

Financial stress shocks and digital asset performance across market conditions

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Abstract

Purpose – This study examines the predictive capacity of the Financial Stress Index (FSI) for major digital asset categories - Bitcoin, DeFi tokens, and NFT tokens - across bearish, normal, and bullish market regimes.

Design/methodology/approach – We deploy a rolling-window wavelet quantile Granger causality (RWWQGC) framework capturing time variation, frequency heterogeneity, and distributional asymmetries, supported by quantile-on-quantile regressions (QQR) for robustness.

Findings – FSI predictability is state- and horizon-dependent. Under normal market conditions, predictive power stabilizes at lower frequencies. Conversely, in bearish and bullish regimes, predictability shifts toward higher frequencies. QQR estimates confirm nonlinear, asymmetric, and tail-dependent systemic risk transmission.

Practical implications – Systemic financial stress drives long-horizon portfolio rebalancing during normal market states, but induces short-term speculative trading in extreme regimes, offering direct implications for cross-asset hedging and macroprudential oversight.

Originality/value – This study extends the systemic risk literature across heterogeneous crypto segments through a unified time–frequency–quantile framework, uncovering state-contingent risk propagation overlooked by conventional linear models.

Keywords Financial stress, Digital assets, Bitcoin, DeFi, NFTs, Wavelet quantile Granger causality, Quantile-on-quantile regression, Systemic risk

Paper type Research article

1. Introduction

The Financial Stress Index (FSI) serves as a comprehensive proxy for systemic risk, capturing tensions across credit markets, funding liquidity, equity volatility, and risk premia (Patra & Singh, 2025; Nur & Korkmaz, 2022; Napari, Khan, Kaplan, & Vergil, 2025). Periods of elevated financial stress reflect tightening financial conditions, heightened uncertainty, and increased risk aversion, triggering portfolio rebalancing, liquidity contractions, and cross-market spillovers (Diebold & Yilmaz, 2014; Antonakakis, Chatziantoniou, & Gabauer, 2020). Concurrently, digital assets - spanning Bitcoin, decentralized finance (DeFi), and metaverse tokens - have expanded into a sizable, interconnected segment of global markets (Steen, Graves, D'Alessandro, & Shi, 2024; Güleç, Erer, & Duramaz, 2026). Despite their decentralized design, digital assets exhibit pronounced co-movements with global liquidity

JEL Classification — C32, C58, G15

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conditions, investor sentiment, and systemic disruptions (Bouri, Gupta, Lau, Roubaud, & Wang, 2018; Ullah & Khan, 2025; Kammoun, 2026).

Financial stress transmits to digital assets through risk-off portfolio reallocations, funding and leverage constraints within crypto ecosystems, and sentiment-driven speculation (Selmi, Mensi, Hammoudeh, & Bouoiyour, 2018; Güleç *et al.*, 2026; Kammoun, 2026). Conversely, severe crypto market downturns may feed back into the broader financial system via wealth effects, confidence shocks, and institutional exposures (Colombage, Jayawardhana, & Oatley, 2025; Ullah & Khan, 2025). Despite these plausible bidirectional linkages, empirical research has not systematically evaluated how systemic financial stress interacts with digital assets across distinct market states and distributional regimes (Bouri *et al.*, 2018; Patra & Singh, 2025). Given the growing institutional integration of crypto assets and their heightened volatility during distress episodes (Güleç *et al.*, 2026; Kammoun, 2026), examining this state-contingent relationship is essential for market participants and macroprudential regulators.

We proxy systemic risk using the Office of Financial Research (OFR) Financial Stress Index (FSI). Conceptually, the OFR FSI aggregates five key dimensions of macro-financial instability, namely credit markets, equity valuations, funding liquidity, safe assets, and volatility (Monin, 2019; Hoque & Low, 2022; Hoque, Soo-Wah, Tiwari, & Akhter, 2023; Khan, Yaya, Vo, & Zada, 2025). This composite structure provides a comprehensive gauge of systemic strain rather than an isolated risk proxy. Empirically, assets such as gold and Bitcoin demonstrate quantile-dependent responses to stress subcategories, underscoring the index's utility for stress-transmission modeling (Bouri *et al.*, 2018; Jareño, González, Tolentino, & Sierra, 2020; Hoque & Low, 2022). The multidimensional design of the FSI aligns directly with the pricing dynamics of digital assets, which are driven by liquidity conditions, credit availability, volatility shocks, and shifts in aggregate risk tolerance.

Prior empirical literature primarily examines volatility spillovers, connectedness, and safe-haven properties using linear frameworks, ordinary least squares (OLS), or conventional vector autoregressive models (Diebold & Yılmaz, 2014; Bouri *et al.*, 2018; Selmi *et al.*, 2018; Antonakakis *et al.*, 2020; Nur & Korkmaz, 2022; Colombage *et al.*, 2025; Patra & Singh, 2025; Güleç *et al.*, 2026; Kammoun, 2026). However, linear specifications obscure structural asymmetries, nonlinearities, and tail dependencies that materialize during market distress (Bouri *et al.*, 2018; Hung, 2023; Ullah & Khan, 2025; Güleç *et al.*, 2026). Stress shocks rarely exert uniform effects across asset return distributions; rather, their impact is state-dependent (varying across bearish, normal, and bullish regimes) and frequency-specific (differentiating short-term speculative behavior from long-horizon allocations) (Basty & Abidly, 2025; Güleç *et al.*, 2026).

To address these gaps, this study investigates the time-varying, frequency-dependent, and quantile-specific linkages between the FSI and representative digital assets, including Bitcoin (BTC) as the benchmark store-of-value proxy, Chainlink (LINK) as the DeFi benchmark, and Decentraland (MANA) as the NFT proxy. Specifically, we address four research questions: (1) Does financial stress exert predictive power over digital asset returns? (2) Does this predictive relationship exhibit frequency heterogeneity across short-, medium-, and long-term horizons? (3) Is the FSI–digital asset nexus nonlinear and regime-dependent across joint return quantiles? (4) Do digital asset shocks generate feedback effects on financial stress during extreme market states?

Methodologically, we deploy two complementary empirical frameworks. First, we employ the rolling-window wavelet quantile Granger causality (RWWQGC) model (Usman, Ozkan, Alola, & Ike, 2026). Wavelet decomposition separates time series into short-, medium-, and long-run frequency bands, while quantile Granger causality tests evaluate predictive capacity across conditional return distributions. Implementing this within a rolling-window structure captures structural breaks and regime shifts over time (Usman *et al.*, 2026). Second, we apply quantile-on-quantile regressions (QQR) as a robustness check to estimate the relationship across the joint distribution of financial stress and crypto returns, uncovering tail asymmetries overlooked by standard conditional-mean models (Sim & Zhou, 2015).

Our empirical results show that the FSI - digital asset nexus is asymmetric, horizon-dependent, and regime-contingent. FSI predictability intensifies in lower return quantiles during market extremes. While Bitcoin demonstrates relative resilience under moderate stress, DeFi and NFT tokens exhibit heightened tail sensitivity and liquidity-driven transmission. Furthermore, extreme negative digital asset shocks feed back into elevated systemic stress, confirming bidirectional causality during crisis episodes.

This study makes three distinct and interrelated contributions to existing literature. First, this study extends the financial stress literature by examining heterogeneous digital asset segments, including BTC, DeFi (LINK), and NFT-related assets (MANA), within a nonlinear framework. While prior studies primarily focus on Bitcoin and conventional cryptocurrencies (Bouri *et al.*, 2018; Hoque & Low, 2022; Colombage *et al.*, 2025), evidence regarding the differential responses of broader digital asset categories to financial stress remains limited.

Second, this study contributes methodologically by integrating RWWQGC and QQR to account for time variation, frequency heterogeneity, and distributional asymmetry. While previous studies have typically employed either wavelet-based approaches (Hoque *et al.*, 2023, 2024) or quantile-based techniques (Bouri *et al.*, 2018; Jareño *et al.*, 2020) in isolation, studies combining these dimensions within the FSI–digital asset literature remain scarce.

Third, this study contributes to the macroprudential monitoring literature by providing evidence of bidirectional and state-dependent interactions between financial stress and digital asset markets. In doing so, it complements recent studies highlighting the growing systemic relevance of digital assets (Yin, Chen, Luo, & Kirkulak-Uludag, 2024; Güleç *et al.*, 2026; Steen *et al.*, 2024) and suggests that selected digital asset segments may contain valuable information regarding the evolution of systemic risk.

The remainder of this paper is organized as follows. Section 2 represents the theoretical background and reviews the related literature. Section 3 outlines the research methodology and data. Section 4 reports and discusses the empirical findings. Section 5 concludes the study.

2. Literature review

The Financial Stress Index (FSI) serves as a comprehensive proxy for systemic risk, capturing multi-market tensions across credit conditions, equity volatility, funding liquidity, and risk premia (Bouri *et al.*, 2018). Escalations in the FSI reflect deteriorating funding liquidity and heightened macro-level risk aversion across the broader financial architecture (Zhang & Wang, 2021). As digital assets become increasingly integrated into mainstream global finance, evaluating how systemic stress propagates across crypto sub-segments is critical. Because stress transmission is non-uniform across asset classes and market states, standard linear, conditional-mean specifications are structurally inadequate, necessitating a distribution-sensitive, state-contingent analytical framework (Hoque, Billah, Alam, & Tiwari, 2024).

Theoretically, systemic financial stress transmits to digital asset markets through three primary, interrelated channels. First, under the risk-appetite and portfolio-rebalancing channel, elevated stress induces a shift from risk-on to risk-off allocations, prompting investors to divest from highly volatile crypto assets, particularly DeFi and NFT segments, thereby amplifying downside drawdowns during market turbulence (Aljughaiman, Tabash, Issa, & Almulhim, 2025; Colombage *et al.*, 2025). Second, through the liquidity and funding constraints channel, tighter credit conditions and funding pressures trigger forced deleveraging and cascading liquidations, disproportionately impairing liquidity-dependent protocols (Bouri, Gupta, Tiwari, & Roubaud, 2017; Patra & Singh, 2025). Third, via the speculative sentiment channel, distress episodes exacerbate sentiment spillovers and speculative portfolio adjustments, inducing high-frequency trading reactions (Patra & Singh, 2025).

Conversely, feedback mechanisms operate in reverse, as severe dislocations in crypto markets spill back into the traditional financial system. Sharp downturns in digital asset markets impair broader investor confidence and heighten perceptions of financial fragility through institutional linkages, balance-sheet exposures, and liquidity mismatches (Zhang & Wang, 2021; Yin *et al.*,

2024). Consequently, liquidity-sensitive sub-segments such as DeFi and NFTs can function as leading indicators of shifting global risk appetite and systemic vulnerability (Hoque *et al.*, 2024).

Empirical literature spans three interrelated strands. The first examines macro-financial stress propagation, documenting that elevated FSI levels amplify downside risk, heighten volatility spillovers, and strengthen cross-market contagion nonlinearly during crisis episodes (Bouri *et al.*, 2018; Zhang & Wang, 2021; Yin *et al.*, 2024).

The second strand explores crypto-market connectedness and safe-haven dynamics. While initial studies report mixed evidence regarding Bitcoin's hedging capacity (Hoque & Low, 2022; Colombage *et al.*, 2025), recent work shows that its diversification properties deteriorate during severe turmoil as crypto-equity co-movements rise (Hoque & Low, 2022; Hoque *et al.*, 2024). Expanding beyond Bitcoin, DeFi and NFT assets display higher speculative sensitivity, severe tail dependence, and strong dynamic connectedness with conventional markets (Zhang & Wang, 2021; Aljughaiman *et al.*, 2025; Chen, 2025; Colombage *et al.*, 2025). Empirical studies confirm that systemic stress and macro uncertainty generate significant volatility spillovers across cryptocurrencies, particularly around structural breaks and crisis regimes (Nur & Korkmaz, 2022; Patra & Singh, 2025). Recent findings further establish the systemic integration of digital assets: Bitcoin and Ethereum act as key spillover transmitters during crises (Kammoun, 2026), metaverse tokens display time-varying linkages with macro assets (Basty & Abidly, 2025), and cryptocurrencies transmit higher-order moment risks under heightened economic and geopolitical uncertainty (Steen *et al.*, 2024; Güleç *et al.*, 2026).

The third strand addresses methodological advances. Linear Granger causality and vector autoregressions (VAR) fail to account for fat tails, structural shifts, and asymmetric dependencies (Selmi *et al.*, 2018). While quantile causality captures regime heterogeneity across market conditions (Bouri *et al.*, 2018) and wavelet decompositions differentiate short-from long-horizon dynamics (Hoque *et al.*, 2024), existing frameworks rarely evaluate time variation, frequency heterogeneity, and distributional asymmetry simultaneously.

Two critical gaps persist in the literature: (1) studies primarily analyze Bitcoin or aggregate indices, leaving sub-segment heterogeneity (DeFi, NFTs) under financial stress largely unaddressed (Bouri *et al.*, 2018; Hoque & Low, 2022; Colombage *et al.*, 2025); and (2) empirical models fail to unify rolling-window time dynamics, multiscale frequency decompositions, and tail-quantile dependencies. We bridge these gaps by deploying a time-frequency-quantile framework to evaluate FSI predictability across heterogeneous digital asset classes.

3. Hypotheses development

Financial stress captures systemic vulnerabilities across credit, equity, funding, and volatility dimensions (Monin, 2019; Hoque & Low, 2022). As digital assets integrate into mainstream finance, shifts in systemic stress alter investor risk appetite, funding liquidity, and asset allocation. Given the structural heterogeneity of digital markets, these transmission effects are expected to vary across market states. We therefore hypothesize:

- H1.* FSI significantly predicts digital asset returns in a nonlinear and state-contingent manner, with predictive power intensifying during extreme bearish and bullish regimes relative to normal market conditions.

Cross-market asset linkages are inherently multiscale, short-term movements reflect speculative sentiment and high-frequency trading, whereas long-term co-movements are governed by fundamental macro-financial rebalancing (Hoque *et al.*, 2024). Therefore, the predictive transmission of systemic stress should vary across holding horizons:

- H2.* The predictive relationship between financial stress and digital asset returns exhibits frequency heterogeneity, displaying distinct transmission dynamics across short-term, medium-term, and long-term investment horizons.

Digital asset sub-segments respond heterogeneously to systemic shocks (Zhang & Wang, 2021; Colombage *et al.*, 2025). Relative to Bitcoin's established liquidity and store-of-value profile, DeFi and NFT tokens are characterized by elevated speculative trading and acute liquidity fragility, amplifying their downside exposure during market distress:

- H3. The impact of financial stress is distributionally asymmetric, exerting stronger downside effects in lower return quantiles, with DeFi and NFT tokens exhibiting greater tail sensitivity than Bitcoin.

Accelerating institutional participation binds digital assets to conventional financial markets. Hence, severe crypto downturns may feed back into aggregate systemic risk perceptions via balance-sheet channels, confidence shocks, and margin constraints (Yin *et al.*, 2024; Güleç *et al.*, 2026). These feedback mechanisms should intensify during market turmoil:

- H4. Financial stress and digital asset returns exhibit bidirectional Granger causality under extreme market conditions, such that digital asset returns contain forward-looking predictive information for systemic financial stress.

4. Methodology

To evaluate the nonlinear and regime-dependent transmission of systemic risk, we employ two complementary econometric frameworks, including Rolling Window Wavelet Quantile Granger Causality (RWWQGC) and Quantile-on-Quantile Regression (QQR). Digital asset markets exhibit pronounced volatility, speculative dynamics, and liquidity fragility, causing stress transmission to vary across market regimes (bearish, normal, bullish) and investment horizons (short-medium and long-term) (Bouri *et al.*, 2017; Güleç *et al.*, 2026). Standard linear, mean-based specifications (static VAR, linear Granger causality) impose restrictive distributional assumptions and obscure structural asymmetries and tail dependencies (Diebold & Yilmaz, 2014; Antonakakis *et al.*, 2020).

The RWWQGC approach unifies time variation, multiscale frequency decomposition, and quantile-specific causality (Usman *et al.*, 2026). Specifically, Maximal Overlap Discrete Wavelet Transform (MODWT) decomposes series into distinct frequency bands (Percival & Walden, 2000), while rolling-window quantile Granger causality tests trace dynamic parameter shifts across conditional return distributions over time (Usman *et al.*, 2026; Hoque *et al.*, 2024). This multiscale framework accounts for structural breaks and captures nonlinear dependence confirmed by the BDS test (Brock, Dechert, & Scheinkman, 1996).

Complementing this, QQR extends traditional quantile regression by allowing both the conditioning and dependent variables to vary across quantile spectra simultaneously (Sim & Zhou, 2015). This maps tail-to-tail and cross-quantile dependence, identifying how varying intensities of financial stress affect digital asset returns across distinct market states (Bouri *et al.*, 2018; Jareño *et al.*, 2020; Hoque & Low, 2022). Furthermore, QQR provides a flexible, nonparametric alternative to parametric copula formulations, avoiding restrictive distributional assumptions and substantial computational overhead while uncovering localized nonlinearities (Bouri *et al.*, 2017; Selmi *et al.*, 2018; Khan *et al.*, 2025).

In synthesis, RWWQGC determines the direction, timing, and horizon specificity of dynamic causality across return regimes (Usman *et al.*, 2026), whereas QQR delineates the full joint distributional dependency structure (Sim & Zhou, 2015). Integrating both models resolves the constraints of isolated wavelet (Hoque *et al.*, 2023, 2024) or quantile techniques (Bouri *et al.*, 2018; Patra & Singh, 2025), addressing calls for unified time–frequency–quantile frameworks in crypto-financial research (Hung, 2023; Ullah & Khan, 2025). Additional methodological details are provided in Appendix A.

5. Data

The current study uses daily data to look into the time-varying association between financial stress (FSI) and digital asset returns over the period from 1 January 2018 to 2 January 2026, a timeframe that encompasses multiple episodes of market turbulence and relative stability in both traditional and digital financial markets. FSI is obtained from the Office of Financial Research (OFR). The OFR Financial Stress Index captures stress conditions across key segments of the U.S. financial system by aggregating information from credit, equity, funding, and volatility markets. The index is widely used in literature as a comprehensive indicator of systemic financial stress and macro-financial uncertainty (Hoque & Low, 2022), and is extracted directly from the OFR's official website (<https://www.financialresearch.gov/financial-stress-index>, accessed on 1 January 2026).

We take into account three distinct segments to represent digital asset markets. Bitcoin (BTC) is used as a proxy for the broader cryptocurrency market due to its dominant market capitalization, liquidity, and benchmark role in the digital asset ecosystem. Chainlink (LINK) is employed to represent the decentralized finance (DeFi) sector, reflecting its critical function as a decentralized oracle network that underpins many DeFi protocols. Decentraland (MANA) is used as a proxy for the non-fungible token (NFT) market, given its strong association with digital ownership, virtual assets, and NFT-related applications (Abdullah, Adeabah, Lee, Abakah, & Bhuiyan, 2025). Daily closing prices for BTC, LINK, and MANA are collected from <https://coinmarketcap.com/>. These assets are computed as continuously compounded returns, defined as the first difference of the natural logarithm of prices.

Preliminary diagnostic tests and distributional properties of the variables are detailed in Appendix B. Specifically, descriptive statistics and ADF unit root results are presented in Table B1, the BDS nonlinearity test results in Table B2, Q-Q plots confirming non-normality in Figure B1, and the correlation heatmap in Figure B2.

6. Empirical results

In this section, we first examine the causal linkages between FSI and BTC, LINK, and MANA across different investment horizons and market conditions. Second, to assess the robustness of the identified nonlinear and distribution-dependent interplay, we apply the QQR model as a complementary analysis of the FSI–digital asset nexus.

The RWWQGC results are presented as time–frequency–quantile heatmaps that visualize the evolution of Granger causality over time, investment horizons, and market conditions. The horizontal axis represents time, while the vertical axis denotes wavelet scales corresponding to various investment horizons, with lower (higher) scales capturing short-term (long-term) co-movement. Each panel corresponds to a specific quantile, representing bearish ($\tau = 0.05$), normal ($\tau = 0.50$), and bullish ($\tau = 0.95$) market situations. Colored markers indicate statistically significant causality at traditional significance levels, with clustered significance highlighting periods when the predictive interaction is stronger and economically meaningful. In contrast, sparse or insignificant regions suggest weak or absent transmission, indicating temporary decoupling between the variables.

6.1 Financial stress and cryptocurrency

Figure 1 presents the time–frequency–quantile causal associations between FSI and BTC across bearish ($\tau = 0.05$), normal ($\tau = 0.50$), and bullish ($\tau = 0.95$) market conditions.

In bearish market regimes, Figure 1 reveals a bidirectional causal association between BTC and FSI that is more evident than in normal or bullish conditions. Statistically significant causality is observed in both directions ($\text{BTC} \rightarrow \text{FSI}$ and $\text{FSI} \rightarrow \text{BTC}$) across a range of short-, medium-, and long-term horizons, although the intensity and persistence vary through time. This bidirectional causality points out that during the extreme market conditions, FSI not only has predictive power over BTC returns, but movements in Bitcoin prices also contain

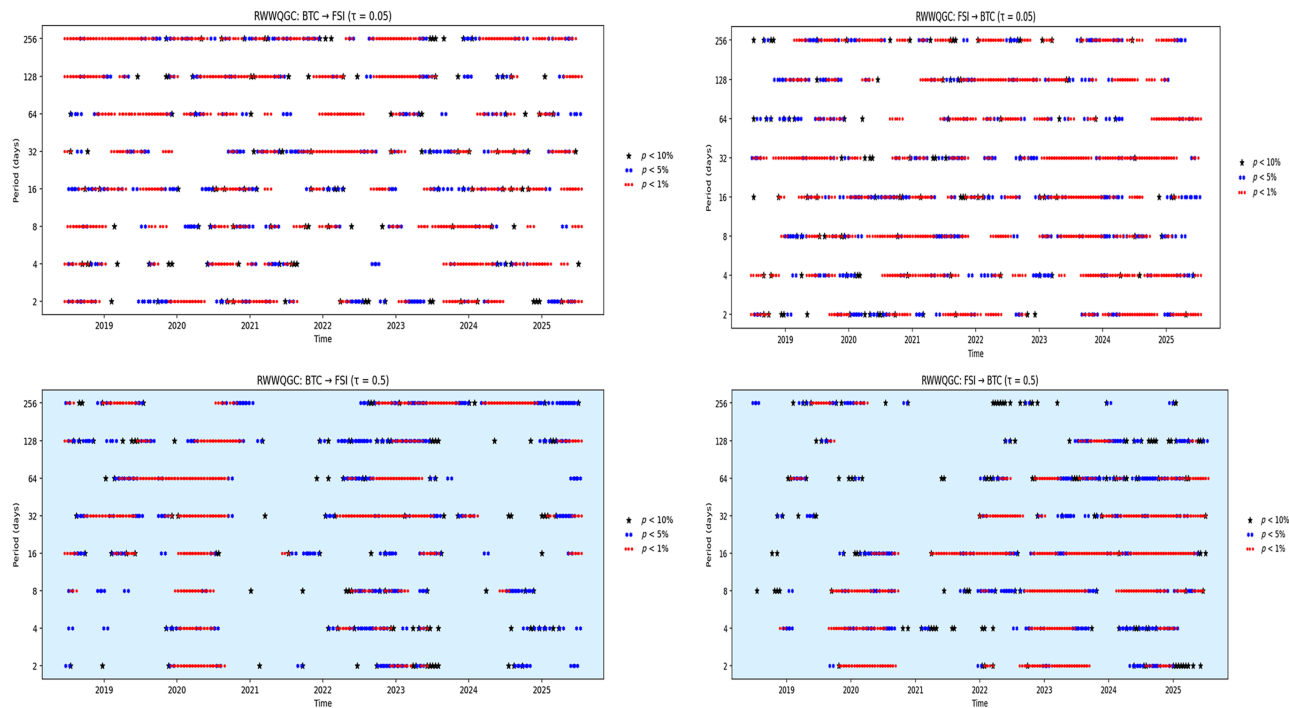


Figure 1. Time-frequency-quantile causal associations between FSI and BTC. The window size is 250 and the step size is 10

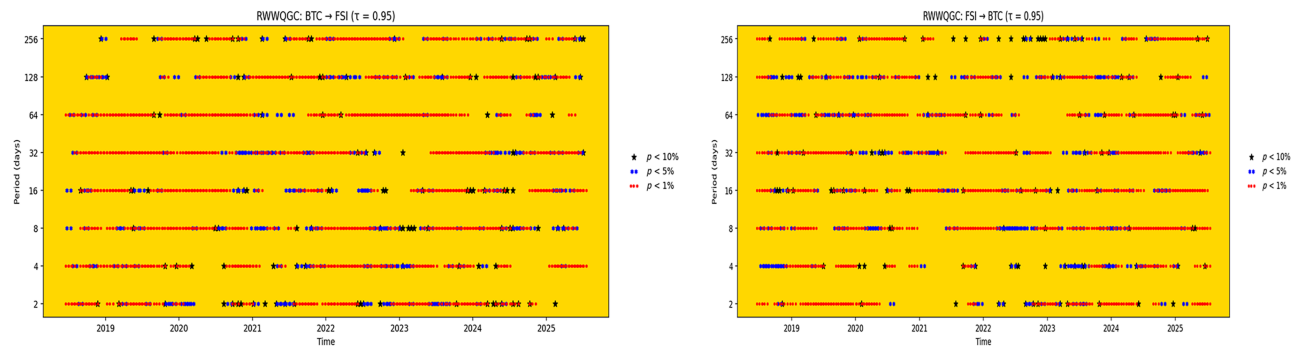


Figure 1. (continued)

information relevant for subsequent changes in financial stress. Economically, this implies the existence of a feedback mechanism under stress conditions, whereby increasing FSI triggers rapid adjustments in Bitcoin markets, while sharp Bitcoin price movements associated with liquidity shocks, forced deleveraging, or investor panic can reinforce perceptions of broader financial instability.

Under normal market conditions, the evidence of causality is noticeably weaker and less pervasive compared to bearish and bullish regimes. Statistically significant causal episodes do not persist continuously over time but instead emerge significantly in relatively limited segments, with most occurrences concentrated in the later part of the sample period (2022–2025). In this regime, causality from FSI to BTC appears mainly at medium-to-lower frequency horizons, whereas causality from BTC to FSI remains sparse and scattered across both time and frequencies. Findings indicate that during stable periods, the FSI has only limited influence on Bitcoin, likely through long-term macro channels rather than short-term trading. The lack of significant BTC → FSI causality confirms that Bitcoin does not provide systematic feedback to aggregate financial stress under normal conditions. From an economic perspective, these broadly insignificant causal relationships imply that Bitcoin remains a partially segmented asset, largely decoupled from traditional financial stress when macro forces are not dominant.

In bullish regimes, statistically significant causality is observed in both directions, and the effects are distinctly time-dependent and horizon-specific. Significant causal episodes appear across multiple frequencies over much of the sample period, reflecting stronger nonlinear dependence during periods of market scenarios. Economically, this suggests that bullish conditions encourage speculative trading and rapid price adjustment, enabling both FSI → BTC and BTC → FSI causality to emerge in conjunction with broader shifts in investor risk sentiment.

6.2 Financial stress and NFT

Figure 2 reports the bidirectional RWWQGC results between FSI and the NFT proxy (MANA) across bearish, normal, and bullish market conditions.

In bearish conditions, statistically significant causality is detected in both directions (MANA → FSI and FSI → MANA) across different horizons, and this significance extends across most of the sample period. From an economic perspective, this reflects a stress-induced feedback mechanism. Increasing FSI can swiftly weaken NFT-related tokens via liquidity constraints and risk-aversion channels. Investors tend to deleverage, shift toward safer assets, and scale back exposure to speculative markets. Concurrently, steady declines in MANA driven by forced liquidations and collapsing sentiment align with reduced risk appetite captured by the FSI, reinforcing a reverse predictive relationship.

In stable market environments, the bidirectional causality between FSI and MANA grows more scattered, reflecting weaker informational transmissions. These findings imply that NFT valuations become predominantly driven by idiosyncratic factors during these phases, thereby reducing the systematic relevance of financial stress indices for NFT markets. When markets are bullish, the heatmaps document strong two-way links across different time and frequencies. This points to exuberant phases where NFTs move like high-risk assets rising fast when confidence builds and easier money flows through the system. In turn, NFT rallies reflect greater risk-taking in the broader market. The results suggest that the connection between FSI and NFTs is most pronounced in extreme environments, shaped by shifting risk appetite and speculative cycles.

6.3 Financial stress and DeFi

Figure 3 reports the time–frequency–quantile causal associations between the FSI and the DeFi proxy (LINK) under various market conditions.

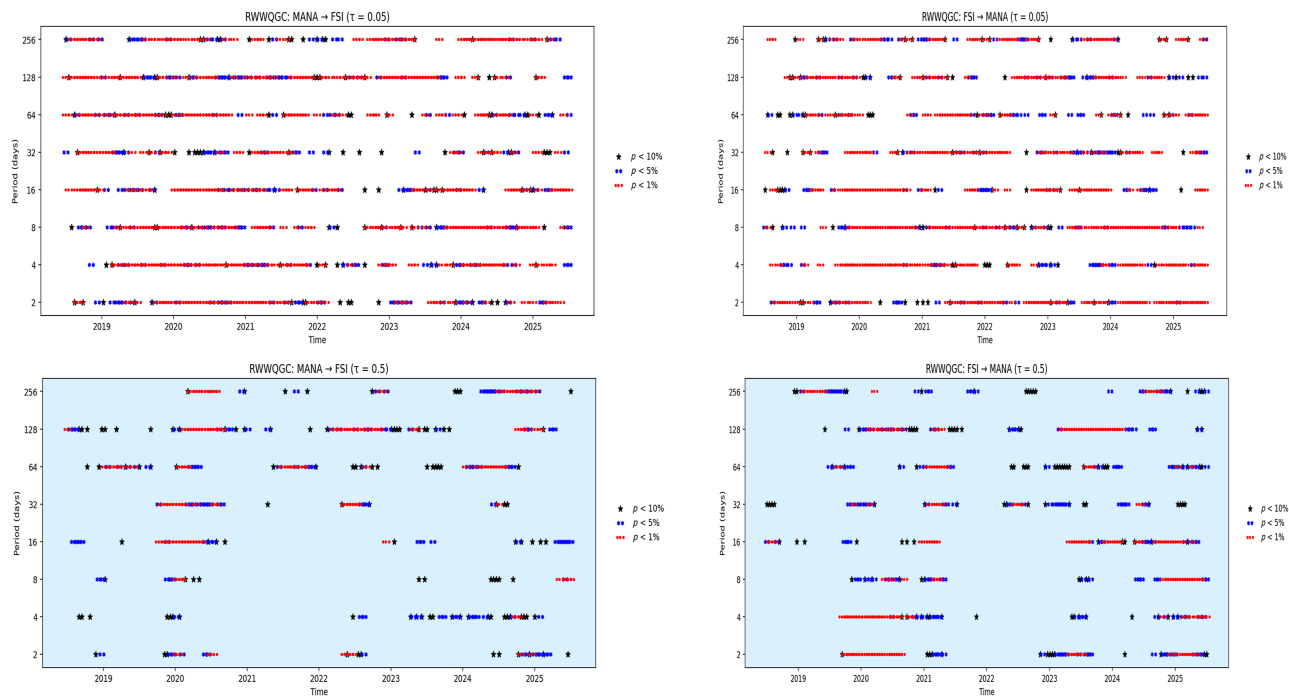


Figure 2. Time-frequency-quantile causal associations between FSI and NFTs. The window size is 250 and the step size is 10

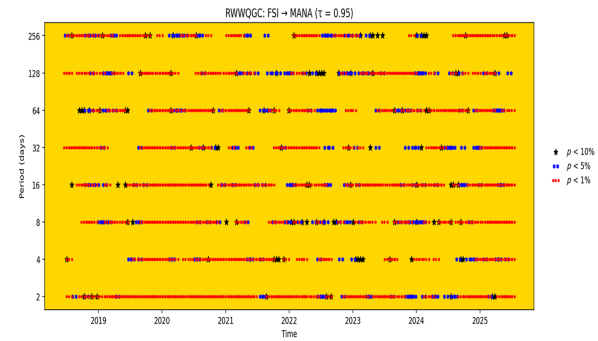
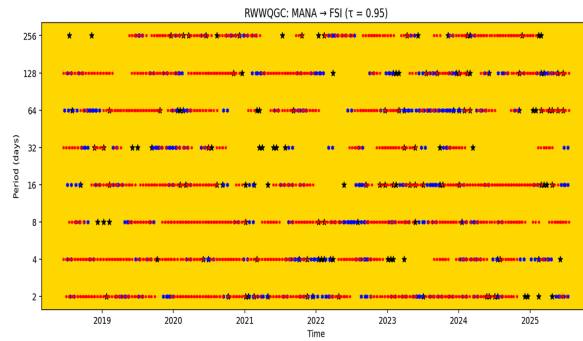


Figure 2. (continued)

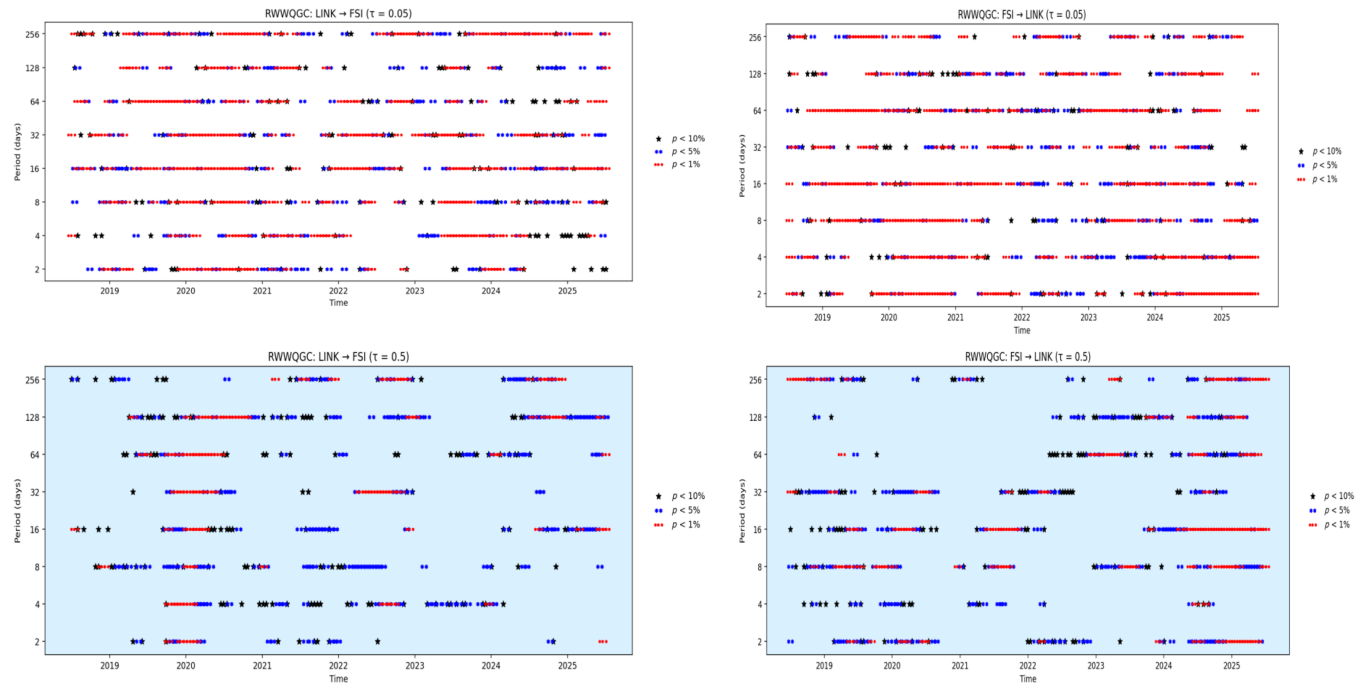


Figure 3. Time-frequency-quantile causal associations between FSI and DeFi. The window size is 250 and the step size is 10

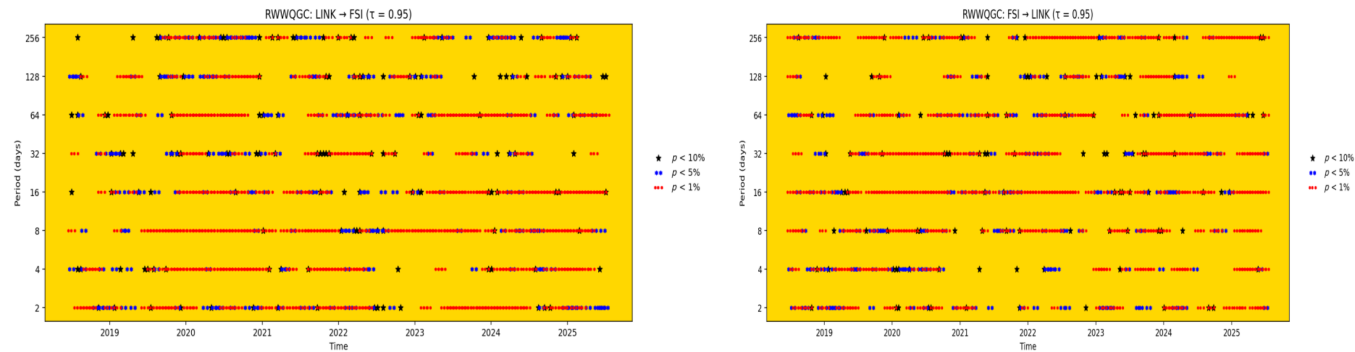


Figure 3. (continued)

During bearish market phases, the observed FSI→LINK causality suggests that FSI propagates into DeFi markets via liquidity contractions and forced deleveraging. As funding conditions tighten, investors withdraw from high-volatile assets, and the token-collateralized structure of DeFi amplifies price declines. Conversely, the significant LINK → FSI causality observed in these periods indicates that DeFi has evolved into a leading signal of systemic risk. Substantial repricing within DeFi markets often precedes broader financial strain, underscoring the existence of an integrated feedback mechanism between decentralized and traditional finance sentiment. On the other hand, in normal regimes, the weaker causal links in both directions point to a degree of separation between DeFi and the broader financial environment. Sector-specific factors tend to drive DeFi valuations, and LINK fluctuations carry less information about overall market stress.

In bullish regimes, the reemergence of broad bidirectional causality across multiple horizons aligns with the economic intuition of risk-on feedback loops. Improved financial conditions tend to foster speculative demand and capital inflows into DeFi, while pronounced DeFi rallies frequently fueled by leverage reflect heightened risk-taking consistent with overall market sentiment. Collectively, the LINK–FSI movements highlight a state-dependent and horizon-specific transmission process, with the strongest interdependence arising in extreme market conditions and significantly weaker connections during stable periods.

Overall, the results uncover that FSI-digital asset association is time-varying and state dependent. The RWWQGC tests demonstrate that causal associations are most pronounced and bidirectional during extreme market conditions, both bearish and bullish, while they become noticeably weaker and more fragmented under normal market regimes. These outcomes suggest that digital assets behave as risk-sensitive and sentiment-driven instruments whose integration with the broader financial system intensifies during extreme regimes. These results are consistent with prior studies documenting nonlinear and time-varying linkages between cryptocurrencies and macro-financial risk factors (Zhang & Wang, 2021; Bouri *et al.*, 2018) and reinforce evidence that digital assets fail to act as safe havens during periods of financial turmoil. By jointly accounting for time, frequency, and distributional asymmetries, this study extends the existing literature and provides a more comprehensive understanding of how financial stress shapes digital asset markets across different market conditions and investment horizons.

6.4 Robustness analysis

To further assess the robustness of the baseline findings, this study employs QQR approach as an alternative nonlinear estimation technique. While the RWWQGC framework captures state-dependent and time–frequency causality, it does not model how different segments of the digital asset return distribution respond to varying levels of financial stress. The QQR model addresses this limitation by jointly linking the conditional quantiles of digital asset returns with the quantiles of FSI, thereby allowing for a richer characterization of distributional heterogeneity and asymmetric dependence.

QQR is suitable as a robustness analysis because of the given the pronounced non-normality, excess kurtosis, and tail behavior observed in both financial stress and digital asset returns. By examining interactions across bearish, normal, and bullish market states under low-, medium-, and high-stress conditions, this approach verifies whether the nonlinear and tail-driven relationships identified in the main analysis persist across alternative empirical specifications. Consistent results across the RWWQGC and QQR frameworks would therefore strengthen the reliability of the study's conclusions regarding the stress transmission mechanism between the financial system and digital asset markets.

Figure 4 presents the QQR surface plots and corresponding p-value significance maps for the FSI–MANA, FSI–BTC, and FSI–LINK pairs, respectively.

Figure 4 illustrates QQR estimates between FSI and selected digital asset returns. For each asset, the left panel displays the three-dimensional QQR parameter surface, where elevated

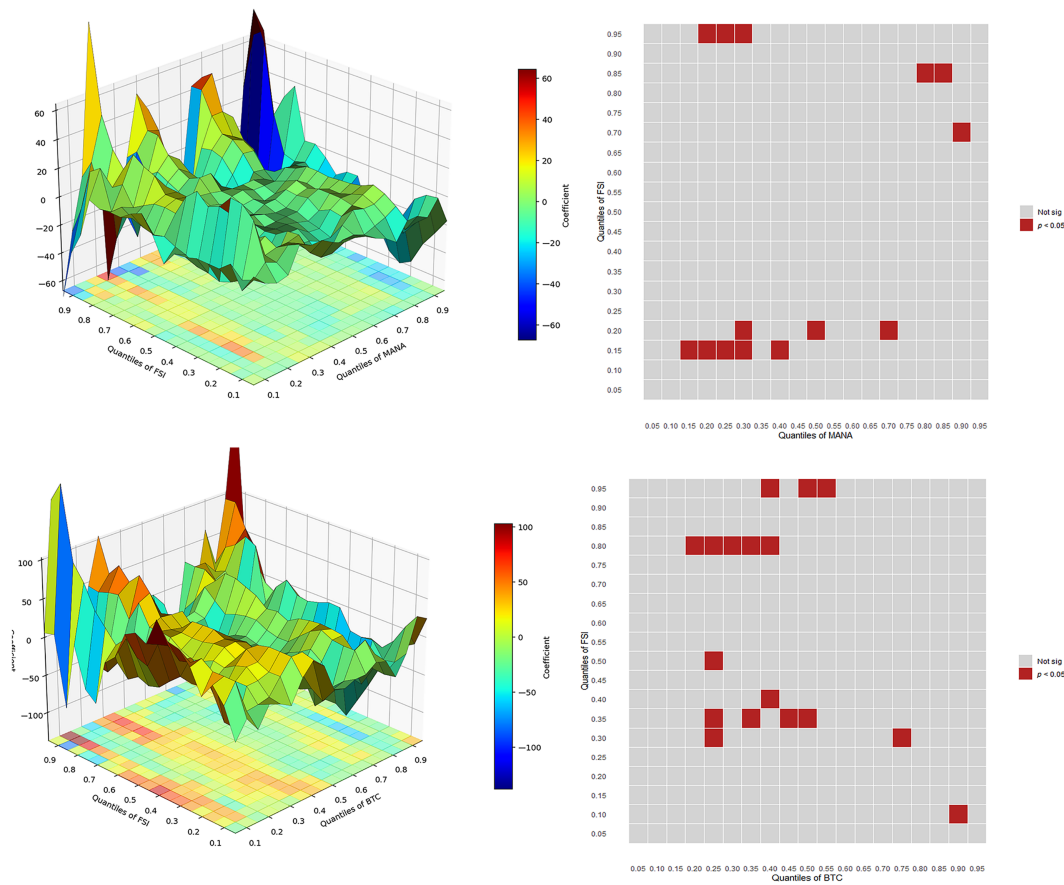


Figure 4. QQR between FSI and digital assets

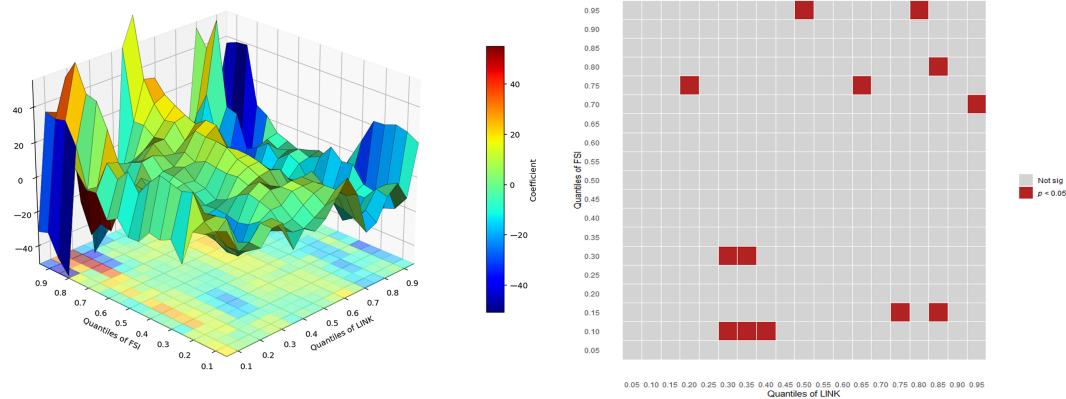


Figure 4. (continued)

regions (warm colors) indicate positive dependence and depressed regions (cool colors) indicate negative dependence across FSI and return quantiles. The right panel presents the corresponding significance map, where red cells denote statistical significance at the 5% level ($p < 0.05$) and gray cells represent non-significant parameter estimates.

For the FSI - MANA pair, the empirical estimates document a pronounced nonlinear and asymmetric dependence structure. The three-dimensional surface exhibits substantial amplitude shifts, particularly in the upper FSI quantiles, demonstrating that extreme financial stress generates amplified return responses in Decentraland. The corresponding p -value map indicates that statistical significance is concentrated predominantly in extreme quantile combinations, while middle quantile regions remain largely insignificant. This pattern confirms that the FSI - MANA relationship is state-dependent, materializing primarily during systemic tail events rather than normal market regimes. Rather than acting as a safe haven, MANA amplifies downside risk during crisis episodes, heightening portfolio vulnerability under elevated stress.

The FSI - BTC estimates similarly reveal a nonlinear and asymmetric dependence pattern across the joint distribution. Large positive parameter spikes emerge when upper FSI quantiles interact with lower-to-middle BTC return quantiles, while significant negative dependence materializes during moderate stress levels paired with low BTC returns. The significance heatmap confirms that meaningful co-movements concentrate within upper FSI quantiles and lower-to-middle BTC quantiles, leaving intermediate regions largely non-significant. Economically, these findings establish that Bitcoin does not serve as an unconditioned safe haven; rather, its exposure to macro-financial stress increases during market turmoil, eroding its diversification benefits precisely when financial instability intensifies.

The FSI - LINK nexus displays a nonlinear yet comparatively moderate dependence structure relative to Bitcoin. The three-dimensional parameter surface oscillates between positive and negative coefficients during high-stress episodes, but the magnitude is more dispersed across LINK return quantiles. High FSI quantiles induce positive coefficients at median LINK quantiles but negative coefficients at lower return quantiles. Statistically significant cells are dispersed across upper and lower quantile pairs without forming a concentrated cluster in upper stress regions, indicating that Chainlink exhibits a heterogeneous, less systematic response to systemic stress shocks.

Overall, the QQR robustness analysis confirms that systemic stress transmission to digital assets is governed by tail dependence and regime contingency. Across BTC, MANA, and LINK, statistically significant relationships concentrate within extreme quantile combinations, validating the premise that cross-market risk propagation intensifies during crisis episodes while underscoring substantial cross-asset heterogeneity.

6.5 Discussion

The empirical findings demonstrate that systemic risk transmission from FSI to digital asset returns is state-contingent, frequency-dependent, and distributionally asymmetric. The primary RWWQGC estimates document that directional predictability is heavily concentrated in tail quantiles, indicating that financial stress serves as a leading indicator primarily during market distress rather than tranquil periods. The QQR estimates validate these nonlinear tail dynamics across the joint distribution, establishing that the FSI-crypto nexus is governed by regime-specific dependencies rather than uniform mean-based relationships.

These empirical results support our theoretical hypotheses. Supporting H1, FSI exhibits statistically significant predictive power for BTC, LINK, and MANA returns under extreme bearish and bullish regimes, corroborating Bouri *et al.* (2018) while extending predictability to DeFi and NFT segments. H2 receives partial support, while causality concentrates at medium- and long-term horizons during tranquil periods, it shifts toward short-term frequencies during crisis episodes, confirming the multiscale transmission dynamics identified by Hoque *et al.* (2024). Supporting H3, stress transmission is markedly asymmetric, with predictive power

concentrated in lower return quantiles. In addition, LINK and MANA display more persistent downside exposure than BTC, reflecting their elevated speculative intensity and liquidity fragility (Zhang & Wang, 2021; Bastý & Abidly, 2025). Finally, supporting H4, significant reverse causality from digital assets to FSI emerges during market extremes, extending Yin *et al.* (2024) by showing that crypto distress transmits early-warning signals regarding macro-financial fragility.

Theoretically, these findings align with systemic risk, contagion, and behavioral finance paradigms, where shifting investor sentiment, liquidity contractions, and tightening margin constraints amplify cross-market spillovers during crisis regimes. Our results also corroborate and extend recent empirical literature. The horizon-specific spillovers mirror central bank digital currency (CBDC) uncertainty dynamics documented by Lü, Ozcelebi, and Yoon (2025), while the tail dependencies align with asymmetric ETF spillovers identified by Omri and Ozcelebi (2024). Furthermore, the corporate risk mediation channels observed by Liu and Guo (2026) explain the broader institutional transmission pathways, and the crisis-driven connectedness reinforces the quantile VAR evidence in Hedhili Zaier, Raggad, and Arfaoui (2026).

These insights reconcile conflicting evidence in the safe-haven literature (Hoque & Low, 2022; Aljughaiman *et al.*, 2025; Colombage *et al.*, 2025). Digital assets decouple from systemic risk factors during tranquil regimes but exhibit strong co-movements during crisis states (Zhang & Wang, 2021; Patra & Singh, 2025). Consequently, the diversification benefits of digital assets deteriorate precisely during systemic stress episodes when hedging is most required. Robustness tests re-estimating the RWWQGC model across alternative rolling windows of 200 and 300 observations reported in Appendix C (Figure C) confirm that the concentration of causality in tail states and the frequency-dependent transmission structure remain qualitatively invariant.

7. Conclusion

This study investigates the time-varying and quantile nexus between FSI and digital asset markets, with a particular focus on BTC, DeFi and NFT tokens. By employing the RWWQGC and QQR approaches, the analysis aims to uncover whether the transmission mechanism between FSI and digital assets is nonlinear, state-dependent, and concentrated in specific regions of the conditional distribution. Unlike traditional models, the present work accounts for tail behavior and regime heterogeneity, thereby providing a more comprehensive understanding of stress spillovers in digital asset markets.

Regarding theoretical contributions, this study demonstrates that the FSI–digital asset relationship cannot be adequately characterized by linear mean-based models. The time-varying and distributional framework adopted reveals that stress transmission is fundamentally episodic, state-contingent, and horizon-specific, properties that emerge when time, frequency, and quantile dimensions are examined jointly. These results enrich contagion theory by documenting that digital assets transition from partial market segmentation during normal regimes to systemic co-integration during extreme episodes, with the transition being sharp and regime-dependent rather than gradual.

The RWWQGC outcomes illustrate that the causal associations between FSI and digital assets are not uniform across time or market conditions. The association is nonlinear and concentrated in extreme markets, with stress levels affecting assets most during sharp downturns. Additionally, there is a clear divide in resilience: BTC exhibits comparatively greater resilience during periods of financial stress compared to DeFi and NFT tokens, although its sensitivity to systemic risk remains significant during extreme market conditions. Finally, the relationship is asymmetric, meaning financial stress drives prices down much more effectively than it helps them rise, disqualifying digital assets as reliable safe havens.

The QQR results further reinforce and validate the main findings obtained from the RWWQGC technique. It reveals that the impact of FSI on digital asset returns is highly

asymmetric and remarkably concentrated in the tails of the distribution. In particular, the most statistically significant effects emerge when digital assets lie in their lower quantiles and the FSI is in its upper quantiles, suggesting that heightened systemic stress amplifies downside risks in crypto markets. On the other hand, the dependence structure weakens significantly around the median quantiles, suggesting limited interaction under normal market conditions.

These findings carry important implications for investors, portfolio managers, and policymakers.

For portfolio managers and institutional investors, the regime-specific nature of FSI transmission implies that static diversification strategies based on average correlations are likely to fail during market turmoil. Risk management frameworks should incorporate dynamic, quantile-based hedging ratios that adjust as market conditions shift from normal to extreme states. The tail-concentration of significant FSI effects further suggests that Value-at-Risk and Expected Shortfall models for portfolios with digital asset exposure should use nonlinear and distribution-sensitive inputs rather than normality-assuming approaches.

For regulators and macroprudential authorities, the evidence of feedback transmission from DeFi and NFT markets to FSI under extreme conditions indicates that these segments are no longer peripheral to the broader financial system. Stress-testing frameworks and systemic risk monitoring dashboards should incorporate real-time DeFi and NFT market indicators as leading signals, particularly during periods of elevated global financial stress. The asymmetric and state-dependent integration documented here suggests that macroprudential buffers may need to be calibrated differently for periods of market exuberance versus crisis.

Despite its contributions, this study has several limitations. First, LINK and MANA serve as single-asset proxies for the DeFi and NFT markets, which may not fully capture the heterogeneity of these ecosystems. Future studies could employ market-wide indices as longer time series become available. Second, although RWWQGC and QQR effectively uncover nonlinear and distributional dependencies, they do not identify the underlying structural transmission channels. Future research may complement these findings using structural approaches, such as sign-restricted SVARs or narrative identification strategies. Finally, incorporating financial stress measures from multiple jurisdictions (European Systemic Risk Board indicators or the IMF Financial Conditions Index) would help determine whether the observed relationships reflect a global phenomenon.

Supplementary material

The supplementary material for this article can be found online.

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