section 2 reviews the related literature and situates the study within the existing evidence. Section 3 outlines the methodological framework and econometric tools employed in the analysis. Section 4 presents the empirical results and discusses their implications in light of the research objectives. Section 5 concludes with a summary of the main findings and discusses their relevance for market participants and policymakers, while also outlining the limitations of the study.

2 Literature review

Following the Introduction, this section reviews the literature most relevant to asset price bubbles and market stress. The discussion covers evidence on bubble formation in equity markets, speculative dynamics in cryptocurrency markets, the role of gold as a safe-haven asset, and the econometric approaches commonly used to identify and analyze bubble behavior.

2.1 Bubbles and the equity markets

From an economic perspective, bubbles reflect persistent deviations of asset prices from fundamentals, commonly associated with investor sentiment, speculation, and herd behavior (Morck 2022). Such deviations can distort price signals, increase financial instability, and may culminate in sharp corrections with broad economic consequences (Taipalus 2012; Jones 2015). Beyond valuation errors, bubbles may also amplify cross-market spillovers and systemic transmission channels, increasing vulnerability to localized shocks. Despite broad agreement on these outcomes, the literature remains divided on the mechanisms underlying bubble formation and persistence, particularly regarding the relative roles of market-wide forces and firm-level behavior. More recent evidence suggests that managerial traits and communication strategies, including CEO overconfidence and risk signaling, can reinforce speculative dynamics and contribute to the persistence of bubble episodes (Hassanein et al. 2024a, b). From a theoretical and empirical standpoint, early work debated the role of rational bubbles driven by resale expectations (Gürkaynak 2008; Evans 1991), while subsequent behavioral finance research shifted attention toward cognitive biases and overreaction. Empirical evidence supports the relevance of behavioral channels, as trader overconfidence is associated with larger price deviations and higher volatility (Michailova and Schmidt 2016). However, the extent to which such distortions are amplified or constrained by market institutions and information environments remains unresolved. Bubble episodes may also spill over into the real economy, influencing monetary policy (Filardo 2004), household wealth (Jordà et al. 2015), and corporate financing decisions (Campello and Graham 2013).

At the firm level, information transmission plays an important role in shaping equity market reactions, particularly when sentiment diffuses rapidly. Hassanein et al. (2024a, b) show that sentiment embedded in firms' financial tweets generates statistically significant abnormal returns, with negative sentiment exerting stronger and more persistent effects. Taken together, these findings support behavioral interpretations but also raise unresolved questions about whether new information technologies enhance price discovery or instead intensify noise and herding during periods of heightened uncertainty. From an empirical perspective, evidence documents equity bubbles across markets and methodologies (Nneji 2015; Hon et al. 2007; Wang et al. 2021). Studies report multi-horizon bubble detection in G7 indices (Van Eyden et al. 2023), as well as market-specific evidence from Israel (Caspi and Graham 2018) and China (Liu et al. 2016). In addition, cross-regional spillovers from U.S. equity bubbles highlight their systemic dimension (Escobari et al. 2017). At the corporate level, disclosure-related studies add an additional layer of complexity. Risk disclosure appears to affect stock returns in a nonlinear manner and may induce information overload rather than improve price efficiency (Hassanein 2022; Hassanein and Albitar 2025), challenging the stabilizing role often attributed to transparency. More recently, research highlights the difficulty of identifying early-warning signals: bubbles may remain "quiet," characterized by elevated prices and subdued trading activity (Hong and Sraer 2013), yet become destabilizing when amplified by credit expansion (Jordà et al. 2015). Valuation gaps relative to macroeconomic fundamentals may signal bubble conditions during expansions (Ielpo and Niahnin 2020), while crisis-period evidence points to asymmetric price discovery under stress (Al-Khasawneh and Hassanein 2024). Taken together, this body of work reveals persistent tensions between rational and behavioral explanations, limits to transparency, and ongoing challenges in distinguishing speculative dynamics from fundamentals in real time.

2.2 Bubbles and the cryptocurrency market

Compared to equity markets, cryptocurrencies represent a relatively new and structurally distinct asset class, characterized by high volatility, pronounced price swings, and limited regulatory oversight. The absence of conventional valuation anchors and the decentralized market structure further differentiate cryptocurrencies from traditional assets, potentially amplifying speculative behavior (Liu and Tsyvinski 2021). At the same time, the lack of consensus on valuation benchmarks complicates the distinction between speculative bubbles and fundamental price movements, making cryptocurrency markets particularly relevant for the analysis of bubble dynamics.

A growing literature examines cryptocurrencies in general (Yue et al. 2021; Sousa et al. 2022; García-Corral et al. 2022) and crypto bubbles specifically (Kyriazis et al. 2020). Kyriazis et al. (2020) document recurrent explosive episodes prior to 2020, while Cross et al. (2021) analyze the 2017–18 bubble and identify time-varying return–volatility relationships and risk premia in major cryptocurrencies, showing that negative news played an important role in the subsequent crash. Their results also indicate weak-form inefficiency, as models with stochastic volatility and fat tails outperform random walks. Using a complementary perspective, Fruehwirt et al. (2021) employ high-frequency data and find that cryptocurrencies became increasingly interdependent and unstable after Bitcoin's 2017 peak, attributing this pattern to market psychology and retail investor dominance. Beyond bubble identification, other studies emphasize interconnectedness during speculative phases. Chowdhury et al. (2022) show, using a quantile VAR framework, that Bitcoin transmits shocks during downturns and absorbs shocks during upswings, highlighting asymmetric spillover dynamics. While these studies broadly agree on the prevalence of speculative behavior, they diverge in interpretation: rising interconnectedness may signal market maturation or, alternatively, increased systemic fragility and limited diversification benefits. Comparative evidence lends support to the latter view, suggesting that cryptocurrency bubbles occur more frequently but are typically shorter-lived than equity bubbles, consistent with rapid sentiment shifts and fast information diffusion (Yamaguchi 2025).

2.3 Gold as a safe-haven asset

Gold is commonly viewed as a safe-haven asset, with extensive evidence documenting investors' flight-to-gold during periods of market stress (Wen et al. 2022; Sakurai 2021; Baur et al. 2021). Foundational work by Baur and Lucey (2010) distinguishes gold's average hedging role from its safe-haven function during crises, while Baur and McDermott (2010) show that gold tends to provide stronger protection in developed markets and during severe shocks. However, subsequent studies question the stability of these properties across market regimes and asset classes. Recent evidence further extends gold's role beyond crisis hedging, indicating asymmetric linkages with corporate green bonds and sensitivity to environmental and policy uncertainty (Tsagkanos et al. 2025).

Empirical results also reveal considerable heterogeneity across markets. Gürgün and Ünalmis (2014) find that gold's hedge and safe-haven properties depend on investor perspective, while Hood and Malik (2013) show that gold does not consistently hedge U.S. equities during periods of extreme volatility, with the VIX often performing better. This divergence has prompted debate over whether gold's appeal is fundamentally financial or behavioral, with behavioral explanations emphasized by Baur and McDermott (2016). High-frequency evidence confirms rapid flight-to-gold responses following equity market losses (Baur and Kuck 2020), while regime-dependent analyses show that gold's safe-haven behavior varies across market states (Chen et al. 2023), despite its strong performance during the COVID-19 crisis (Salisu et al. 2021). Beyond crisis episodes, gold is widely held for diversification and inflation hedging (Batten et al. 2014; Lucey et al. 2017; Lean and Wong 2015; Bouri et al. 2020; Cui et al. 2023). Its role as a signal of systemic stress, however, remains comparatively underexplored. Early evidence indicates that gold responds asymmetrically to market downturns and can transmit information to other asset classes (Klein 2018), while quantile and dynamic correlation approaches isolate gold-driven stress components in stock and bond volatility (Reboredo 2013a,b). More recent studies document statistically significant causal and predictive linkages between gold and a broad set of financial assets, although their direction and stability remain contested (Ciner et al. 2013; Coronado et al. 2018; Hong et al. 2022; Papadamou et al. 2021; Fasanya et al. 2023; Zhang et al. 2025).

2.4 Econometric approaches

From a methodological perspective, recursive right-tailed unit root tests such as SADF and GSADF (Phillips et al. 2011, 2015) have become standard tools for identifying explosive price dynamics across asset classes. Recent applications document bubble episodes in carbon markets (Huang and Wang 2024), natural gas markets (Li et al. 2020), Bitcoin (Li et al. 2021) and DeFi relative to conventional cryptocurrencies (Corbet et al. 2023). While these studies provide detailed evidence on the timing and recurrence of speculative episodes, bubble detection is typically treated as a standalone exercise. As a consequence, relatively limited attention has been paid to how identified bubbles interact with spillovers, predictive transmission, or safe-haven behavior, particularly in cross-asset settings involving equities and cryptocurrencies. Despite these methodological advances, only a small number of studies combine recursive bubble detection with causality or spillover frameworks, and none explicitly integrate safe-haven dynamics into the bubble identification process.

A parallel literature addresses evolving predictability using time-varying and recursive causality frameworks (Shi et al. 2020). Evidence suggests that assuming constant causal relationships can be restrictive in environments shaped by regime shifts, policy changes, and crises (Shojaie and Fox 2022). Consequently, TVGC and related approaches have been widely applied to financial and energy markets (Baum et al. 2022), documenting dynamic causal structures in asset prices (Fromentin 2022; Mohamad 2025), contagion and systemic risk transmission (Atasoy and Özkan 2024), and sustainability-, geopolitical risk–, and cryptocurrency-related interactions (Gunay et al. 2025a,b). However, these approaches are typically implemented independently of formal bubble detection, leaving the interaction between speculative episodes, evolving causality, and safe-haven behavior largely unexplored.

Related evidence from MFDFA highlights scale-dependent dependence and heterogeneous dynamics in both traditional and cryptocurrency markets (Filho et al. 2018; Temel and Tuğay 2025). Recent studies show that multifractal properties are asymmetric and crisis-sensitive, indicating time-varying market efficiency and persistent departures from random-walk behavior, particularly in cryptocurrency markets (Meng and Khan 2024; Gunay and Kaşkaloğlu 2019). However, multifractal analysis is typically applied in isolation, which limits its contribution to descriptive characterization rather than integration within a unified framework that jointly considers bubble dynamics, causality, and safe-haven behavior.

In sum, the reviewed literature provides extensive evidence on asset price bubbles in both equity and cryptocurrency markets, while also demonstrating the safe-haven properties of gold. In addition, we summarized the key econometric approaches commonly used to study bubble formation, crisis dynamics, and market stress. Accordingly, the next section outlines in detail the methodological tools applied in our analysis.

3 Methodology

Building on the preceding discussion, this section presents the methodological framework used to examine bubble dynamics under market-wide stress. It introduces the gold price filtering procedure, followed by the econometric tools employed to detect and analyze bubbles, time-varying causal relationships, and persistence across different time scales.

3.1 Gold price filtering procedure

The gold-filtering procedure rests on the premise that asset prices reflect both asset-specific dynamics and a common market-wide stress component. Because gold returns tend to co-move with global risk aversion and flight-to-quality behavior, gold is used as a parsimonious proxy for this stress factor. Following a Fisher-type filtering logic, asset returns are expressed relative to gold returns, treating gold as a stress numeraire. The resulting filtered prices remove contemporaneous gold-related, stress-driven return components, yielding valuation paths that are net of market-wide risk sentiment. Importantly, this transformation abstracts from common stress effects without imposing a structural causal interpretation, thereby enabling a clearer empirical separation between market-wide stress influences and asset-specific bubble dynamics.

Let P_t^x denote the observed price of a generic asset x at time t, and let P_t^g denote the price of gold. Define gross returns as:

$$1 + r_t^x = \frac{P_t^x}{P_{t-1}^x}, 1 + r_t^g = \frac{P_t^g}{P_{t-1}^g} \tag{1}$$

The classical Fisher equation decomposes nominal returns into real returns and inflation,

$$1 + i_t = (1 + r_t)(1 + \pi_t) \tag{2}$$

where i_t is the nominal rate, r_t the real rate, and π_t inflation. Solving for the real component yields

$$r_t = \frac{1 + i_t}{1 + \pi_t} - 1 \tag{3}$$

We adopt this logic in an asset-pricing context by treating gold returns as an observable stress (or "risk inflation") component embedded in asset returns. Accordingly, the gold-adjusted (stress-filtered) return of asset x is defined as:

$$\widetilde{r}_t^x = \frac{1 + r_t^x}{1 + r_t^g} - 1 \tag{4}$$

This transformation removes the contemporaneous gold-related component from asset returns, isolating price dynamics net of market-wide stress effects. To recover the corresponding gold-filtered price series, we reconstruct prices recursively using the initial observed price P_0^x:

$$\widetilde{P}_t^x = P_0^x \prod_{s=1}^{t} (1 + \widetilde{r}_s^x) \tag{5}$$

The resulting series $\widetilde{P}_t^x$ represents a "stress-free" valuation path of asset x, analogous to real prices in macroeconomics. By construction, any divergence between P_t^x and $\widetilde{P}_t^x$ reflects the cumulative influence of gold-related market stress. In this study, market stress refers to periods of heightened uncertainty and risk aversion marked by portfolio reallocation from risky assets toward safe havens, reflecting shifts in aggregate risk sentiment rather than asset-specific fundamentals. Empirically, stress is proxied by gold price dynamics, as gold returns tend to rise during episodes of financial turbulence, policy uncertainty, and flight-to-quality behavior, as it was shown in the literature review. This Fisher-type adjustment provides a theoretically grounded framework to assess whether explosive price behavior persists once economy-wide risk sentiment, as captured by gold, is filtered out. Although the gold-filtering mechanism is not intended to resolve endogeneity, it helps mitigate bias by removing price components associated with aggregate stress, thereby emphasizing residual, asset-specific dynamics over contemporaneous co-movement driven by global risk factors.

3.2 Generalized supremum augmented Dickey–Fuller (GSADF) test

Building on Phillips et al. (2011), the right-tailed unit root test is a widely used tool for detecting bubbles in financial time series. The underlying model accommodates mild drifts in price series and is expressed in its weak intercept form as:

$$y_t = dT^{-\eta} + \theta y_{t-1} + \varepsilon_t, \varepsilon_t \sim^{iid} \left(0, \sigma^2\right), \theta = 1 \tag{6}$$

where d is a constant, T represents the sample size and η is a localizing coefficient controlling the intercept and drift magnitude as $T \to \infty$. When $\eta > 0.5$ the drift becomes negligible relative to the stochastic trend of y_t leading the process to follow random walk which forms the null hypothesis in the Supremum Augmented Dickey-Fuller (SADF) test.

To detect bubbles, this model is estimated recursively using rolling-window ADF regressions. Suppose the estimation window starts at the fractional observation r_1 and ends at r_2, with the fractional window size defined as $r_w = r_2 - r_1$. The ADF statistic computed over this window, denoted as ADF_{r1}^{r2}, is obtained using the regression:

$$\Delta y_t = \hat{\alpha}_{r_1,r_2} \ + \ \hat{\beta}_{r_1,r_2} y_{t-1} + \sum_{i=1}^{k} \hat{\psi}_{r_1,r_2}^{i} \Delta y_{t-i} + \hat{\varepsilon}_t \tag{7}$$

where *k* is the selected lag length. The number of observations in the regression is denoted by$T_w = Tr_w$, where [.] is the floor function. The SADF test involves calculating the ADF statistic over a sequence of forward-expanding windows, where $r_1 = 0$ and r_2 increases from a minimum window fraction r_0 to 1. The test statistic is defined as:

$$SADF\left(r_0\right) = \sup_{r_2 \epsilon [r_0, 1]} ADF_0^{r_2} \tag{8}$$

While effective for detecting single bubble episodes, the SADF test may exhibit reduced power in the presence of multiple bubbles within the sample. To address this limitation, Phillips et al. (2015) introduced the Generalized Supremum ADF (GSADF) test, which extends the SADF framework by allowing the starting point r_1 to vary within a feasible range. This increases the flexibility of window selection in the recursive process, enabling the detection of multiple explosive episodes and supporting accurate time-stamping of bubble origination and collapse using a backward recursive regression approach. While the method continues to rely on recursive right-tailed ADF tests, it improves implementation by incorporating flexible window widths. The GSADF statistic is defined as:

$$GSADF\left(r_0\right) = \sup_{\substack{r_2\epsilon\left[r_0,1\right] \\ r_1\epsilon\left[0,r_2-r_0\right]}} \left\{ADF_{r1}^{r_2}\right\} \tag{9}$$

Unlike the SADF approach, which uses a forward recursive structure, the GSADF methodology employs a backward supremum ADF (BSADF) testing procedure for bubble dating to improve the accuracy of identifying the timing of bubble origination and collapse, especially in samples containing multiple bubbles. In this procedure, the endpoint r_2 remains fixed while the starting point r_1 varies from 0 to $r_2 - r_0$. The bubble origination ($\widehat{r}_e$) and termination ($\widehat{r}_f$) dates are identified using the first-crossing time criteria:

$$\widehat{r}_e = \inf_{r_2\epsilon\left[r_0,1\right]} \left\{r_2 : BSADF_{r2}\left(r_0\right) > scv_{r_2}^{\beta_T}\right\} \tag{10}$$

$$\widehat{r}_f = \inf_{r_2\epsilon\left[\widehat{r}_e,\frac{\delta\log(T)}{T},1\right]} \left\{r_2 : BSADF_{r2}\left(r_0\right) < scv_{r_2}^{\beta_T}\right\} \tag{11}$$

where T is sample size and $scv_{\beta_T}^{r_2}$ denotes the critical value of the backward supremum ADF statistic at the significance level β_T. δ adjusts for the minimum duration of a bubble to filter out short-lived fluctuations.

Equivalently, the GSADF statistic previously defined can also be expressed as the supremum of the backward supremum ADF (BSADF) statistics across all feasible endpoints:

$$GSADF(r_0) = \sup_{r_2\epsilon\left[r_0,1\right]} \left\{BSADF_{r2}\left(r_0\right)\right\} \tag{12}$$

3.3 Time-varying granger causality (TVGC) analysis

To capture the evolving nature of predictive relationships, we follow Shi et al. (2020) and implement a TVGC framework. As a first step, we estimate a bivariate lag-augmented VAR (LA-VAR) model allowing for a maximum order of integration d.

$$y_{1t} = \alpha_{10} + \alpha_{11}t + \sum\nolimits_{i=1}^{k+d} \beta_{1i}y_{1t-i} + \sum\nolimits_{i=1}^{k+d} \delta_{1i}y_{2t-i} + \varepsilon_{1t} \tag{13}$$

$$y_{2t} = \alpha_{20} + \alpha_{21}t + \sum\nolimits_{i=1}^{k+d} \beta_{2i}y_{1t-i} + \sum\nolimits_{i=1}^{k+d} \delta_{2i}y_{2t-i} + \varepsilon_{2t} \tag{14}$$

where *k* denotes the lag order of the base VAR model. *t* and $\varepsilon_{i,t}$ are a time trend and the error terms, respectively. The absence of Granger causality from y_{2t} to y_{1t} implies that including the past k lags of y_{2t} does not enhance the prediction of y_{1t}. For an n-dimensional y_t, the model can be written as below:

$$y_t = \gamma_0 + \gamma_1 t + \sum_{i=1}^{k} J_i y_{t-i} + \sum_{j=k+1}^{k+d} J_j y_{t-j} + \varepsilon_t \tag{15}$$

In this version of the equation $J_{k+1} = \cdots = J_{k+d} = 0$. A more compact version of this equation can be expressed in matrix form:

$$Y = \tau\Gamma\prime + X\Phi\prime + Z\Psi\prime + \varepsilon \tag{16}$$

where $\tau = (1,\, t)$ contains the intercept and time trend and the ordinary least square estimator is:

$$\widehat{\Phi} = \mathrm{Y}\prime QX(X\prime QX)^{-1} \tag{17}$$

With projection matrices defined as in Shi et al. (2020). The Wald test statistic W in testing of null hypothesis is computed as below:

$$W = \left(R\widehat{\varnothing}\right)\prime\left[R\{\widehat{\Sigma}_\varepsilon \otimes (X\prime QX)^{-1}\}R\prime\right]^{-1} R\widehat{\varnothing} \tag{18}$$

where $\widehat{\varnothing} = vec(\widehat{\Phi})$ and $\otimes$ is the Kronecker product. Under the null, W asymptotically follows a chi-squared distribution with m restrictions.

TVGC Wald statistics are calculated through subsamples that possess starting and ending points of f_1 and f_2 respectively and range is $f_2 - f_1 = f_w$ under total sample size of T. The minimum window size is given by $s_0 = f_0 T$ and $s_1 = f_1 T,\ s_2 = f_2 T,\ s_w = f_w T$. The authors use three different procedures in estimating TVGC; forward expanding, rolling windows and recursive evolving windows. In the forward expanding method, starting point s_1 is fixed at the first observation and regression window expands from s_0 to T as s_2 moves from s_0 to T. In the rolling window method, window size s_0 is fixed and s_1 moves from 1 to $T - s_0 + 1$ with $s_2 = s_1 + s_0 - 1$. When it comes to the recursive evolving window, end point s_2 moves from s_0 to T. starting point s_1 varies from 1 to $s_2 - s_0 + 1$ by allowing all possible subsample variations for each s_2. For each procedure the supremum of the Wald statistic sequence is:

$$SW_f(f_0) = \sup_{f_2 = f,\, f_1 \epsilon \{0, f_2 - f_0\}} \{W_{f1}^{f_2}\} \tag{19}$$

3.4 Multifractal detrended fluctuation analysis (MFDFA)

To characterize scale-dependent dependence in potentially non-stationary time series, we employ MFDFA, following Kantelhardt et al. (2002) and Kantelhardt (2015). By extending DFA to higher-order moments, MFDFA allows scaling properties to vary across fluctuation magnitudes, enabling the characterization of heterogeneous dependence and long-range correlations within a unified framework. This makes MFDFA well suited for capturing complex temporal dynamics that cannot be described by monofractal models. Given a time series $x(i)$, $i = 1, \ldots, N$, the MF-DFA procedure begins by constructing the cumulative profile:

$$Y\left(j\right)=\sum_{i=1}^{j}\left[x\left(i\right)-\bar{x}\right],j=1,\ldots,N, \tag{20}$$

where $\bar{x}$ denotes the sample mean. This integration step transforms the original series into a random-walk-like process, facilitating the detection of long-range dependence while preserving scaling properties.

The profile $Y\left(j\right)$ is divided into $N_s=\lfloor N/s\rfloor$ non-overlapping segments of equal length s. To ensure full data utilization, the segmentation is repeated from the opposite end, yielding $2N_s$ segments in total.

Within each segment, a polynomial trend of order m is fitted using least squares and subsequently removed. The choice of m determines the degree of polynomial non-stationarity eliminated (e.g., linear or quadratic trends), ensuring robustness against low-frequency deterministic components. For each detrended segment ν, the local variance is computed as:

$$F^2(\nu,s)=\frac{1}{s}\sum_{j=1}^{s}\left[Y_\nu(j)-Y_{\nu,\mathrm{fit}}(j)\right]^2 \tag{21}$$

where $Y_{\nu,\mathrm{fit}}\left(j\right)$ denotes the fitted polynomial trend within segment ν. This step isolates intrinsic fluctuations from deterministic trends at scale s. The multifractal extension is introduced through the q-order fluctuation function:

$$F_q(s)=\left\{\frac{1}{2N_s}\sum_{\nu=1}^{2N_s}\left[F^2(\nu,s)\right]^{q/2}\right\}^{1/q} \tag{22}$$

for $q\in\mathbb{R}$, $q\neq0$. For $q=0$, logarithmic averaging is applied. Positive values of q emphasize large fluctuations, whereas negative values highlight small fluctuations. This moment-based formulation allows MF-DFA to capture scale-dependent heterogeneity in fluctuation behavior that is not observable under monofractal analysis. If the series exhibits multifractal scaling, the fluctuation function follows a power-law relationship:

$$F_q(s)\sim s^{h(q)} \tag{23}$$

where $h(q)$ is the generalized Hurst exponent. For monofractal processes, $h(q)$ remains constant across different values of q. In contrast, a non-linear dependence of $h(q)$ on q indicates multifractality and heterogeneous scaling behavior across fluctuation magnitudes. The generalized Hurst exponents are linked to the mass exponent:

$$\tau(q)=qh(q)-1 \tag{24}$$

from which the multifractal (singularity) spectrum is derived via a Legendre transformation:

$$\alpha=\frac{d\tau(q)}{dq},f(\alpha)=q\alpha-\tau(q) \tag{25}$$

The width and shape of the spectrum quantify the strength and nature of multifractality. A wider spectrum reflects stronger scale heterogeneity, while a narrow spectrum indicates behavior closer to monofractality.

4 Empirical analysis

Having established the methodological framework, this section presents the empirical analysis of bubble dynamics in the S&P 500 Index and Bitcoin. The results are reported for both original and gold-filtered price series, allowing a systematic comparison of explosiveness, causal linkages, and persistence under varying market stress conditions.

Because bubble episodes are commonly interpreted as departures from conditions implied by the Efficient Market Hypothesis (Fama 1970), identifying their presence and characteristics offers both statistical and practical insights for market participants. Accordingly, we implement an integrated framework that combines the GSADF bubble detection method (Phillips et al. 2015), the TVGC test (Shi et al. 2020), and MFDFA to assess persistence and scale heterogeneity, applied to both original and gold-filtered data. The filtered data consist of price series from which gold-related return components have been removed for the S&P 500 and Bitcoin. As discussed earlier, this filtering procedure is intended to attenuate shifts in market risk appetite—often associated with fear and greed dynamics reflected in gold prices—thereby yielding a more stress-adjusted representation of asset price dynamics. Given gold's well-documented role as a flight-to-safety asset, its price movements are closely linked to market sentiment and perceived risk (Ming et al. 2023; Baur and Kuck 2020; Baur and McDermott 2016; O'Connor et al. 2015). Removing these components facilitates a clearer empirical assessment of bubble dynamics that are less influenced by broad market stress. The analysis covers the period from July 2, 2018, to May 23, 2025, using daily price data.

Table 1 reports descriptive statistics for the variables used in the analysis, grouped into raw price series, gold-adjusted price series, and log-return series. Following gold filtering, the mean price of Bitcoin declines more than that of the S&P 500, whereas the reduction in standard deviation is larger for the S&P 500. Among return series, Bitcoin records the highest average return, although mean returns for all assets remain close to zero, as expected. Bitcoin also exhibits the highest volatility across both raw and adjusted price measures. Skewness and kurtosis statistics indicate notable departures from normality across all variables. All price and adjusted series are positively skewed, with the exception of the filtered

Table 1 Descriptive statistics

	Mean	Median	Std. Dev	Skewness	Kurtosis	JB	ADF	PP
SP500	4043	4057	971	0.3364	2.2136	80.34*	− 0.5630	− 0.6358
BTC	33,156	26,965	26,337	0.9212	3.0405	254.71*	0.3417	0.3836
GOLD	1870	1823	443	0.9854	4.2174	402.47*	1.5670	2.1623
A_SP500	2707	2748	282	− 0.5876	3.0977	104.28*	− 1.2197	− 1.2086
A_BTC	19,977	17,267	12,675	0.4290	1.9298	141.11*	− 43.5915	− 43.5803
RSP500	0.0004	0.0005	0.0126	− 0.6278	18.0035	17,001*	− 13.4232	− 45.9945
RBTC	0.0016	0.0010	0.0393	− 0.3434	8.5549	2350*	− 43.4682	− 43.4664
RGOLD	0.0005	0.0002	0.0091	− 0.1466	6.1617	756*	− 43.1552	− 43.4359

* indicates the significance at the 1% level

S&P 500, which displays negative skewness, suggesting relatively more extreme positive outcomes. Kurtosis values are substantially higher for return series than for price series, indicating heavier tails and pronounced leptokurtosis, while price series display a mix of leptokurtic and platykurtic behavior. These deviations from normality are supported by statistically significant Jarque–Bera test results. Finally, ADF and PP unit root tests indicate that both raw and gold-adjusted price series are non-stationary, whereas return series are stationary, i.e., integrated of order zero.

Figure 1 shows that the S&P 500, Bitcoin, and gold exhibit long-term upward trends punctuated by intermittent corrections. During the COVID-19 shock in 2020, the S&P 500 experienced a sharp decline, whereas Bitcoin did not display a comparable correction, underscoring differences in market dynamics between equities and cryptocurrencies. Gold prices followed a distinct trajectory, which is consistent with evidence that Bitcoin and gold play differentiated diversification roles (Kajtazi and Moro 2019; Pho et al. 2021; Guesmi et al. 2019; Bhuiyan et al. 2023). Gold filtering materially alters the S&P 500 trajectory, particularly after 2022, flattening the previously strong upward trend and followed by a subsequent decline. This pattern is indicative of elevated market-wide stress coinciding with continued risk-taking. By contrast, during the pandemic period (2020–2022), gold prices remained relatively stable while equity markets exhibited a V-shaped recovery, suggesting comparatively lower perceived stress and a sustained risk appetite.

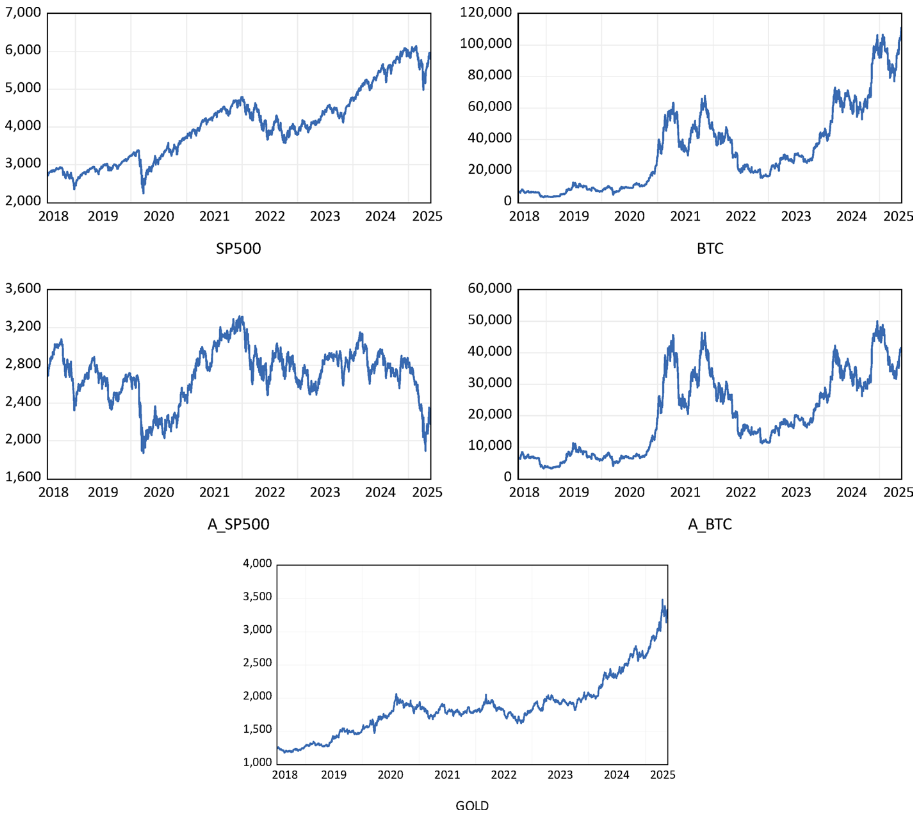


Fig. 1 Raw and gold-filtered price series

To detect bubble formations, we apply the GSADF test of Phillips et al. (2015), which is designed to identify multiple episodes of mildly explosive behavior within a single time series. GSADF and BSADF statistics are computed using a recursive ADF framework implemented via the *Exuber* package (Vasilopoulos et al. 2025), while time-varying critical values are obtained through Monte Carlo simulation using the *rtadfr* package. The minimum window size follows the Phillips et al. (2015) rule, with the initial subsample fraction set to 0.01 and adjusted by a sample-size–dependent constant of 1.8, which balances stability with sensitivity to relatively short-lived explosive episodes. Critical values are generated under the unit-root null using 1,000 replications and are computed once per sample length, then applied uniformly across all series to ensure comparability. Dynamic BSADF statistics are evaluated against their date-specific critical values, with inference conducted at the 10%, 5%, and 1% significance levels. All simulations rely on fixed random seeds to ensure full reproducibility.

Table 2 presents the results of the static bubble tests for the raw S&P 500 and Bitcoin series based on the ADF, SADF, and GSADF statistics. The results indicate a clear contrast between the two assets. For Bitcoin, both the SADF and GSADF statistics exceed their respective critical values at conventional significance levels, leading to rejection of the null hypothesis of no explosive behavior and indicating the presence of bubble-like dynamics. In contrast, the corresponding statistics for the S&P 500 remain below the critical values, providing no evidence of explosive behavior over the sample period. Taken together, the static tests suggest that Bitcoin exhibits comparatively stronger and more persistent explosive behavior than the S&P 500 within the sample considered.

The dynamic BSADF results reported in Fig. 2 further highlight differences in bubble behavior between Bitcoin and the S&P 500. Bitcoin exhibits more frequent and longer-lasting BSADF exceedances, suggesting repeated episodes of explosive dynamics. In contrast, the S&P 500 displays only a small number of short-lived spikes—around late 2018, April–May 2020, and the second quarter of 2025—which are brief and non-persistent. These patterns are consistent with the static test results and do not point to sustained bubble regimes. The spike observed in 2020 coincides with the rapid V-shaped recovery in equity markets following the initial COVID-19 shock and is more indicative of a temporary adjustment in expectations than prolonged speculative behavior. By comparison, Bitcoin shows several distinct and comparatively persistent episodes of explosive dynamics, notably in early 2019, late 2021 to mid-2022, early 2024, and late 2024. The late-2021 to mid-2022 episode stands out in both duration and magnitude, suggesting an extended phase of heightened explosiveness. Overall, these patterns are consistent with prior evidence documenting Bitcoin's tendency toward pronounced price accelerations and subsequent reversals in speculative settings.

Table 2 Bubble test results of variables (raw data)

	SP500	BTC
ADF	− 0.5785	0.4165*
	[− 0.1036] [0.4061] [1.5052]	[0.2125] [0.8248] [1.9923]
SADF	1.0384	7.6981**
	[3.3159] [4.4587] [6.4837]	[5.0455] [6.1768] [7.6004]
GSADF	3.3536	7.7308**
	[5.7046] [6.9922] [9.2515]	[5.8028] [6.8265] [8.5167]

The critical values are given within brackets for 90%, 95% and 99% respectively. *,** and *** indicate the significance at the 10%, 5% and 1% levels, respectively.

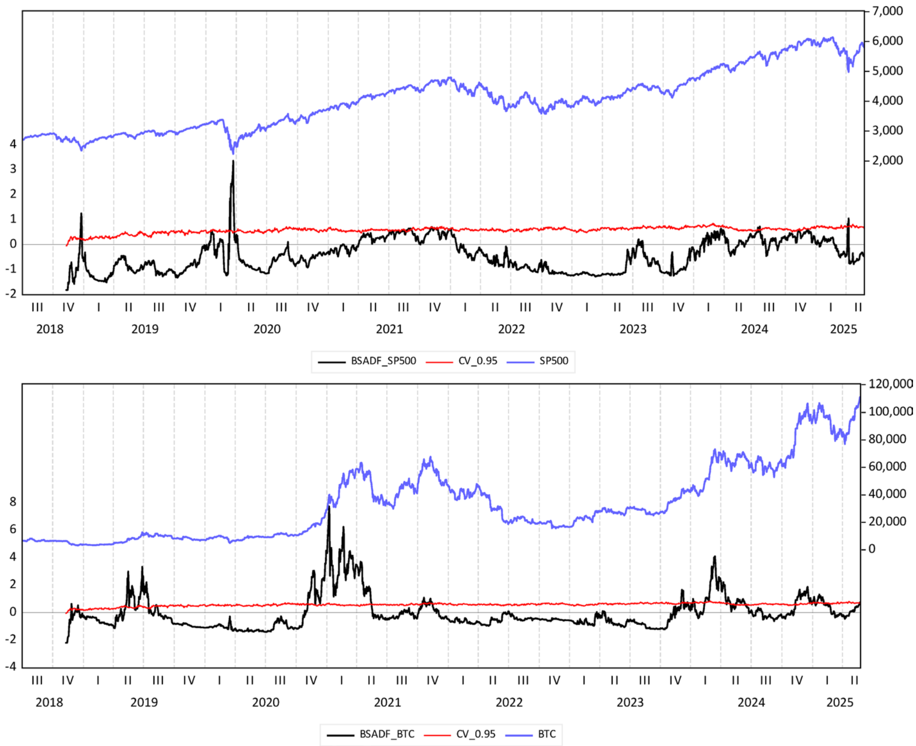


Fig. 2 Time-stamped results of the bubble analysis (raw data). *Notes*: Bubble tests use a recursive ADF procedure with Monte Carlo critical values (1000 replications) and a PSY minimum window with an initial fraction of 0.01 and adjustment constant 1.8

Following the bubble detection analysis, we apply the TVGC test of Shi et al. (2020). A key advantage of this framework is that it does not require prior knowledge of the integration properties of the series; accordingly, we use price levels, consistent with the preceding analysis. Shi et al. (2020) show that recursive and rolling-window implementations tend to outperform forward-expanding alternatives (Thoma 1994; Swanson 1998; Balcilar et al. 2010). The TVGC approach builds on the lag-augmented VAR framework of Toda and Yamamoto (1995), which makes lag selection an important consideration. Using the Bayesian Information Criterion (BIC), we select a one-day lag for both the Gold–S&P 500 and Gold–Bitcoin systems. Guided by the study's theoretical focus, we examine unidirectional Granger causality from gold to each asset. Consistent with Shi et al. (2020), who use approximately 11% of the sample as the rolling window, we adopt a 200-day window starting from 198 observations, a choice also in line with prior applications (Elsayed et al. 2022; Lovcha and Perez-Laborda 2020). Results from the full-sample Granger causality tests are reported in Table 3.

Table 3 reports the static Granger causality results, indicating that gold exhibits statistically significant predictive content for both the S&P 500 and Bitcoin at the 5% level across all estimation schemes—forward expanding, rolling window, and recursive rolling. Within the Granger causality framework, these results suggest that past gold price movements contain information that improves forecasts of both assets. This evidence is consistent with

Table 3 TVGC analysis of entire sample (raw data)

	Forward	Rolling	Recursive
Gold to SP500	9.647** [6.915, 8.481, 12.302] (1) 19.29070	12.252** [7.301, 9.755, 12.992] (1) 19.29070	13.381*** [7.320, 10.283, 12.992] (1) 19.29070
Gold to BTC	11.985** [7.218, 8.215, 15.906] (1) 26.14289	11.006** [7.107, 7.970, 21.655] (1) 26.14289	13.347** [7.527, 8.704, 21.655] (1) 26.14289

The values within [] represent the critical values at the 10%, 5%, and 1% significance levels, respectively. (1) indicates the optimal lag length in the VAR model selected based on the Bayesian Information Criterion (BIC), followed by the corresponding BIC value.

theoretical and empirical arguments that view gold as an indicator of market stress (Das et al. 2018) and as a safe-haven asset under certain conditions (Reboredo 2013a,b; Baur and Lucey 2010; Areal et al. 2015; Gomis-Porqueras et al. 2022). Taken together, the static results imply that gold may embed forward-looking information relevant for anticipating the dynamics of risk-sensitive markets, beyond reflecting contemporaneous sentiment. To examine whether this predictive relationship varies over time, we next turn to the dynamic TVGC results presented in Fig. 3.

Following Shi et al. (2016, 2020), we focus on the Rolling Window and Recursive Rolling TVGC results. The findings indicate that gold exerts a statistically significant but time-varying causal influence on both the S&P 500 and Bitcoin, with effects that appear weaker and more short-lived for Bitcoin. For the Gold–S&P 500 pair, a pronounced causal episode emerges in 2020 under the Rolling Window approach, coinciding with the onset of the COVID-19 pandemic, while the Recursive Rolling method reveals a similar effect that persists into 2021. These periods coincide with elevated uncertainty and shifts in risk appetite associated with the pandemic. A further statistically significant causal episode is detected in the second half of 2024, again running from gold to the S&P 500. By contrast, despite heightened geopolitical tensions during the Russia–Ukraine war, no comparable causal effect is observed, suggesting that gold-related flight-to-safety dynamics may respond more strongly to U.S.-centric developments. The late-2024 spike identified by the Recursive Rolling algorithm may reflect market anticipation related to the U.S. presidential election and its potential implications for monetary policy and international relations. This pattern is consistent with expectation-driven behavior—often described as “buy the rumor, sell the news”—where investor positioning responds to anticipated developments rather than realized events.

For the gold–Bitcoin pair, the causal relationship appears considerably weaker, with statistically significant causality from gold to Bitcoin observed only around mid-2019. Notably, although the sample period encompasses several major global events—including the COVID-19 pandemic, the Russia–Ukraine war, the Israeli–Palestinian conflict, crypto market collapses (Manahov 2024), and widespread hacks and exploits (Charoenwong and Bernardi 2024)—none is associated with a persistent causal linkage. The mid-2019 episode coincides with heightened U.S.–China trade tensions and the onset of Federal Reserve rate cuts, suggesting that the detected causality is more consistent with a shared response to shifts in global risk appetite than with direct transmission from gold to Bitcoin. During this

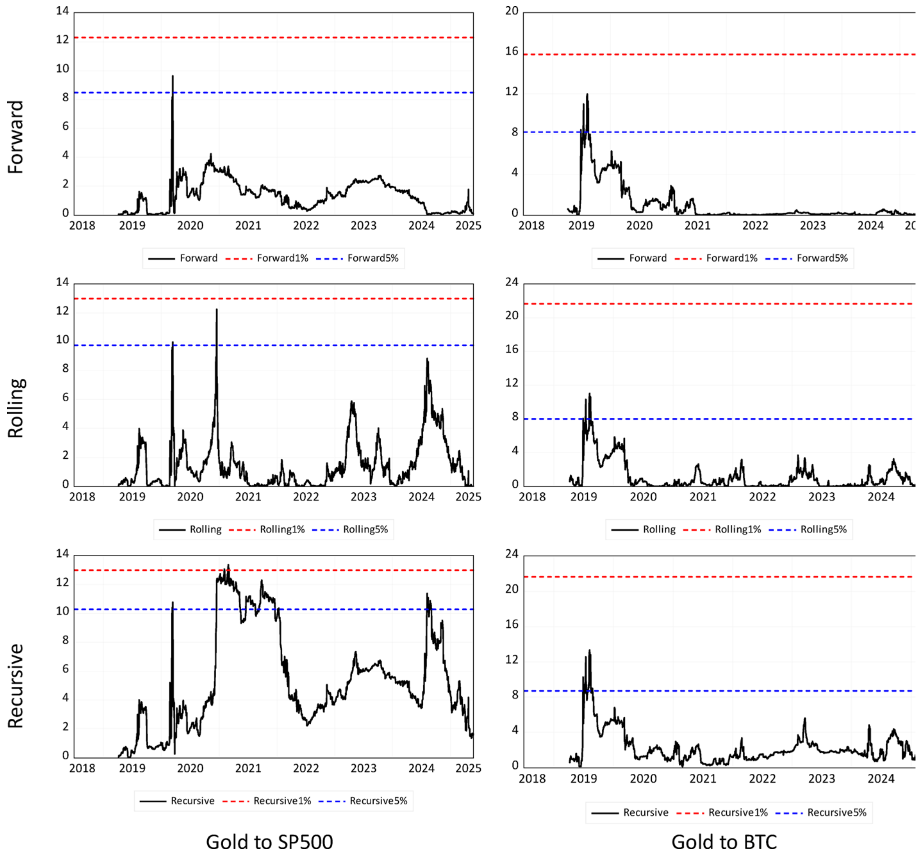


Fig. 3 TGVC analysis (raw data). *Note*: Following Shi et al. (2020), lag length is selected using the BIC, and unidirectional Granger causality from gold to the S&P 500 and Bitcoin is tested using a rolling window of 200 days, corresponding to approximately 11% of the sample size

period, simultaneous portfolio reallocations toward both assets may have contributed to the temporary causal connection.

Having identified bubble behavior in the raw series, we extend the analysis to the gold-filtered counterparts. Using the same GSADF settings as in the baseline analysis (Phillips et al. 2015), this step ensures full comparability and allows us to assess whether explosive dynamics persist once gold-related price movements are removed. The filtering procedure is designed to isolate the role of gold insofar as it captures market-wide stress and sentiment dynamics. Existing evidence indicates that asset prices containing bubble components may respond differently to macroeconomic and policy shocks than predicted by fundamentals-based models. Galí and Gambetti (2015) show that bubbles can alter price responses to monetary shocks, while Fullana et al. (2021) document that restrictive monetary policy tends to have limited effects on stock returns during expansionary phases—periods often associated with bubble formation—suggesting a greater role for non-fundamental forces. Gold's relevance in this context is well documented. As a safe-haven asset (Vayanos 2004; Baur and Lucey 2010; Miyazaki and Hamori 2013), gold prices tend to reflect shifts in macroeconomic conditions, policy uncertainty, and aggregate risk sentiment. During speculative expansions, capital often reallocates toward rapidly appreciating assets, which can reduce demand for gold, whereas periods of market stress or bubble corrections are commonly associated with flight-to-quality flows into gold. As a result, gold price movements may co-move with phases of optimism and fear, embedding information related to both speculative sentiment and systemic stress.

Table 4 presents the static bubble test results for the gold-filtered series. The S&P 500 continues to show no statistically significant evidence of explosive behavior, as both the SADF and GSADF statistics remain below their critical values after filtering out gold-related price movements. This outcome suggests that equity price dynamics remain broadly non-explosive once market-wide stress components captured by gold are removed. By contrast, Bitcoin continues to exhibit statistically significant evidence of bubble-like behavior in the filtered series. Both the SADF and GSADF statistics exceed their critical values at conventional significance levels, indicating that explosive dynamics persist even after controlling for gold-related stress effects. Taken together, these results suggest that Bitcoin's bubble behavior appears less closely associated with gold-driven market stress than is the case for equities.

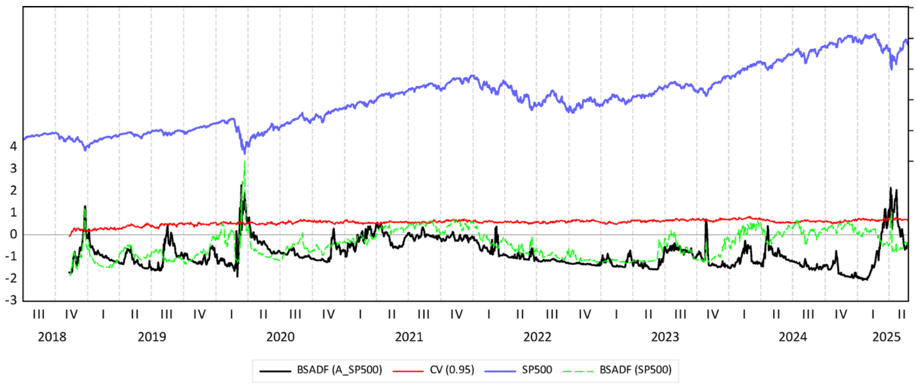
The dynamic BSADF results for the gold-filtered series reported in Fig. 4 further highlight asymmetries in bubble behavior across the two assets. For the gold-filtered S&P 500, BSADF statistics remain largely below the critical threshold throughout the sample. Although a small number of short-lived spikes appear—around late 2018, the onset of COVID-19 in 2020, and briefly near the end of the sample—these episodes are transitory and lack persistence, particularly when compared with Bitcoin. This pattern suggests that, once gold-related stress components are removed, equity prices do not display sustained explosive dynamics. In contrast, the gold-filtered Bitcoin series continues to exhibit pronounced and persistent BSADF exceedances. Distinct episodes remain evident in early 2019, from late 2021 to mid-2022, and again in early 2024, with the late-2021 to mid-2022 episode standing out in terms of both duration and magnitude. Taken together, these results indicate that while gold filtering further attenuates the already limited explosive signals observed in equity markets, it has a more limited effect on the persistence of Bitcoin's explosive dynamics. Overall, the findings are consistent with the view that Bitcoin price behavior is less closely linked to conventional market sentiment and macroeconomic conditions, highlighting its distinct dynamics within the broader financial system (Corbet et al. 2018; Sifat 2021; Bianchi 2020; Hairudin et al. 2022) (Table).

To evaluate how filtering affects causal relationships, we apply the Shi et al. (2020) TVGC framework to the gold-filtered data using the same specification as in the baseline analysis to ensure comparability. As before, we test unidirectional causality from gold to

Table 4 Bubble test results of gold-filtered variables

	A_SP500	A_BTC
ADF	− 2.2299 [− 0.4714] [− 0.1050] [0.4966]	− 1.1693 [− 0.1168] [0.2424] [1.3088]
SADF	0.9505 [2.5480] [3.3843] [4.8789]	6.7366** [4.5367] [5.5684] [7.2041]
GSADF	2.2597 [4.4446] [5.3339] [7.7346]	7.3744** [5.5674] [6.3384] [7.9271]

The critical values are given within brackets for 90%, 95% and 99% respectively. *,** and *** indicate the significance at the 10%, 5% and 1% levels, respectively.



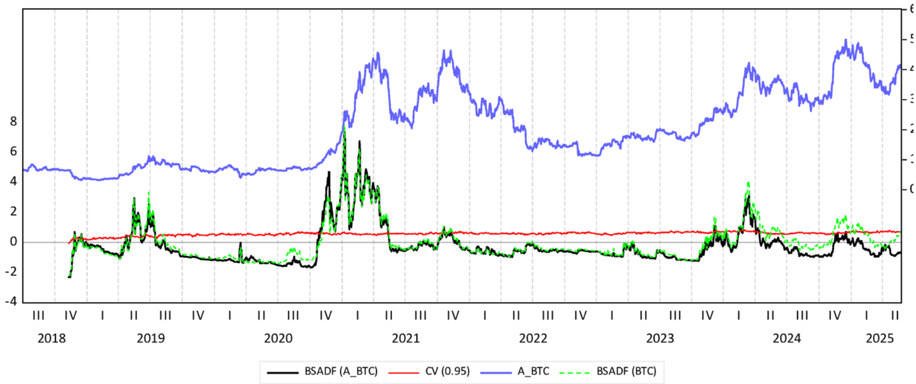


Fig. 4 Time-stamped results of the bubble analysis of gold-filtered variables. *Notes*: Bubble tests use a recursive ADF procedure with Monte Carlo critical values (1000 replications) and a PSY minimum window with an initial fraction of 0.01 and adjustment constant 1.8. Green lines represent the results for the raw series shown in Fig. 2, facilitating direct comparison

Table 5 TVGC analysis of the entire sample (gold-filtered variables)

	Forward	Rolling	Recursive
Gold to A_SP500	21.384*** [6.541, 8.579, 14.818] 18.49072 (2)	20.154 [7.525, 9.124, 14.497] 18.49072 (2)	28.282*** [7.703, 9.219, 14.818] 18.49072 (2)
Gold to A_BTC	9.099** [5.862, 7.607, 15.317] 25.11745 (1)	7.460 * [6.784, 7.751, 14.885] 25.11745 (1)	9.804** [6.985, 8.753, 15.317] 25.11745 (1)

The values within [] represent the critical values at the 10%, 5%, and 1% significance levels, respectively. (1) indicates the optimal lag length in the VAR model selected based on the Bayesian Information Criterion (BIC), followed by the corresponding BIC value. A_SP500 and A_BTC denote the gold-filtered (adjusted) S&P 500 and Bitcoin series, respectively.

the filtered S&P 500 and Bitcoin series. Optimal lag selection from bivariate VAR models yields two lags for the Gold–S&P 500 pair and one lag for the Gold–Bitcoin pair. The full-sample results in Table 5 indicate a notable contrast across assets. For the Gold–S&P 500 pair, the Wald statistic increases substantially after filtering, suggesting a stronger predictive relationship once gold-related contemporaneous stress components are removed. By contrast, the Wald statistic for the Gold–Bitcoin pair declines. Taken together, these results suggest that filtering may sharpen the predictive content of gold for equity prices by attenuating overlapping stress signals, thereby revealing a clearer association with underlying equity market dynamics. To assess whether these relationships vary over time, we next examine the dynamic dimension of causality. Figure 5 reports the time-varying Wald statistics from the three algorithms, with primary attention given to the rolling window and recursive rolling results, consistent with the earlier analysis.

Figure 5 shows that filtering gold-related information alters the estimated causal relationships. For the Gold–S&P 500 pair, the filtered data indicate a more persistent causal effect from gold. While the timing of the initial influence remains broadly similar, the statistical

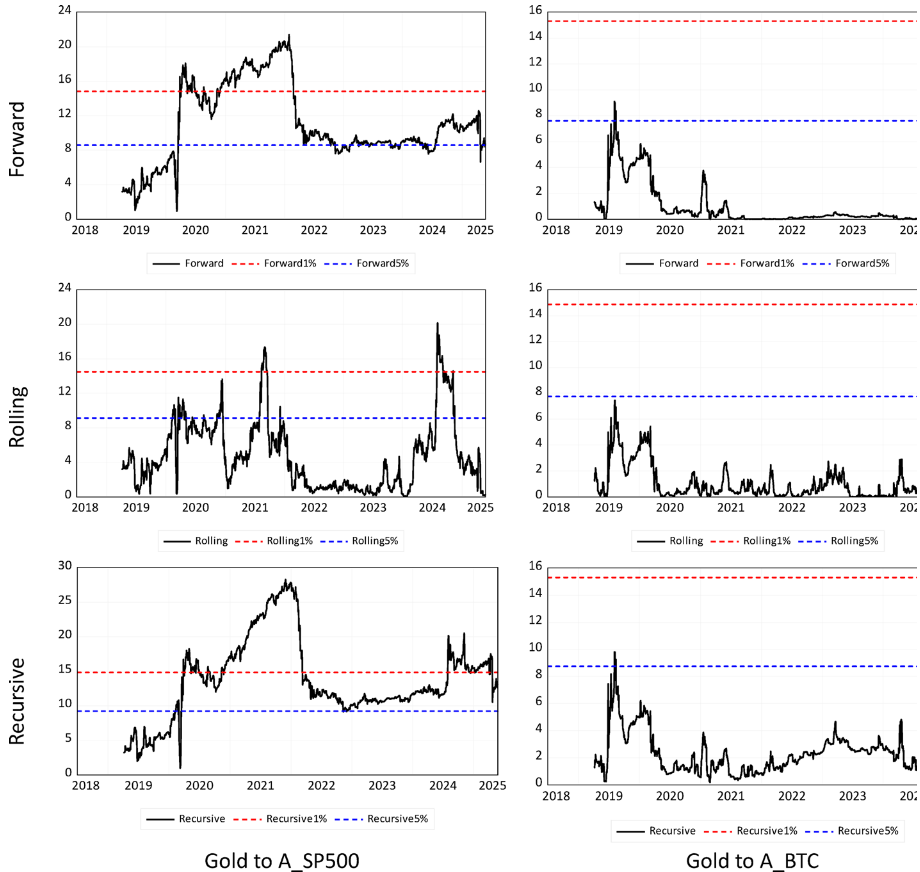


Fig. 5 TGVC analysis of gold-filtered variables. *Note*: Following Shi et al. (2020), lag length is selected using the BIC, and unidirectional Granger causality from gold to the S&P 500 and Bitcoin is tested using a rolling window of 200 days, corresponding to approximately 11% of the sample size. A_SP500 and A_BTC denote the gold-filtered (adjusted) S&P 500 and Bitcoin series, respectively

significance of the Wald statistics extends over longer intervals. Under the rolling window approach, the unfiltered series displays only two short-lived spikes in early and late 2020, whereas the filtered series exhibits statistically significant causality over much of that year. Similarly, the recursive rolling algorithm indicates a largely continuous causal influence from gold to the S&P 500 during 2020, 2021, and into the first quarter of 2022. By contrast, the Gold–Bitcoin relationship weakens after filtering. The rolling window method no longer detects statistically significant causality, and the stronger influence observed in the unfiltered series largely dissipates. Taken together, these patterns suggest that removing stress-related components embedded in gold prices may enhance the measured predictive relationship between gold and U.S. equity markets by reducing overlapping stress signals. For Bitcoin, however, filtering appears to reduce gold's predictive content. This pattern is consistent with Bitcoin's higher volatility, speculative market structure, and relatively limited linkage to macro-financial conditions, whereby asset-specific dynamics become more prominent once common stress components are attenuated.

Before concluding the empirical analysis, we examine weak-form market efficiency by assessing the long-memory properties of asset prices using multifractal analysis. This extension is directly motivated by the preceding bubble detection results, as the pronounced contrast between the S&P 500 and Bitcoin raises the question of whether their differing bubble dynamics are associated with differences in information processing and market efficiency. Under the EMH, weak-form efficient markets are not expected to sustain persistent explosive behavior, whereas long memory and persistent dependence are commonly interpreted as indicative of departures from efficiency, consistent with gradual information diffusion, heterogeneous trading horizons, and feedback-driven behavior emphasized in behavioral finance and bubble theories. To explore these mechanisms, we estimate multifractal Hurst exponents and scaling functions across a wide range of moments. Unlike single-scale measures, multifractal analysis allows dependence structures to vary across fluctuation magnitudes, providing a richer characterization of market efficiency. In weak-form efficient markets, the generalized Hurst exponent H_q is expected to remain close to 0.5 across scales, indicating short memory. By contrast, systematic deviations from 0.5 and pronounced variation in H_q across moments are typically associated with long-range dependence, multifractality, and reduced weak-form efficiency linked to heterogeneous agents and regime-dependent trading intensity.

Table 6 reports the multifractal analysis results for the S&P 500, Bitcoin, and their gold-filtered counterparts. The upper panel presents the generalized Hurst exponents H_q across negative and positive moment orders, capturing the scaling behavior of small and large fluctuations, while the lower panel reports the corresponding mass exponent functions τ_q, which summarize nonlinear scaling properties. Linear τ_q profiles are commonly associated with monofractality and relatively higher market efficiency, whereas pronounced curvature indicates multifractality and heterogeneous dependence. The S&P 500 exhibits H_q values that remain close to the martingale benchmark of 0.5 across most moments, particularly around $q = 0$ and positive values, indicating at most weak persistence. This pattern is consistent with weak-form efficiency and aligns with the bubble test results, which show no statistically significant explosive episodes even after gold filtering. The limited variation in both H_q and τ_q suggests mild multifractality and a relatively homogeneous information environment in which inefficiencies appear to be short-lived. By contrast, Bitcoin displays substantially higher H_q values—especially for negative and small positive moments—indicating

Table 6 Multifractal Hurst Exponent Results

	q	− 5	− 3	− 1	0	1	3	5
SP500	H_q	0.6064	0.5805	0.5474	0.5295	0.5151	0.4926	0.4560
BTC	H_q	0.8131	0.7169	0.6193	0.5782	0.5418	0.4729	0.4030
A_SP500	H_q	0.6395	0.5906	0.5460	0.5231	0.4973	0.4428	0.4016
A_BTC	H_q	0.7474	0.6738	0.5962	0.5612	0.5291	0.4697	0.4128
SP500	τ_q	− 4.0320	− 2.7415	− 1.5474	− 1.0000	− 0.4849	0.4778	1.2800
BTC	τ_q	− 5.0655	− 3.1507	− 1.6193	− 1.0000	− 0.4582	0.4187	1.0150
A_SP500	τ_q	− 4.1975	− 2.7718	− 1.5460	− 1.0000	− 0.5027	0.3284	1.0080
A_BTC	τ_q	− 4.7370	− 3.0214	− 1.5962	− 1.0000	− 0.4709	0.4091	1.0640

A_SP500 and A_BTC denote the gold-filtered S&P 500 and Bitcoin series, respectively. H_q denotes the generalized Hurst exponent. τ_q is the scaling (mass) exponent, summarizing how fluctuations of order q scale across time horizons.

stronger persistence and more pronounced long-memory behavior. The wide dispersion of H_q across moments and the nonlinearity of τ_q point to a higher degree of multifractality, consistent with heterogeneous trading behavior and slower information assimilation. Taken together, the multifractal results are consistent with the bubble detection findings: assets characterized by weak persistence and limited multifractality, such as the S&P 500, appear less prone to sustained explosive dynamics, whereas assets exhibiting stronger long memory and pronounced multifractality, such as Bitcoin, remain more susceptible to persistent speculative behavior, even after controlling for gold-related stress effects.

5 Discussion

The empirical findings of this study can be interpreted through the combined lenses of market efficiency, behavioral finance, and safe-haven theory, with macroeconomic conditions—and their associated social consequences—serving as an important mediating context. Rather than documenting the mere presence of sentiment-driven or flight-to-quality effects, the results shed light on when and through which assets these forces are more likely to translate into persistent bubble-like dynamics, thereby offering a more nuanced interpretation of their role across different market environments.

From the perspective of the EMH, weak-form efficiency is associated with short memory and rapid incorporation of information into prices. The absence of persistent bubbles in the S&P 500—both in the raw data and after filtering out global stress components—together with Hurst exponents close to 0.5 (Cajueiro and Tabak 2004), is consistent with this interpretation. Equity price fluctuations therefore appear to reflect largely transitory adjustments to new information and evolving risk premia rather than sustained mispricing. Importantly, these results suggest that even after attenuating market-wide stress signals captured by gold, equity prices do not exhibit self-reinforcing explosive dynamics. By contrast, Bitcoin displays long-range dependence and pronounced multifractality, patterns commonly interpreted as indicative of persistent departures from weak-form efficiency. Such features are consistent with market environments in which information diffusion is slower and speculative dynamics may facilitate prolonged deviations from fundamental valuation.

The pronounced and recurrent bubble episodes observed in Bitcoin are broadly consistent with behavioral finance explanations that emphasize speculative amplification and herding behavior (Youssef 2022; Wanidwaranan and Termprasertsakul 2024). Persistent explosive dynamics suggest the presence of self-reinforcing price movements that can sustain elevated valuations beyond levels implied by fundamentals. An important contribution of this study is the finding that such dynamics remain evident even after filtering out market-wide stress components, indicating that speculative behavior in cryptocurrency markets may be more closely linked to asset-specific factors than to broader flight-to-quality forces. By contrast, these mechanisms appear less prominent in the S&P 500, where higher liquidity, greater institutional participation, and stronger informational discipline may limit the persistence of self-reinforcing speculative dynamics.

The TVGC results, both before and after filtering, indicate that gold's safe-haven role is more closely associated with equity markets than with cryptocurrency markets. After attenuating hype- and fear-driven components in equity prices, the causal influence from gold to the S&P 500 becomes more persistent, particularly during and following the pandemic period. This state-dependent pattern suggests that gold may function not only as a contemporaneous hedge, as emphasized in the flight-to-quality literature, but also as a forward-looking stress signal for equity markets under heightened uncertainty. The increase in gold's predictive content during the COVID-19 episode is consistent with its potential role as an early-warning indicator of financial stress, though this role appears to be more evident for equities. By contrast, causal effects from gold to Bitcoin remain weak and episodic, with no sustained time-varying pattern. Taken together, these results suggest that safe-haven dynamics documented in the literature do not transmit uniformly across asset classes.

The persistent causal association between the S&P 500 and gold—even after filtering—suggests that equity markets remain closely connected to broader macroeconomic and policy-relevant conditions (Christiano et al. 2010), while gold price dynamics continue to reflect episodes of financial stress and global turbulence (Baur and McDermott 2010). This linkage indicates that equity prices continue to incorporate information related to monetary policy, business-cycle fluctuations, and aggregate risk sentiment, even after attenuating market-wide hype and fear components. By contrast, the weaker and less stable association between gold and Bitcoin is consistent with the view that Bitcoin price dynamics are less tightly anchored in macroeconomic fundamentals, in line with recent evidence reported by Aydoğan et al. (2024). Instead, Bitcoin price movements appear to be more strongly influenced by asset-specific factors, including herding behavior and sentiment-driven trading.

From a broader economic and social perspective, the results suggest that persistent bubble dynamics in Bitcoin may be associated with heightened wealth redistribution and social costs, with retail investors potentially being more exposed to downside risk. By contrast, the absence of sustained bubbles in the S&P 500 indicates that equity price movements are more consistent with temporary risk reallocations than with prolonged mispricing. By distinguishing market-wide stress-driven reallocations from asset-specific speculative bubbles, the analysis helps clarify why the social and distributional consequences of bubbles may differ across asset classes. These findings are consistent with Mills (2002), who argues that financial bubbles tend to generate limited net wealth creation but substantial wealth transfers, with social consequences shaped by market structure, investor composition, and informational efficiency.

Taken together, the results suggest that gold-related market stress functions as a channel for transmission and predictability in equity markets without giving rise to self-reinforcing explosive dynamics, whereas bubble behavior in cryptocurrency markets appears less responsive to such stress signals. For the S&P 500, gold filtering helps clarify the role of aggregate risk sentiment while leaving the absence of sustained bubbles unchanged, a pattern consistent with relatively rapid information absorption and market depth. By contrast, Bitcoin's explosive behavior persists after filtering, indicating that its bubble dynamics are more plausibly linked to endogenous speculative feedback and behavioral forces than to market-wide flight-to-quality mechanisms.

6 Conclusion

6.1 Empirical results

This study provides empirical evidence suggesting that bubble dynamics differ between equity and cryptocurrency markets once market-wide stress components are explicitly accounted for. By jointly examining raw and gold-filtered price series, the analysis helps disentangle asset-specific speculative behavior from broader risk sentiment and highlights notable asymmetries in price formation, adjustment, and persistence across the two markets.

Across the specifications considered, the S&P 500 shows no evidence of sustained explosive behavior. Neither the static nor the dynamic GSADF results identify economically meaningful bubble episodes, regardless of whether gold-related dynamics are removed. This consistency suggests that equity prices tend to remain anchored by mechanisms that limit prolonged deviations from fundamentals, even during periods of heightened stress. By contrast, Bitcoin exhibits recurrent episodes of explosive behavior that persist after gold filtering, indicating that its bubble dynamics are less closely tied to market-wide stress conditions. The persistence of these patterns across raw and filtered series is consistent with the presence of asset-specific speculative amplification in cryptocurrency markets.

The TVGC results further help to clarify these differences. Gold continues to display a relatively stable and economically relevant predictive relationship with the S&P 500, even after filtering, suggesting that equity markets may still internalize forward-looking information embedded in gold prices beyond contemporaneous stress reallocations. For Bitcoin, by contrast, gold's influence weakens noticeably once common stress components are removed, with statistically significant causality limited to short-lived episodes. This divergence suggests that Bitcoin's price dynamics are less closely connected to conventional macro-financial transmission channels and may instead be shaped to a greater extent by internal, market-specific factors.

Multifractal analysis further supports this interpretation by relating bubble persistence to underlying dependence structures. The S&P 500 exhibits scaling behavior consistent with relatively rapid information absorption and limited long memory, which may constrain the emergence of self-reinforcing price dynamics. Bitcoin, by contrast, displays pronounced multifractal persistence and scale heterogeneity, characteristics commonly associated with slower information diffusion and sustained speculative feedback. When considered alongside the evidence from explosiveness and time-varying causality, these patterns help explain why bubble regimes in equities tend to be episodic and short-lived, whereas similar dynamics in cryptocurrencies appear more recurrent and persistent.

6.2 Policy implications

The results suggest that the role of gold in conveying stress-related information differs across equity and cryptocurrency markets, with implications primarily for monitoring bubble-related risks rather than for direct intervention. In equity markets, gold appears to function mainly as an informational signal rather than as a source of speculative excess. Although no sustained bubble behavior is identified in the S&P 500, the presence of a stable and time-varying predictive relationship from gold to equities indicates that gold prices may embed forward-looking information related to shifts in risk sentiment. From a policy and risk-monitoring perspective, this suggests that movements in gold prices can provide useful signals about emerging vulnerability regimes in equity markets, potentially complementing existing surveillance tools without implying the presence of speculative bubbles.

The implications for cryptocurrency markets are more limited and necessarily tentative. Bitcoin's explosive price behavior persists even after removing gold-related components, suggesting that conventional safe-haven signals and macro-financial indicators may have reduced explanatory power for its speculative dynamics. This relative detachment implies that stress signals derived from traditional financial markets are likely to provide only partial insight into bubble formation in decentralized digital assets. In this context, the multifractal persistence observed in Bitcoin prices may offer additional descriptive information on dependence structures associated with speculative amplification, rather than functioning as a standalone early-warning or policy tool.

Given the decentralized nature of cryptocurrency markets and the limited scope for direct intervention, policy responses to bubble-related risks remain inherently challenging. The evidence does not support specific regulatory prescriptions; however, it suggests that indirect and incentive-based measures—such as those influencing short-term trading intensity—may merit consideration within broader risk-mitigation discussions. Complementary monitoring of market- and network-level indicators could further support situational awareness. Any such approaches should be interpreted cautiously, as their effectiveness is likely to depend on institutional context and market structure, and they are unlikely to eliminate speculative cycles entirely.

6.3 Limitations

While this study employs a broad empirical framework and a filtering approach to examine bubble dynamics, several limitations warrant consideration. First, the analysis relies on gold as the sole safe-haven asset in the filtering procedure. Although gold is widely used as a proxy for market-wide risk sentiment, alternative assets—such as U.S. Treasury bills or government bonds—may capture different dimensions of stress and could be explored in future research to assess the robustness of the findings. Second, the empirical analysis focuses on the U.S. equity market as a representative advanced financial system. Extending the framework to emerging or frontier markets may yield additional insights, as differences in market depth, regulatory environments, and investor composition could influence bubble formation and persistence. Finally, while Bitcoin represents the largest and most mature cryptocurrency, examining a broader set of digital assets may reveal heterogeneous speculative dynamics and market structures, thereby enriching the understanding of bubble behavior in decentralized markets.

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Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare no conflict of interest.

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