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Tail risk connectedness between tokenized and traditional derivatives: Time-frequency analysis and portfolio insights

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ABSTRACT
This research explores the tail risk connectedness between tokenized and traditional derivatives while accounting for the portfolio implications. Using a quantile-based spillover approach, we reveal the presence of varying levels of tail risk spillover across different quantiles, with heightened contagion seen during extreme market conditions. We also observe the time-varying patterns of the risk transmission, indicating the influence of market events on the noted interconnectedness, while the VIX and SSR emerge as significant drivers of the tail risk contagion. Additionally, our portfolio analysis reveals the diversification benefits of combining tokenised and traditional derivatives, providing valuable insights for investors seeking to optimise the risk–return trade-offs for different investment horizons.

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1. Introduction

Derivatives have historically played a significant role in financial markets, providing essential functions such as liquidity provision, price discovery, and risk management. Derivatives are structured financial agreements whose pricing is linked to the movements of underlying variables such as assets, indices, or interest rates (Emm et al., 2022; Jin et al., 2022; Yousaf et al., 2024). They are important tools for managing financial risk, facilitating price discovery, and increasing market liquidity. Futures contracts, options contracts, forwards, and swaps are examples of common derivatives. Investors can use these instruments to speculate on price movements, hedge against adverse price changes, and diversify their portfolios. In recent years, the financial landscape has witnessed the emergence of derivative tokens – a novel class of digital assets that combine the characteristics of traditional derivatives with the technological advancements of blockchain and cryptocurrency platforms (Schär, 2021).[1] Unlike Non-Fungible Tokens (NFTs), derivative tokens are digital representations of derivative contracts that

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utilize smart contracts and blockchain infrastructure to enable the trading and settlement of derivatives in a decentralised and transparent manner.

Derivative tokens represent a digital evolution of traditional derivatives, harnessing blockchain and smart contract technology for automated execution and transparency (Schär, 2021; Yousaf et al., 2024). They promise broader market access and increased inclusivity that transcend geographical constraints. Transparency and efficiency are bolstered through public ledger records and streamlined processes, while innovation opens doors to novel functionalities like decentralised finance (DeFi) integration.[2] Nonetheless, regulatory frameworks are still taking shape, varying across jurisdictions and necessitating careful oversight as these digital assets continue to reshape financial markets (Lo & Medda, 2020).

Derivative tokens offer several advantages over traditional derivatives. First, they leverage the benefits of blockchain technology, such as immutability, transparency, and increased efficiency in trade execution and settlement (Laroiya et al., 2020). Second, the use of blockchain technology enables global accessibility, removing geographical barriers and allowing investors from around the world to participate in derivative markets. Third, these tokens provide exposure to a diverse range of underlying assets, including cryptocurrencies, commodities, indices, and even real-world assets through tokenisation. This expands the investment universe and allows for innovative strategies and portfolio diversification.

Considering the growing concerns and attention of derivative tokens, this research explores the tail risk spillover between tokenised and traditional derivatives. Tail risk pertains to the potential occurrence of extreme and unforeseen events, typically situated at the extremes of the probability distribution (the "tails" of the distribution) (Chatziantoniou et al., 2022b; Kelly & Jiang, 2014; Naeem et al., 2023). These events could result in significant losses or gains in financial terms and are typically distinguished by their low probability of occurrence. In finance and investment, understanding and managing tail risk are critical. Traditional derivatives, such as options and futures, have proven to be effective tools for managing and mitigating tail risk (Bohmann et al., 2019; Qiao & Han, 2023). These instruments are used by investors and institutions to hedge against adverse price movements and to protect their portfolios from unexpected events. They attract a broader range of investors, because they are more accessible and tradeable on blockchain platforms. Sudden and significant price swings in the underlying assets impact the value of derivative tokens, potentially resulting in substantial gains or losses. Therefore, comprehending tail risk and identifying the determinants are important for investors to make informed decisions, construct balanced portfolios, and employ appropriate risk management strategies in the rapidly evolving landscape of digital finance.

Tail risk spillover effects emerge from the interconnected mechanisms in financial markets, which are amplified by the increasing integration of the markets. Moreover, the growing prominence of both decentralised finance and blockchain technology facilitates the convergence of tokenised and traditional derivatives (Abdullah et al., 2023b; Ersan et al., 2022). Extreme events, such as sharp market corrections or regulatory changes, can have cascading effects that impact tokenised and traditional derivatives. Market integration theory offers a theoretical lens for understanding these dynamics, positing that financial markets are not isolated but rather interrelated, with the integration levels varying over time (Liow & Song, 2022). During periods of heightened integration, shocks and information are transmitted rapidly across tokenised and traditional derivatives, driven by both technological advancements and the global financial system's growing interconnectedness. While derivative tokens are a relatively recent innovation, their structural and functional similarities to traditional derivatives foster a strong degree of interconnectedness among them. Despite the increasing interest in crypto-tokenised assets (e.g., energy tokens, fan tokens, borrowing tokens, tourism tokens, healthcare tokens) and cryptocurrencies in terms of enhancing the risk–return profile of alternative and traditional asset portfolios (e.g., Abdullah et al., 2023b; Bouri et al., 2017; Corbet et al., 2018; Kajtazi & Moro, 2019; Yousaf et al., 2022a; Yousaf et al., 2022b; Yousaf et al., 2023a; Yousaf et al., 2022c), the specific relationship between derivative tokens and traditional derivatives remains underexplored.

Drawing from theoretical underpinnings and identified gaps in the literature, this research investigates the tail risk spillover between tokenised and traditional derivatives, providing insights into the uncertainty factors influencing the spillover and portfolio benefits. For empirical analysis, we first use six derivative tokens and three traditional derivative datasets. We next employ Conditional Autoregressive Value at Risk (CAViaR) to assess the asset-level downside risk and the time-frequency quantile vector autoregression (TF-QVAR)-based connectedness approach to examine the tail risk connectedness. Finally, we employ a minimum connectedness portfolio approach for portfolio analysis.

Our empirical analysis reveals time-varying tail risk transmission dynamics across different quantiles. In the lower quantile, assets like HGET and SPOPTIONS play key roles, offering diversification potential due to lower interconnectedness. The mid-quantile exhibits persistent patterns, while the upper quantile shows increased risk transmission during extreme market conditions, highlighting the need for robust risk management. Dynamic connectedness analysis reflects fluctuations tied to major events, emphasising the influence of economic events on risk transmission. Moreover, the influence of uncertainty elements on tail risk contagion shows a significantly positive influence on the middle and upper quantiles. Finally, portfolio analysis shows that combining tokenised and traditional derivatives may provide diversification benefits, with optimal weights varying for short- and long-term investment horizons.

Several meaningful contributions are made to the literature through this research. First, it extends the discourse on the interconnectedness between crypto-based tokens and traditional assets. Unlike other studies focusing on other crypto-tokens (e.g., Ersan et al., 2022; Yousaf et al., 2022b; Yousaf et al., 2023a), our research broadens this scope by specifically investigating the connectedness between derivative tokens and traditional assets. Specifically, different from Yousaf et al. (2024) we explore extreme tail risk spillover across different time frequencies using a TF-QVAR-based connectedness technique. By analysing the dynamic nature of connectedness, we shed light on the changing patterns of risk transmission and the influence of market events on the interconnectedness of derivative tokens and traditional assets.

Second, while most related studies focus on return or volatility connectedness (Abdullah et al., 2023b), our study expands the literature on derivative tokens by examining tail risk spillover. By analysing the transmission of tail risk between derivative tokens and traditional assets, we offer insightful information on tail risk dynamics and its potential contagion effects. This unique perspective enhances our understanding of the interconnectedness between these assets and provides insights into the systemic risks that may emerge during extreme market conditions.

Third, our exploration of the drivers of tail risk spillover reveals crucial insights for investors and regulators alike. By highlighting the substantial impact of variables like VIX and SSR, our study equips investors with a deeper understanding of potential contagion effects across various market conditions. Furthermore, these findings can assist regulators in crafting customised regulations for derivative tokens within the digital finance era, thereby fostering market stability and enhancing investor protection. Ultimately, our research enhances decision-making capabilities and bolsters regulatory measures in the dynamically evolving realm of digital finance.

Finally, we broaden the literature by comprehensively analysing short-term and long-term portfolio dynamics. While other research has often focused on minimum variance-based portfolio (Abdullah et al., 2023b; Yousaf et al., 2024), we recognise the importance of considering both investment horizons based on minimum connectedness portfolio (Broadstock et al., 2022). By examining the optimal portfolio weights and performance metrics across different time frames, we provide valuable insights for investors seeking to balance their risk and return objectives over different holding periods.

The organisation of the paper proceeds as follows. Section 2 provides a review of the relevant literature, while Section 3 elaborates on the empirical strategy and modelling techniques employed in the analysis. The empirical dataset underpinning the analysis is detailed in Section 4, followed by the presentation of key findings in Section 5 and a discussion of policy implications in Section 6.

2. Literature review

There is a growing body of crypto-based token literature. Conlon et al. (2024) examine FTT Token's role in price discovery during FTX's financial decline, revealing its informational lead over assets like Ethereum and interactions with Robinhood shares and Serum. Yousaf et al. (2024) find significant spillovers between major cryptocurrencies and derivative tokens, particularly during stressed periods, with Ethereum exerting more influence than Bitcoin.

Abdullah et al. (2023a) assess the extent of tail risk interdependence between tech-industry tokens and equity investments, find moderate time-varying interconnectedness, and identify global uncertainty factors driving contagion with implications for portfolio diversification. Guan et al. (2024) explore Metaverse tokens, highlighting trading volume's role in return dynamics, documenting lead-lag effects among token clusters, and suggesting volume as a key predictor of cross-correlation patterns. Swinkels (2024) investigates blockchain-based trading of voluntary carbon credits, noting limited liquidity but alignment of token prices with broader market trends and offering insights into carbon market innovations. Zhang et al. (2019) analyse ICO white-paper readability's impact on initial returns, finding that clearer disclosures correlate with higher investor returns. Proelss et al. (2023) examine GameFi, detailing its unique blend of blockchain, tokens, DeFi, and NFTs, as well as the social dynamics within play-to-earn games, while also outlining challenges in this emerging sector.

Kreppmeier et al. (2023) explore real estate security token offerings and secondary markets, highlighting how tokens provide fractional ownership and low entry barriers and expand real estate ownership to a broader base of small investors. The interconnected behaviour of returns and volatility among real estate tokens, REITs, and other assets are evaluated by Abdullah et al. (2023a). They provide evidence of a fluctuating increase over time in the nexus between real estate tokens and REITs.

Beyond real estate tokens, other studies have also explored the interconnectedness of various tokenised assets with their traditional counterparts in different sectors. Ersan et al. (2022) examine the dynamic interlinkages between fan tokens and football club stocks, showing that fan tokens act as prominent channels for shock transmission to both asset types. Aharon and Demir (2022) explore how NFTs interact dynamically with broader financial markets, suggesting NFTs could provide portfolio diversification benefits due to their independence from financial asset shocks.

Building on this line of inquiry, a growing body of literature has assessed the interconnectedness within other tokenised sectors. Yousaf and Yarovaya (2022) explore how returns and volatilities are transmitted between emerging digital assets – such as NFTs and DeFi – and traditional financial assets, reporting weak spillovers and diversification benefits during the initial period of the COVID-19 pandemic. Other researchers have also addressed cross-sector connectedness among tourism tokens and stocks, healthcare tokens and equities, renewable energy tokens and fossil fuel assets, AI-linked tokens and equities, and tokens and equities in the asset management industry. Each one sheds light on the interdependencies within these asset classes (Jareño & Yousaf, 2023; Yousaf et al., 2022a; Yousaf et al., 2022c; Yousaf et al., 2023b).

The recent literature highlights the growing importance of DeFi and the role of Automated Market Makers (AMMs) in enabling decentralised exchange (DEX) functionality. For instance, Mohan (2022) conceptualises AMMs using a neoclassical framework, treating them as systems that transform token inputs into price outputs based on an underlying exchange function. His work categorises various AMM models, including the constant product, constant mean, constant sum, hybrid, and dynamic types, and he emphasises the implications of concentrated liquidity for the shaping of market dynamics. Complementing this, Aspris (2021) analyses the distinct trading environments of centralised versus decentralised exchanges. His findings indicate that while decentralised platforms dominate the initial trading of tokens, the transition to centralised exchanges typically leads to an increased trading volume and greater liquidity, underscoring market participants' preference for more liquid, centralised markets despite the enhanced privacy offered by decentralised ones.

The above studies overall clearly show a dynamic relationship between tokens and traditional assets. However, the interconnection between tokenised and conventional derivatives remains underexplored in academic research. This study addresses this gap by presenting the tail risk spillover between tokenised and traditional derivatives, offering insights into the impact of uncertainty factors on this spillover and the potential portfolio benefits it may entail.

3. Methodology

We employ three robust estimation approaches for our empirical analysis. First, asset-level downside tail risk is measured using the CAViaR methodology. Second, tail risk connectedness is examined through a TF-QVAR-based spillover framework. Finally, a minimum connectedness portfolio strategy is employed to conduct portfolio analysis.

3.1. CAViaR model

We utilise the CAViaR model, following the technique outlined in Chatziantoniou et al. (2022b), to assess downside tail risk for tokenised and traditional derivatives. Specifically, we implement Engle and Manganelli's (2004) asymmetric slope CAViaR technique, which enables direct estimation of Value-at-Risk (VaR). In contrast to other studies that estimate VaR by initially modelling return distributions and then indirectly deriving quantiles, the mentioned approach offers greater flexibility by accounting for asymmetric effects. Such flexibility is not incorporated in either the symmetric absolute value specification or the indirect GARCH(1,1) model. Additionally, the VaR at a particular quantile is modelled as an autoregressive process, represented by the following equation:

$$f_{\alpha,t}(\beta) = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^{+}_{t-1} + \beta_3 x^{-}_{t-1} \tag{1}$$

In this context, $f_{\alpha,t}$ represents VaR at a specific confidence level α, which in our case is set at 5% to measure downside risk on day t. The model incorporates a constant term, denoted as β_0. β_1 represents the coefficients for lagged VaRs, and $f_{\alpha,t-1}(\beta)$ represents the lagged VaRs themselves. β_2 and β_3 account for the asymmetric influence of positive and negative returns on VaR.

3.2. TF-QVAR approach

We use the TF-QVAR-based connectedness technique to examine the tail risk connectedness between tokenised and traditional derivatives. This method has the advantage of capturing the quantile propagation mechanism and is suitable for fat-tailed datasets like ours. Specifically, we adopt the framework proposed by Chatziantoniou et al. (2022a) that builds upon the seminal work of Diebold and Yılmaz (2012; 2014). Unlike traditional rolling-window approaches, the quantile connectedness method captures asymmetries in risk transmission by focusing on extreme positive and negative shocks across different quantiles. This is particularly relevant for tail risk analysis, where standard models such as Bayesian VAR or TVP-VAR may not adequately reflect distributional dependence during extreme events. By integrating quantile-based analysis with frequency-domain decomposition, the TF-QVAR model offers a more detailed view of how short- and long-term shocks drive interconnectedness. This renders it a suitable and robust choice for examining the complex, non-linear relationships between tokenised and traditional derivatives, especially under volatile market conditions.

Building upon the spectral decomposition framework of Stiassny (1996), we investigate the interconnectedness relationship across different time frequencies. Initially, we examine the frequency response function denoted as $\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega}\Psi_h$, where i stands for the imaginary unit, whereas ω represents the frequency. The spectral density of x_t at a given frequency ω is subsequently characterised as the Fourier transform of the $QVMA(\infty)$ representation:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_i x'_{t-h})e^{-i\omega h} = \Psi(e^{-i\omega h})\Sigma_t \Psi'(e^{+i\omega h}) \tag{2}$$

The spectral density $S_x(\omega)$ combines the frequency response characteristics with the GFEVD. For comparability, we normalise the frequency-domain decomposition as follows:

$$\theta_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1} \, |\Sigma_{h=0}^{\infty} \Psi_h(e^{-i\omega h})\Sigma(\tau))_{ij}|^2}{\Sigma_{h=0}^{H}((\Psi_h(e^{-i\omega h})\Sigma(\tau)\Psi(\tau)(e^{i\omega h}))_{ij}} \tag{3}$$

$$\tilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\Sigma_{k=1}^{N} \; \theta_{ij}(\omega)} \tag{4}$$

Furthermore, to evaluate connectedness over specific frequency bands, we aggregate the spectral measures within the interval ($d = (a, \; b)$: $a, b \in (-\pi, \; \pi)$, $a < b$:), as defined below:

$$\tilde{\theta}_{ij}(d) = \int_a^b \tilde{\theta}_{ij}(\omega)d\omega \tag{5}$$

Through this procedure, we derive connectedness indicators across the frequency domain, akin to the methodology of Diebold and Yılmaz (2012; 2014), which facilitate the examination of spillover effects over distinct frequency ranges (d):

$$NPDC_{ij}(f) = \tilde{\theta}_{ij}(d) - \tilde{\theta}_{ji}(d) \tag{6}$$

$$TO_i(d) = \sum_{i=1, i \neq 1}^{N} \tilde{\theta}_{ji}(d) \tag{7}$$

$$FROM_i(d) = \sum_{i=1, i \neq 1}^{N} \tilde{\theta}_{ij}(d) \tag{8}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{9}$$

$$TCI(d) = N^{-1} \sum_{i=1}^{N} TO_i(d) = N^{-1} \sum_{i=1}^{N} FROM(d) \tag{10}$$

In line with Chatziantoniou et al. (2022a), we define two distinct frequency bands: i) a short-term horizon corresponding to 1 to 5 days (weekly), represented by $d_1 = (\pi/5, \; \pi)$; and ii) a long-term horizon covering 6 days and beyond, represented by $d_2 = (0, \; \pi/5)$. The model implements a 126-day rolling window to reflect a biannual trading period, with a forecasting horizon of 20 days.

3.3. Portfolio analysis approach

We conduct a portfolio evaluation by calculating the optimal portfolio weights and hedge ratios for the combinations of tokenised and traditional derivatives. To develop a bivariate portfolio we employ minimum connectedness portfolios of Broadstock et al. (2022), who allocate portfolios based on the pair-wise connectedness index. Subsequently, we apply the frameworks of Kroner and Ng (2015) and Kroner and Sultan (1993) to derive the optimal portfolio weights and hedge ratios.

4. Data and sample

We select the top six derivatives tokens based on their extensive data availability and market capitalisation: Hegic (*HEGIC*), Hedget (*HGET*), PowerTrade Fuel (*PTF*), Synthetix (*SNX*), Serum (*SRM*), and UMA (*UMA*).[3] *HEGIC* is associated with decentralised options, allowing users to create and trade options contracts on the Ethereum network. *HGET* is another decentralised options platform, providing hedging and risk management solutions. *PTF* is linked to the PowerTrade mobile crypto options trading platform, facilitating options trading and management on mobile devices. *SNX* operates a decentralised protocol enabling the creation and trading of synthetic assets that mirror the value of real-world assets. *SRM* is the native utility token of Serum - a decentralised exchange and ecosystem built on the Solana blockchain, providing fast and low-cost trading services. *UMA* powers the UMA protocol, enabling the creation of synthetic assets and financial contracts through its decentralised platform. The derivatives tokens hold considerable significance by providing decentralised options, hedging solutions, and synthetic asset creation in the rapidly evolving cryptocurrency and blockchain ecosystem. Thus, examining these assets' tail risk connectedness provides valuable information for regulators and investors.

We choose E-mini S&P 500 index futures (*SPFUTURE*), S&P 500 exchange-traded funds (*SPETF*), and S&P 500 index options (*SPOPTIONS*) as traditional derivatives. The sample period of our study spans from 28 September 2020 to 26 May 2023. The starting period is determined by data availability for *PTF*. Data for the derivatives tokens are from the website of CoinMarketCap (https://coinmarketcap.com/), while data for traditional derivatives are from Datastream. The sample period encompasses some major crises, like COVID-19, Russia-Ukraine war, FTX collapse, and Silicon Valley Bank collapse. Analysing the tail risk spillover during these crises gives valuable insights into the behaviour and interdependencies of derivatives tokens and traditional assets under extreme market conditions.

4.1. Tail risk and summary statistics

We employ the CAViaR method to capture the downside tail risk at the 5% level. Fig. A1 illustrates the downside tail risk of tokenised and traditional derivatives. The results reveal several similar low points across the assets during the third phase of the COVID-19 pandemic, Russia-Ukraine war, and FTX collapse, except for UMA. We assess the changes in tail risk by measuring daily percentage change and present results and corresponding discussions in the ***Supplementary Material A***.

4.2. Data on uncertainty factors

Our secondary goal is to investigate the impact of uncertainty variables on the transmission of extreme risks in tokenised and traditional derivatives. Thus, following extant literature (Abdullah et al., 2023b; Ma et al., 2022), the Volatility Index (VIX) is utilised as an indicator of fear and greed, the U.S. shadow short rate (SSR) serves as a proxy for changes in monetary (Krippner, 2020), geopolitical risk index (GPRI) is used as a proxy for geopolitical risk (Caldara & Iacoviello, 2022), and economic policy uncertainty index (EPU) is employed as an indicator of economic uncertainty (Baker et al., 2016).[4] Overall, through the incorporation of multiple uncertainty measures, we evaluate the intensity of market distress – capturing fear, panic, and uncertainty – and its role in driving tail risk spillovers between tokenised and traditional derivatives.

5. Results

5.1. Static connectedness results

We begin our spillover analysis by presenting the lower quantile ($\tau = 0.05$) results. The findings are summarised in Table B1 of the ***Supplementary Material B***, displaying the averaged connectedness results across overall, short-term, and long-term frequencies. The diagonal elements capture idiosyncratic risk, reflecting shocks attributable to the asset's own variance, while the off-diagonal values represent the spillover from other assets in the network. For example, HGET exhibits the highest own variance share spillover at 56.27%. Of this, 48.25% represents short-term own-variance spillover, while 8.02.49% corresponds to long-term own-variance spillover. This result indicates that HGET is sensitive to immediate market dynamics and has less exposure to long-term trends and structural changes. The FORM column represents spillover from other assets in the network, indicating highest spillover received by SPOPTIONS (78.49%), where 67.67% is received in the short term and rest at 10.82% received in the long term. The TO row presents the result of spillover to other assets in the network, indicating SPOPTIONS (96.36%) risk transmitted towards other assets, where 83.08% is attributed to short-term frequency and 13.27% to long-term frequency. This suggests that SPOPTIONS plays a critical role in risk propagation, particularly in the short term, warranting focused attention and risk management strategies within the network.

Net spillovers are summarised in the NET row, where negative entries denote risk receivers and positive ones indicate risk transmitters. Here, HGET is identified as the major receiver of shocks in the lower quantile, while SPOPTIONS is the major transmitter. Interestingly, the results also reveal that the transmission of risk spillover is higher for the short term than for the long term. This suggests that SPOPTIONS serves a pivotal function in transmitting risk to other assets over short time horizons. On the other hand, HGET is more susceptible to receiving risk spillover from other assets, indicating its vulnerability to shocks and disturbances in the market. These findings align with earlier studies (Abdullah et al., 2024; Shao et al., 2024; Vidal-Tomás, 2024), who also document lower spillover levels among tokens and traditional assets. The total connectedness index (TCI) result indicates a lower level of connectedness at 67.78% across the assets, suggesting lower tail risk contagion within the network in the lower quantile. This lower interconnectedness could offer portfolio diversification benefits, as shocks are anticipated to have a more contained impact, thus contributing to a more stable and resilient investment portfolio.

We illustrate the risk transmission using a network connectedness plot to better understand the risk-sharing mechanism. The results for the extremely low ($\tau = 0.05$) quantile appear in Figure 1. This figure represents each asset as a node, and the connections between assets are depicted using arrows. The thickness of the arrows indicates the intensity of the risk transmission between assets. Additionally, the nodes are coloured blue (transmitter) or yellow (receiver) to represent their role in spillover.

The result shows that most shocks are transmitted from SPFUTURE, SPETF, and SPOPTIONS. On the other hand, HGET and HEGIC are the assets that receive the most risk. The results for short-term and long-term connectedness indicate similar risk transmission mechanisms. They denote a distinct pattern, where traditional derivatives primarily function as risk transmitters, while tokenized derivatives, for the most

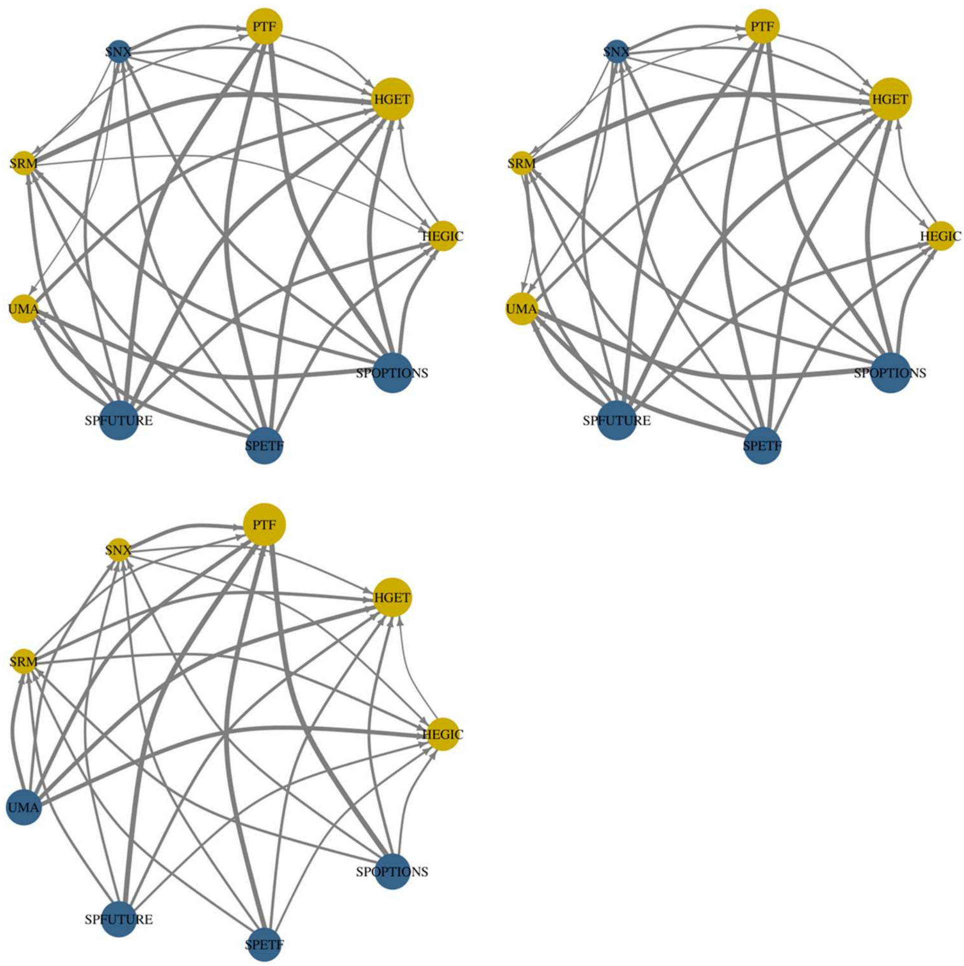

Figure 1. Visualised network of connectedness ($\tau = 0.05$).

Note: Figure 1 presents the connectedness measures across different time horizons: total, short-term, and long-term, respectively. Results are based on a 20-step-ahead GFEVD using a TF-QVAR model with a 126-day rolling window and one lag (AIC). Blue colour denotes transmitters and yellow colour denotes receivers.

part, act as risk receivers. This divergence in risk roles suggests that tokenised derivatives may serve as a valuable risk management tool within the portfolio, potentially offering a hedge against downside risk emanating from traditional derivatives.

Table B2 of the ***Supplementary Material B*** presents the results of the mid-quantile ($\tau = 0.50$) spillover analysis. The diagonal value indicates that HGET exhibits the highest proportion of its own variance spillovers at 83.16%. Within this, 71.55% corresponds to short-term own-variance spillover, while 11.61% represents long-term own-variance spillover. In terms of FROM, SPFUTURE receives the highest share at 70.68%, with 60.88% received in the short term and 9.80% in the long term. Conversely, the TO result shows that SPETF transmits the highest spillover of 79.15% to other assets in the network. The NET result reveals that SPETF acts as the major net transmitter of risk, accounting for 8.78% of risk transmitted to other assets, with 7.22% in the short term and 1.56% in the long term. Notably, PTF is identified as the primary recipient of shocks (-8.31%) in the mid-quantile.

The findings interestingly show that short-term risk spillover exceeds long-term transmission, which is consistent with lower quantile results. This aligns with studies by Ersan et al. (2022) and Abdullah et al. (2023), who also observe lower spillover levels between tokens and traditional assets. The TCI result underscores a lower level of interconnectivity at 44.62% among the assets, indicating lower tail risk contagion within the network in the mid-quantile.

Figure 2 visually illustrates the network of connectedness in the mid-quantile, highlighting SPFUTURE, SPETF, and SPOPTIONS as primary transmitters of shocks, while HEGIC primarily receives risk. The short-term connectedness results align with this risk transmission pattern, but the long-term results indicate that certain tokens are less susceptible to shocks. This reduced interconnectedness suggests potential diversification advantages, as shocks are anticipated to have a more contained impact, enhancing portfolio stability and resilience. These findings imply that the correlation between tokenised and traditional derivatives is weaker in the mid-quantiles, offering potential benefits for portfolio diversification.

Table B3 of the ***Supplementary Material B*** displays the findings from the analysis of upper quantile ($\tau = 0.95$) spillovers. SNX is highlighted as having the highest share of its own variance spillovers, accounting for 12.49%. This self-spillover comprises 10.79% in the short term and 1.70% in the long term. SPFUTURE, in the FROM results, receives the most significant share at 89.59%, with 77.06% in the short term and 12.53% in the long term. Conversely, the TO results reveal that SNX transmits 97.71% of spillovers to other assets in the network. In terms of net transmission, SNX plays a central role, accounting for 10.20% of risk transmitted to other assets. Notably, HEGIC stands out as the primary recipient of shocks at −10.24% within the upper quantile.

An interesting observation is that short-term risk spillovers outweigh long-term transmissions, which is consistent with lower and mid-quantile outcomes. These findings are consistent with the research conducted by Abdullah et al. (2023), who also report reduced spillover levels between tokens and traditional assets. The TCI results indicate higher interconnectivity at 88.44% among the assets within the upper quantile, signifying significant tail risk contagion within the network. It further implies during periods of extreme market stress or shocks that the interconnectedness among these assets is notably pronounced, potentially amplifying the adverse effects of adverse events. For investors,

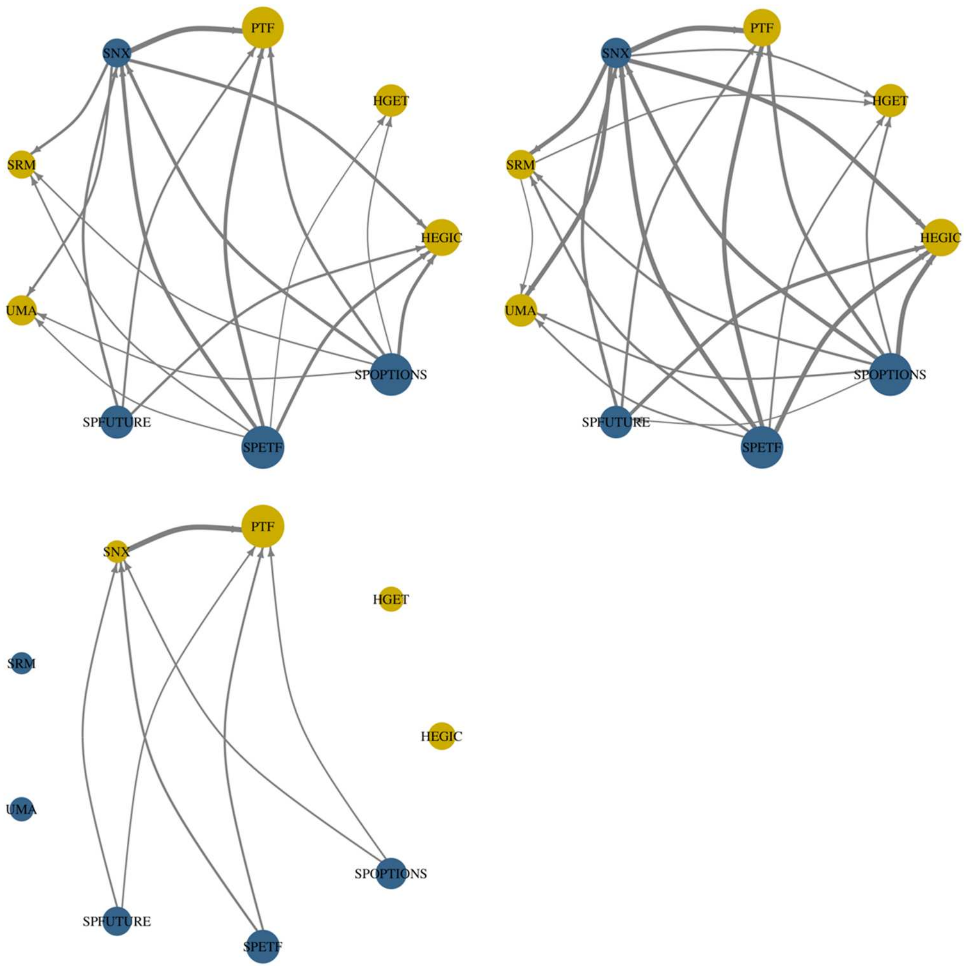

Figure 2. Visualised network of connectedness ($\tau = 0.50$).

Note: Figure 2 presents the connectedness measures across different time horizons: total, short-term, and long-term, respectively. Results are based on a 20-step-ahead GFEVD using a TF-QVAR model with a 126-day rolling window and one lag (AIC). Blue colour denotes transmitters and yellow colour denotes receivers.

this emphasises the significance of conducting thorough assessments and effectively managing risks when constructing portfolios, particularly in the upper quantiles, where the potential for contagion is more pronounced.

Figure 3 provides a visual representation of the connectedness network in the upper quantile, with SNX and SRM emerging as primary transmitters of shocks, while SPOPTIONS and SPFUTURE predominantly act as risk receivers. Interestingly, this network structure contrasts with the patterns observed in the lower and mid-quantiles. The implications are twofold. First, in the upper quantile, risk transmission dynamics are more concentrated among specific assets, potentially leading to heightened market volatility during extreme events. Second, this distinction highlights the importance of tailoring risk management and diversification strategies to the specific quantile, as the risk transmission landscape can vary significantly across different market conditions and quantiles.

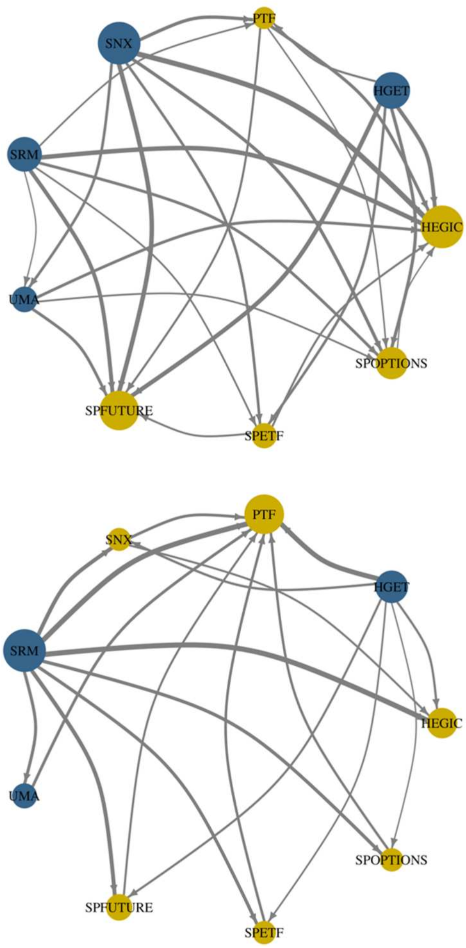

Figure 3. Visualised network of connectedness ($\tau = 0.95$).

Note: Figure 3 presents the connectedness measures across different time horizons: total, short-term, and long-term, respectively. Results are based on a 20-step-ahead GFEVD using a TF-QVAR model with a 126-day rolling window and one lag (AIC). Blue colour denotes transmitters and yellow colour denotes receivers.

The result overall suggests short-term spillover is greater than long-term spillover. There is less contagion effect in the lower and mid-quantiles, suggesting potential portfolio diversification benefits. In contrast, there is significant contagion in the extreme upper quantile. These findings imply that incorporating derivatives tokens into investment portfolios can potentially help investors reduce risk and enhance diversification across lower and mid-quantiles. Our findings are in line with Abdullah et al. (2023b) and Yousaf et al. (2022a), who note similar patterns of diversification benefits for other tokens and traditional assets.

5.2. Dynamic connectedness results

The aforementioned analysis offers a static perspective on connectedness; however, it fails to consider the time-varying nature of connectedness. To address this limitation, we shift our focus to dynamic connectedness measures. The results of TCI across different quantiles (τ = 0.05 to 0.95) are in Figure 4, depicting both static and dynamic TCI. The static TCI results clearly demonstrate asymmetry in connectedness, with the extreme quantiles showing higher values than the mid-quantile. This finding is consistent with our previous static analysis. Additionally, the dynamic TCI reveals periods of increased connectedness during various economic events, such as the third phase of COVID-19, Russia-Ukraine war, and the recent SVB collapse. It is unsurprising to observe such a peak during a major global crisis, as market shocks and disruptions typically propagate across various assets, resulting in heightened interconnectedness. The time-varying and event-dependent nature of TCI is in line with (Abdullah et al., 2023b), who find economic events have a significant impact on the connectedness between tokens and traditional assets. These dynamic fluctuations highlight the changing nature of interconnectedness among the assets and the influence of significant events on the risk transmission within the network.

We next analyse the net directional connectedness across quantiles. The overall directional connectedness result appears in Figure 5, while the short-term and long-term directional connectedness results are in Figures. C1 and C2 of the ***Supplementary Material C***, respectively. The negative (positive) values in the results indicate the receiver (transmitter) of risk spillover, and the roles of assets in transmission can change over time and across quantiles. The findings reveal that traditional derivatives such as SPFUTURE, SPETF, and SPOPTIONS act as net transmitters of shocks in extreme quantiles. Other variables show lower levels of transmission, which is consistent with our static analysis results and indicates a decoupling or weaker interconnectivity between tokenised and traditional derivatives. Additionally, the intensity of risk spillover appears to be higher during the COVID-19 period and Russia-Ukraine war, highlighting the event-dependent nature of risk transmission. The results for short-term and long-term analyses

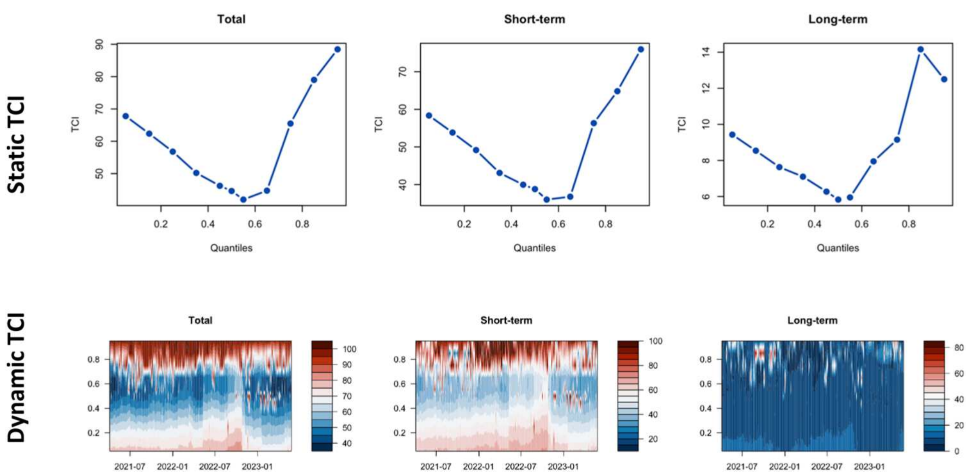

Figure 4. Cross-quantile comparison of static and dynamic connectedness.

Note: Figure 4 presents the connectedness measures across different time horizons: total, short-term, and long-term, respectively. Results are based on a 20-step-ahead GFEVD using a TF-QVAR model with a 126-day rolling window and one lag (AIC). Dynamic TCI colour heatmap denotes bluish colour for lower values and reddish colour for higher values ranging from 0 to 100.

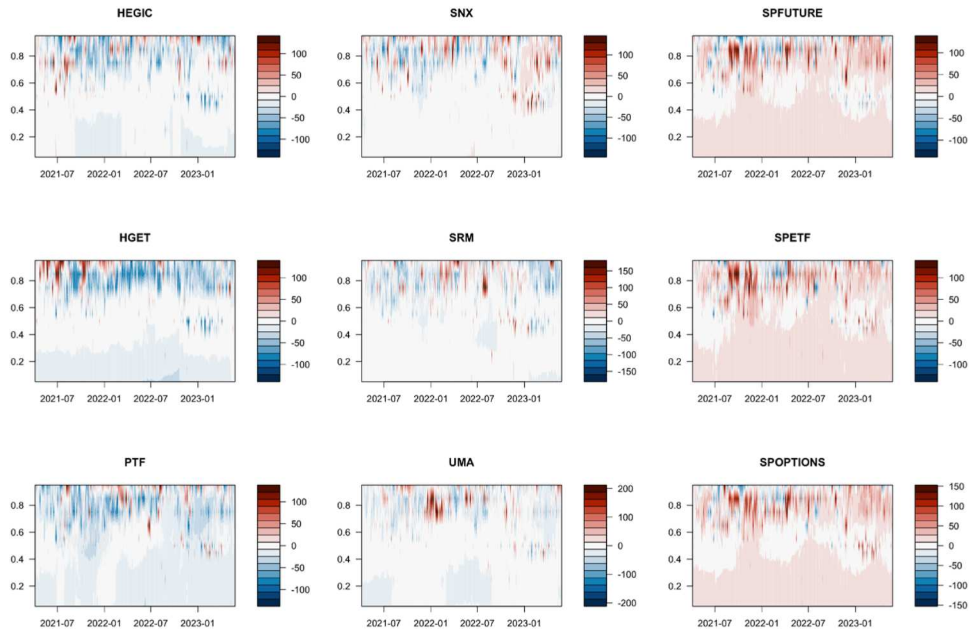

Figure 5. Net total directional connectedness across quantiles (total).

Note: Figure presents the connectedness measures across different time horizons: total, short-term, and long-term, respectively. Results are based on a 20-step-ahead GFEVD using a TF-QVAR model with a 126-day rolling window and one lag (AIC). The heatmap denotes bluish colour for net receiver and reddish colour for net transmitter of shocks.

also demonstrate a similar time-varying pattern. This finding is in line with other studies (Abdullah et al., 2023b; Aharon & Demir, 2022; Ersan et al., 2022; Karim et al., 2022) that also give event-dependent connectedness in the case of other tokens and traditional assets.

5.3. Robustness test results

This section presents the results of our robustness analysis, designed to assess the sensitivity of the connectedness measures to different rolling window sizes and forecasting horizons. Our baseline model utilises a 126-day rolling window and a 20-day forecasting horizon. To evaluate the stability of our findings, we extend the analysis by testing alternative configurations using 63-, 183-, and 252-day rolling windows, in combination with forecasting horizons of 20, 30, and 50 days. Figure 6 illustrates the variations in the TCI across these specifications.

The results indicate that the TCI fluctuates between approximately 30% and 85%, consistent with the range observed in the baseline model. Importantly, the key patterns remain stable: mid-quantile TCIs are consistently lower than those observed in the lower and upper quantiles, reaffirming that tail risk connectedness is most pronounced during extreme market conditions. These outcomes confirm that our central findings are not artifacts of arbitrary model parameters. Shorter rolling windows, such as 63 days, tend to capture higher short-term variability, whereas longer windows like 252 days smooth out these fluctuations, but do not alter the broader trend of heightened connectedness during stress periods. Similarly, extending the forecasting horizon alters the

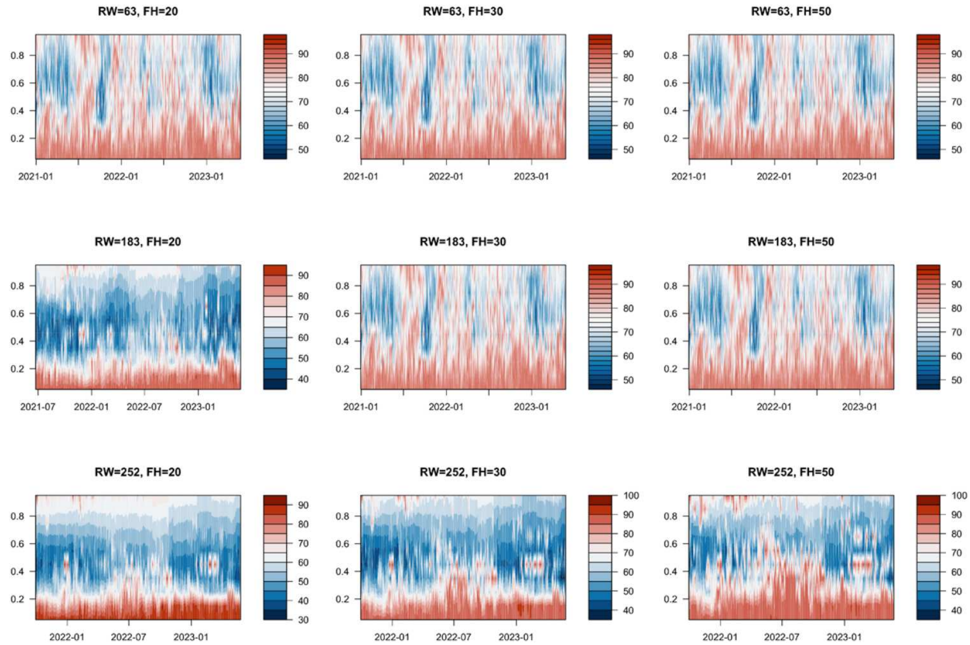

Figure 6. Test for robustness using various forecasting horizons and rolling windows.
Note: RW = rolling window, and FH = forecasting horizons. Dynamic TCI colour heatmap denotes bluish colour for lower values and reddish colour for higher values ranging from 0 to 100.

magnitude but not the direction of connectedness, reinforcing the time-varying nature of contagion between tokenized and traditional derivatives. These findings support the broader literature on dynamic financial interlinkages and suggest that the transmission of tail risk is a persistent and structurally embedded feature of both traditional and decentralised markets (Abdullah et al., 2023b; Aharon & Demir, 2022; Ersan et al., 2022; Karim et al., 2022).

5.4. Impact of uncertainty factors on connectedness results

This section delves deeper into the impact of uncertainty factors on the connectedness between tokenised and traditional derivatives. To assess this impact, we employ key uncertainty indicators, including VIX, SSR, GPRI, and EPU. Our objective is to examine how these uncertainty factors are associated with tail risk contagion across tokenised and traditional derivatives by running regression analyses linking the uncertainty factors to the TCI derived from the previous analyses. Table 1 presents the outcomes of these regression models.

Models 1–3 are constructed using TCI ($\tau = 0.05$), TCI ($\tau = 0.50$), and TCI ($\tau = 0.95$) as dependent variables across all panels. The results indicate no significant impact of uncertainty factors on the lower quantile TCI, with the exception of VIX and SSR. However, these findings reveal a statistically significant positive influence of uncertainty factors on the middle and upper quantiles of TCI, suggesting that these factors significantly contribute to contagion within the tokenised and traditional derivatives, particularly during normal market conditions and periods of extremely high tail risk. Notably, our

Table 1. Analysing how uncertainty factors affect tail risk connectedness.

Variable	(1) TCI (τ=0.05)	(2) TCI (τ=0.50)	(3) TCI (τ=0.95)
VIX	0.027*	0.335**	0.400***
	(0.016)	(0.140)	(0.032)
SSR	-0.146***	1.783***	0.753***
	(0.028)	(0.249)	(0.057)
GPR	-0.001	0.018**	0.004*
	(0.001)	(0.009)	(0.002)
EPU	-0.000	0.019*	0.005**
	(0.001)	(0.010)	(0.002)
Constant	99.350***	44.503***	70.072***
	(0.336)	(2.933)	(0.670)
Observations	538	538	538
R-squared	0.049	0.118	0.355
Adjusted R-squared	0.042	0.112	0.350

Notes: Results presented in this table illustrate the extent to which uncertainty factors shape tail-risk linkages between tokenized and traditional derivatives. Models 1–3 adopt TCI as the dependent variable, with τ values of 0.05, 0.50, and 0.95 respectively. All models are estimated using OLS, with robust standard errors provided in parentheses. *$p < 0.1$, **$p < 0.05$,***$p < 0.01$.

findings highlight that VIX and SSR exhibit higher coefficient values, meaning that they are the primary uncertainty factors driving tail risk contagion throughout the tokenised and traditional derivatives.

This result implies during periods of heightened market volatility, as reflected by an elevated VIX, that there is a greater propensity for tail risk to spread across these asset classes. Such contagion can lead to larger market disruptions and potential losses for investors holding diverse portfolios that include both tokenised and traditional derivatives. Consequently, monitoring the VIX becomes crucial for risk management and decision-making, as it serves as an early warning signal for increased tail risk. Moreover, the result of SSR indicates the market's perception of future short-term interest rates and monetary policy uncertainty. When SSR exhibits a substantial impact on tail risk contagion, it suggests that changes in short-term interest rate expectations and monetary policy-related uncertainties play a critical role in influencing the connectedness between these asset classes. This result implies that shifts in monetary policy and the associated market reactions have a profound effect on the spillover of tail risk across tokenised and traditional derivatives. Our findings are consistent with Abdullah et al. (2023b), who also document that VIX and SSR are significant determinants of return and volatility spillover of real estate tokens and traditional assets. This finding emphasises the significance of monitoring VIX and SSR as key indicators for assessing and managing risk in diversified portfolios containing both tokenised and traditional derivatives. Investors should remain vigilant, particularly during times of elevated volatility signalled by VIX and SSR, to make informed decisions and potentially implement hedging strategies to mitigate the effects of tail risk contagion.

5.5. Portfolio analysis results

The analysis presented above suggests potential diversification benefits when combining tokenised and traditional derivatives in a portfolio. To further explore this, we conduct portfolio analysis using the minimum connectedness portfolio approach. Table 2 lists the

Table 2. Bilateral portfolio estimates (τ = 0.50).

Portfolio	Weight		Hedge Ratio	
	Short-term	Long-term	Short-term	Long-term
HEGIC/SPFUTURE	0.39	0.50	1.42	0.48
HEGIC/SPETF	0.40	0.50	1.75	0.48
HEGIC/SPOPTIONS	0.40	0.49	1.49	0.49
HGET/SPFUTURE	0.58	0.43	0.79	0.30
HGET/SPETF	0.58	0.43	1.33	0.30
HGET/SPOPTIONS	0.61	0.42	1.54	0.31
PTF/SPFUTURE	0.46	0.48	2.05	0.60
PTF/SPETF	0.46	0.47	2.78	0.60
PTF/SPOPTIONS	0.48	0.47	3.19	0.60
SNX/SPFUTURE	0.65	0.42	1.97	0.57
SNX/SPETF	0.65	0.42	2.54	0.58
SNX/SPOPTIONS	0.64	0.41	1.99	0.58
SRM/SPFUTURE	0.33	0.53	1.83	0.45
SRM/SPETF	0.34	0.53	2.04	0.45
SRM/SPOPTIONS	0.33	0.52	2.26	0.45
UMA/SPFUTURE	0.18	0.73	1.33	0.34
UMA/SPETF	0.18	0.73	1.18	0.33
UMA/SPOPTIONS	0.18	0.73	1.52	0.34

Notes: Results are derived from dynamic PCI at τ = 0.50 in accordance with a minimum connectedness portfolio (Broadstock et al., 2022). Hedging ratios and portfolio weights are estimated using the frameworks of Kroner and Sultan (1993) and Kroner and Ng (2015), respectively.

results of the portfolio based on the mid-quantile (τ = 0.50) pairwise connectedness index (PCI). The results for the extreme quantiles are shown in Tables D1 and D2 of the ***Supplementary Material D***. These findings provide practical implications for investors based on their risk preferences and investment time horizon, as the results are for both short-term and long-term investment horizons. Among the portfolio combinations, the highest weight (0.65) is assigned to SNX/SPFUTURE, indicating under short-term frequency that a $1 portfolio consists of a 65-cent investment in SNX and a 35-cent investment in SPFUTURE. Similarly, in the long-term frequency, the highest optimal portfolio weight is observed in UMA/SPFUTURE (0.73), where a $1 portfolio consists of a 73-cent investment in UMA and a 27-cent investment in SPFUTURE.

These findings align with the principles of modern portfolio theory (Markowitz, 1952), which posits that combining assets with lower correlation can reduce overall portfolio risk without sacrificing expected returns. The lower connectedness between certain tokenised and traditional derivatives suggests that these instruments offer complementary risk-return profiles, supporting the case for cross-asset diversification. This is consistent with recent empirical studies highlighting that crypto-based assets and tokenised instruments can enhance portfolio efficiency (e.g., Abdullah et al., 2023b; Ersan et al., 2022; Jareño & Yousaf, 2023; Yousaf et al., 2022b). By incorporating derivatives from both tokenised and traditional markets, investors can potentially optimise their portfolios to better withstand extreme market conditions while achieving more stable returns. The results for other portfolios considering extreme quantiles PCI also display a similar pattern, suggesting potential portfolio diversification benefits using tokenised and traditional derivatives.

Table 2 further provides the hedge ratio estimates for all bivariate portfolio combinations. Our short-term findings indicate that PTF/SPOPTIONS has the highest hedge ratio of 3.19. This means that for each dollar invested in PTF, an investor would need to purchase $3.19 of SPOPTIONS to create an offsetting position that minimises the risk of the portfolio. On the other hand, in the long-term results, the PTF/SPETF portfolio exhibits the highest hedge ratio of 0.60, suggesting that a $1 long position in PTF can be hedged with a 40-cent short position in SPETF. Our result is in line with studies by Abdullah et al. (2023b) and Yousaf et al. (2022a) who identify substantial portfolio diversification opportunities between tokens and traditional assets.

For institutional investors and risk managers, these findings highlight the importance of aligning hedge strategies with investment horizons and asset-specific characteristics. Higher hedge ratios observed in the short term likely reflect increased exposure to abrupt market shocks, emphasising the need for more active and responsive hedging to control tail risk contagion. In contrast, lower hedge ratios in the long term suggest that strategic asset allocation can effectively mitigate risk while minimising transaction costs. However, the implementation of these strategies must also account for the liquidity constraints inherent in tokenised derivatives. Unlike traditional derivatives, tokenised instruments often experience significant fluctuations in trading volume and market depth, particularly during periods of market stress or regulatory uncertainty. Limited liquidity can increase slippage and execution costs, potentially undermining the effectiveness of hedge positions and optimal portfolio weights. As such, investors should factor in liquidity metrics, such as bid-ask spreads, trading volume, and time-to-execution, when designing hedge strategies or constructing diversified portfolios that include tokenised assets. Acknowledging and adjusting for these liquidity dynamics is crucial for the practical viability of risk management strategies in hybrid portfolios.

6. Conclusion

This study investigates the connectedness and spillover effects between derivative tokens and traditional assets. Static analysis reveals varying tail risk contagion dynamics across different quantiles. Assets such as HGET and SPOPTIONS play important roles in the lower quantile, with lower interconnectedness offering diversification potential. The mid-quantile exhibits persistent patterns, while the upper quantile exhibits increased risk transmission during extreme market conditions, emphasising the importance of robust risk management strategies. Dynamic connectedness analysis shows that connectedness fluctuates over time, with significant peaks during major events such as the COVID-19 pandemic, Russia-Ukraine war, and the SVB collapse. This emphasises the impact of economic events on risk transmission across the network. The results of directional connectedness show that traditional derivatives are frequently net risk transmitters, with varying intensities over time and quantiles. This is consistent with static analysis and indicates a degree of decoupling between tokenised and traditional derivatives.

The impact of uncertainty factors, particularly VIX and SSR, on tail risk contagion is quite clear. These variables have a significantly positive influence on the middle and upper quantiles of TCI, indicating their role in contagion, especially during normal market conditions and high tail risk scenarios. The higher the coefficient values of VIX and SSR are, the more important their roles are in driving tail risk contagion across tokenised and traditional derivatives. Finally, portfolio analysis shows that carefully selecting portfolio weights and hedge ratios can help reduce tail risk spillovers.

Portfolios that combine tokenised and traditional derivatives may provide diversification benefits, with optimal weights varying for short- and long-term investment horizons.

The findings of this study offer several valuable insights for investors and regulators. First, the lower and mid-quantiles show lower interconnectedness among these assets, implying that investors may benefit from diversification by including both tokenised and traditional derivatives in their portfolios. This diversification strategy may aid in mitigating the impact of shocks and improving overall portfolio stability. Second, during times of market stress, such as the upper quantile, when interconnectedness is particularly strong, investors should employ robust risk management strategies. It is critical to keep a close eye on key uncertainty factors that have been identified as major drivers of tail risk contagion. To mitigate the effects of tail risk, investors should consider these factors as early warning signals and adjust their portfolios accordingly.

Third, regulators should enhance surveillance and risk monitoring frameworks, particularly during periods of extreme market stress, where tail risk contagion is most pronounced in the upper quantile. Implementing real-time analytics and early warning systems could aid in the timely detection of excessive interconnectedness and systemic vulnerabilities. Moreover, regulatory bodies should consider mandating standardised and transparent reporting of both tokenised and traditional derivative positions, including exposure metrics and risk management practices. This would improve visibility into market dynamics and support proactive intervention. To address risks related to market manipulation and investor protection, specific policies, such as auditing smart contracts, enforcing disclosure requirements for algorithmic trading strategies, and establishing minimum liquidity thresholds for tokenised derivatives could be introduced to ensure greater transparency, accountability, and market integrity amid the rapid evolution of decentralised financial instruments.

This study provides novel insights into tail risk connectedness between tokenised and traditional derivatives but is subject to several limitations. The sample period may not reflect long-term dynamics, and the focus on a narrow set of derivative tokens limits generalisability. The TF-QVAR model may also fall short in capturing structural breaks and nonlinearities, suggesting the need for alternative models like regime-switching frameworks. Future research could incorporate liquidity and transaction volume effects, conduct out-of-sample testing, and compare the Minimum Connectedness Portfolio with traditional strategies such as minimum variance and equal-weighted portfolios. Expanding the analysis to include other token types (e.g., utility, AI, and security tokens) or traditional assets (e.g., equities, bonds) would offer a broader perspective on diversification and the unique role of derivative tokens in portfolio construction.

Notes

1. Blockchain refers to a decentralised and distributed digital ledger system that securely records transactions across a network of computers, ensuring data integrity and resistance to tampering. Individual records, known as blocks, are cryptographically linked in sequential order, forming a continuous and immutable chain. It's commonly used in cryptocurrencies but also has applications in finance, supply chains, and more.
2. Decentralized Finance (DeFi) refers to a blockchain-based financial ecosystem that enables users to engage in services such as lending, borrowing, and trading without the involvement of conventional financial intermediaries.

3. See https://coinmarketcap.com/view/derivatives/ and https://coinmarketcap.com/view/options/ for the details of each token.
4. Data sources: VIX = Datastream, SSR = https://www.ljkmfa.com/visitors/, GPRI = https://www.matteoiacoviello.com/gpr.htm, and EPU = https://www.policyuncertainty.com/

Supplementary material

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