China Accounting and Finance Review

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Real-world asset tokens and commodities: static and dynamic linkages

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Received 3 May 2024
Revised 13 February 2025
5 July 2025
Accepted 29 August 2025

Abstract

Purpose – This study explores the static and dynamic interconnectedness between real world asset (RWA) tokens and traditional commodities. Additionally, the study examines the role of uncertainty factors in explaining the interconnectedness. Finally, the study examines portfolio diversification opportunities.

Design/methodology/approach – A novel R-squared based time-frequency connectedness approach is used to examine interconnectedness using data from March 14, 2018, to June 9, 2023. To compute optimal portfolio weights and hedging ratios for each pair, the DCC-GARCH model is utilized and the best weights and hedge ratios are estimated.

Findings – The static connectedness result shows that RWA tokens and commodities demonstrate a relatively lower level of interconnectedness. The dynamic connectedness measures unveil time-varying interconnectedness, particularly heightened during economic events. Moreover, global uncertainty factors are positively associated with connectedness, emphasizing the multifaceted channels through which shock is transmitted. Portfolio analysis underscores potential diversification opportunities between RWAs and commodities, offering insights for informed decision-making in navigating the evolving landscape of blockchain-based assets and traditional commodities.

Originality/value – The main novelty of this manuscript is the exploration of RWA tokens, an emerging asset class that has received limited academic attention compared to cryptocurrencies, NFTs and DeFi. Unlike prior studies, this research employs a novel R-Squared-based time-frequency connectedness approach to analyze the static and dynamic linkages between RWA and traditional commodities. It also examines global uncertainty factors and incorporates portfolio backtesting, providing insights for investors seeking diversification in tokenized assets.

Keywords Real-world asset tokens, Commodities, R-squared based time-frequency connectedness approach, Spillover, Portfolio analysis

Paper type Research article

1. Introduction

Real-world asset (RWA) tokens are emerging financial innovations at the intersection of blockchain technology and traditional asset markets (Biais, Capponi, Cong, Gaur, & Giesecke, 2023). While significant academic attention has been directed toward cryptocurrencies, NFTs and decentralized finance (DeFi), RWA tokens remain relatively underexplored in DeFi. These

China Accounting and Finance Review
Vol. 27 No. 5, 2025
pp. 759-788
Emerald Publishing Limited
e-ISSN: 2307-3055
p-ISSN: 1029-807X
DOI 10.1108/CAFR-05-2024-0054

tokens represent digitized claims on tangible assets such as real estate, commodities, fine art or precious metals, yet little is known about their interaction with the markets of the underlying assets they represent. Existing literature has focused largely on the price behavior and volatility dynamics of cryptocurrencies and tokenized securities DeFi (see Abakah *et al.*, 2024; Abakah, Hossain, Abdullah, & Goodell, 2023a, Abakah, Wali Ullah, Adekoya, Osei Bonsu, & Abdullah, 2023b; Ghosh, Alfaro-Cortés, Gámez, & García-Rubio, 2023; Gunay, Goodell, Muhammed, & Kirimhan, 2023; Liu, 2023; Proelss, Sévigny, & Schweizer, 2023; Yousaf, Jareño, & Tolentino, 2023a; Yousaf, Nekhili, & Gubareva, 2022b; Yousaf & Yarovaya, 2022), leaving a notable gap in understanding the static and dynamic relationships between RWA tokens and commodities. In particular, the role of RWA tokens in portfolio diversification, volatility transmission and risk management remains insufficiently examined. Moreover, there is a lack of empirical research on how global uncertainty factors influence these relationships. Addressing these gaps is critical for investors seeking diversification through tokenized assets and for policymakers monitoring financial stability as tokenization scales.

The relevance of studying RWA stems from their potential to transform asset ownership and trading mechanisms by increasing liquidity, reducing transaction costs and enabling fractional ownership. As digital financial assets become increasingly integrated into traditional financial systems, their influence on commodity markets demands closer scrutiny. Despite the growing popularity of RWA tokens among investors, key questions remain. For instance, to what extent do the prices of these tokens reflect the fundamentals of the underlying commodities and how do they behave in times of market stress? Are they effective tools for hedging or portfolio diversification compared to traditional commodity derivatives? These concerns are particularly important given recent regulatory initiatives and rising institutional interest in asset tokenization.

RWAs are integral components of the global economy, serving dual roles as investment platforms and as security for loans (Biais *et al.*, 2023). The introduction of blockchain technology is swiftly altering how we interact with these assets. Tokenization promises to make these assets more accessible to a broader investor base, thereby transforming the financial arena and paving the way for novel avenues in investment and wealth generation (Avci & Erzurumlu, 2023; Sunyaev *et al.*, 2021). For example, by incorporating RWA into their portfolios, investors can potentially hedge against market volatility in stocks and bonds. In recent years, the rapid evolution of blockchain technology has ushered in a new era of financial innovation, allowing for the tokenization of RWAs (Biais *et al.*, 2023; Sunyaev *et al.*, 2021).

Tokenization involves converting rights to a RWA into a digital token on a blockchain. For instance, a real estate property can be tokenized into multiple units, with each token representing fractional ownership of the asset (Dicki, 2023). This advancement facilitates seamless transfer of ownership and provides investors with broader access to previously illiquid assets. RWA tokens cover a diverse range of tangible goods, including real estate, fine art, gold, silver, oil and agricultural commodities. These blockchain-based instruments reduce barriers to entry and allow for efficient, fractional and global trading. Commodities, on the other hand, are long-standing components of diversified investment portfolios, valued for their inflation-hedging and risk-diversifying properties (Coughlan & Orlov, 2023; Fang & Shao, 2022; Naeem, Hamouda, & Karim, 2024; Qiao & Han, 2023; Wang, Zhou, & Gao, 2023).

The global adoption of tokenization is gaining momentum. For example, private equity firm Hamilton Lane plans to tokenize part of its $2.1 billion flagship equity funds on the Polygon network. Similarly, the Monetary Authority of Singapore (MAS) launched Project Guardian to tokenize bonds and deposits for use in decentralized finance strategies (Shimron, 2023). The tokenized asset market is expected to reach $7,766.87 million by 2028, growing at a compound annual growth rate of 22.57% from 2021 to 2028. Investors are increasingly drawn to RWA tokens for their potential to unlock access to high-value assets, promote fractional ownership and enable more liquid secondary markets (Benedetti & Rodríguez-

Garnica, 2023). These developments may lead to increased demand for certain assets and influence price dynamics across tokenized and traditional markets.

This study examines the static and dynamic linkages between RWA tokens and commodities and explores the associated diversification and hedging opportunities. We employ a novel R-squared-based time-frequency connectedness approach to analyze co-movements across time and frequency dimensions. Additionally, to assess portfolio implications, we use the DCC-GARCH model (Engle, 2002) and calculate optimal portfolio weights and hedge ratios following the methodologies of Kroner and Ng (2015) and Kroner and Sultan (1993). By integrating econometric modeling with market insights, the study aims to provide a comprehensive understanding of how RWA tokens interact with commodity markets and how these relationships evolve under uncertainty.

This research makes several key contributions to the existing literature. Firstly, while earlier studies mainly focused on cryptocurrency, NFTs and DeFi (Abakah *et al.*, 2024; Abakah *et al.*, 2023a, b; Ghosh *et al.*, 2023; Gunay *et al.*, 2023; Liu, 2023; Proelss *et al.*, 2023; Yousaf, Jareño, & Tolentino, 2023b; Yousaf *et al.*, 2022b; Yousaf & Yarovaya, 2022), our study extends the scope of research by delving into the relatively novel asset class of RWA tokens. As blockchain technology reshapes the financial landscape, understanding the interconnected dynamics between RWA and traditional commodities becomes crucial for investors, portfolio managers and policymakers alike. By incorporating RWA into the analysis, this study provides a detailed exploration of their relationships with commodities, offering insights into the evolving nature of these assets. RWA tokens differ from cryptocurrencies, NFTs and DeFi because they are directly linked to tangible assets like real estate and commodities, providing intrinsic value and stability. This connection enables fractional ownership and enhanced liquidity in traditionally illiquid markets, making high-value assets more accessible to a broader range of investors. Research on RWA tokens can advance theories in asset pricing, market microstructure and portfolio management by integrating digital and traditional financial models. It also offers unique insights into regulatory challenges, as RWA requires more robust legal frameworks than purely digital assets.

Secondly, the study introduces a novel R^2-based time-frequency connectedness approach based on model-free connectedness approach proposed by Gabauer, Chatziantoniou, and Stenfors (2023). The R^2-based time-frequency connectedness approach offers a significant advantage over traditional models by providing a more flexible and robust framework for analyzing return spillovers, especially in dynamic asset markets. This method addresses common challenges like convergence issues and the failure of the total connectedness index to converge to unity. By incorporating the R^2 goodness-of-fit measure, it sets an upper limit for total connectedness, improving the reliability of the results. Unlike static models, this approach captures time-varying relationships and accounts for different investment horizons, making it highly adaptable for studying the interconnectedness between RWA and commodities. This enables a more comprehensive understanding of risk transmission and interdependencies, considering both short- and long- term fluctuations.

Thirdly, the study explores the impact of uncertainty factors on connectedness. By investigating how uncertainty, encompassing market fear, oil market stress, economic policy uncertainty and geopolitical risk, influences the interconnectedness between RWA and commodities, the study provides valuable insights for regulators and investors. Understanding how these uncertainty factors shape market dynamics is crucial for developing effective risk management strategies and regulatory frameworks that align with the evolving nature of blockchain-based assets. Lastly, the study conducts portfolio backtesting, contributing to the practical application of the research findings. Through the evaluation of portfolio weights and bivariate hedge ratios, the study provides investors and portfolio managers with tangible insights into potential diversification opportunities and risk management strategies. This empirical aspect of the study bridges the gap between theoretical insights and practical implications, offering actionable guidance for decision-makers in the financial industry.

The remainder of this study is organized as follows: Section 2 reviews the relevant literature, while Section 3 describes the data and methodology. Section 4 presents the empirical findings and Section 5 presents the discussion. Finally, Section 6 concludes with a summary of key insights and suggestions for future research.

2. Literature review

The intersection of traditional asset classes with emerging blockchain-based technologies has given rise to new investment paradigms, particularly the dynamic linkage between RWA tokens and commodities. This literature review seeks to explore the existing body of research and studies that investigate the relationship between tokenized RWAs and commodities. By examining the key findings and insights from various scholarly works, this review aims to shed light on the potential benefits, challenges and implications of this novel convergence in the financial landscape.

2.1 Tokenization of real-world assets

The concept of tokens was initially introduced in 2012 through Bitcoin's "Colored Coins." This term refers to tokens symbolizing various physical assets like currencies, commodities, stocks, carbon credits, real estate, bonds and artwork (Rosenfeld, 2023). Tokenization of RWAs refers to the process of representing physical or tangible assets as digital tokens on a blockchain or distributed ledger system (Benedetti & Rodríguez-Garnica, 2023). RWA reduces issuance and trading costs, lessens intermediary dependency and facilitates more market liquidity. These tokens represent digitized ownership of tangible assets, ranging from real estate properties and fine art to commodities such as gold, silver, oil and agricultural products. They are often issued on blockchain platforms, offer fractional ownership and enable seamless trading, reducing barriers to entry for a broader range of investors (Hines, 2021). Asset tokenization platforms issue tokens by offering security tokens to secure various types of assets, from financial instruments to intellectual property and enable their transactions within the platform. Moreover, they will have no value if the mentioned things are destroyed (Far, Bamakan, Qu, & Jiang, 2022). Kim (2020) contends that tokenizing an asset increases its price by improving the democracy of the market and its liquidity, which eventually results in a price bubble.

The tokenization of RWA has notable effects on investors. It grants broader access and liquidity to traditionally inaccessible assets, enabling fractional ownership and portfolio diversification. Global market reach, increased transparency and unique investment opportunities arise, but careful attention to regulations and due diligence are crucial. This innovation transforms how investors interact with assets, offering convenience, flexibility and potential for enhanced returns. Real estate tokens are backed by real-world assets and real estate can be made liquid (Rathod, Patel, Bothra, Shanbhag, & Bhalerao, 2020) and be popular with retail investors. The museum sector is beginning to take advantage of the possibilities of crypto collectibles. The Uffizi Gallery made history by selling an NFT of an image of their renowned Michelangelo artwork, "Doni Tondo," for 170,000 USD (Artnet News, 2023). Also, the Hermitage Museum announced that it plans to sell NFTs for famous pieces of its collection, including works by Leonardo Da Vinci and Van Gogh. This marks a significant step in the integration of digital art and traditional masterpieces in the art world. The Ethereum token (ERC-20) can tokenize any object in the real world while exchanging the token among network participants (Richard *et al.*, 2020). Chanson and Senner (2022) conclude by providing an outlook concerning debt-backed stablecoins collateralized with tokenized RWAs. Sternik and Safronova (2021) assert that financialization or the real estate market through tokenization provides more liquidity to markets and significantly affects the prices.

Overall, tokenization of RWAs provides investment opportunity, market liquidity and more access for small investors, making the market more participative.

2.2 Dynamic links between real-world asset tokens and commodities

RWA tokens and traditional commodities are essential components of modern investment strategies, particularly for enhancing portfolio resilience and diversification during economic uncertainty. Commodities, like gold and oil, serve as historical hedges against inflation and market volatility due to their intrinsic value and low correlation with traditional financial markets. Meanwhile, RWA tokens, representing tangible assets such as real estate or art, democratize access to high-value investments while offering liquidity and transparency through blockchain technology. By integrating both asset classes, investors can achieve improved risk-adjusted returns, as commodities can buffer against inflation, while RWA tokens can provide stable cash flows and growth potential. This strategic blend not only mitigates risk but also allows for tactical allocations based on prevailing economic conditions, making the interplay between these assets increasingly vital in navigating the complexities of the investment landscape.

The dynamic relationship between RWA tokens and commodities offers investors significant benefits in diversification, risk mitigation and inflation hedging. By combining these asset classes, investors can enhance portfolio resilience, as commodities typically provide a stabilizing force during market volatility, while tokenized assets, representing tangible items like real estate, increase liquidity and accessibility. This interplay is influenced by market sentiment and macroeconomic indicators, with both asset types responding differently to economic changes. Additionally, evolving regulatory frameworks and technological advancements in blockchain can further strengthen their connection, providing new investment opportunities and facilitating efficient transactions. Ultimately, understanding these dynamics enables investors to navigate the complexities of modern financial markets more effectively.

Modern portfolio theory proposes that gaining insight into the interconnectedness among financial markets provides valuable knowledge for implementing effective strategies to mitigate risk and diversify investments (Markowitz, 1952). The growing strand of literature examines the tail-risk connectedness renewable energy tokens and fossil fuel markets and centralized-commercial bank stocks (Yousaf, Abrar, & Goodell, 2022a, b, Yousaf, Nekhili, & Umar, 2022c); non-fungible tokens (NFTs), decentralized finance (DeFi) coins (Umar, Polat, Choi, & Teplova, 2022). Xia, Li, and Fu (2022) examined quantile connectedness between NFTs, a blockchain technology product and common asset classes. The authors reveal that return and volatility cross-asset spillovers are much higher in extreme market conditions than in regular times. Commodities are considered the most well-received investment tool to hedge, diversify and avoid portfolio risks (Kang & Yoon, 2019). Furthermore, the correlations between commodities and traditional financial markets (such as stock, bond and exchange rate markets) are relatively low, making portfolio managers put more commodity assets with weak or negative correlations with equity assets in their portfolios (Bekiros, Boubaker, Nguyen, & Uddin, 2017). Given the importance of the complex relationship between traditional assessments and commodities in portfolio construction and risk management practice, many studies have investigated the links and spillovers between stock and commodity markets. Wang (2023) investigates tail dependence, dynamic linkages and extreme return spillovers between the stock market and China's commodity markets. Bohl, Irwin, Pütz, and Sulewski (2023) examine how the financialization of commodity futures markets and RWAs is connected and find a positive effect. Umar *et al.* (2022) examined the spillover effects of return and volatility between NFT, DeFi coins and financial assets and found that the long- and short-term connectedness among the volatility of the assets varied over time. Abdullah, Adeabah, Abakah, and Lee (2023) investigated the connection of return and volatility among real estate tokens, real estate investment trusts (REITs) and other assets. The authors find evidence of a time-varying upsurge in the real estate token and REIT connectedness.

Overall, based on the above literature on the dynamic connectedness between RWA tokens and commodities, we find that RWA and commodities are interlinked. However, previous studies did not show the direction of the connectedness. Through this study, we examine the dynamic linkage and portfolio benefits between RWA tokens and commodities, using a novel R^2 based time-frequency connectedness approach. This study contributes to the literature by expanding the research focus beyond cryptocurrencies, NFTs and DeFi (Abakah *et al.*, 2023a, b; Ghosh *et al.*, 2023; Gunay *et al.*, 2023; Liu, 2023; Proelss *et al.*, 2023; Yousaf *et al.*, 2023b; Yousaf *et al.*, 2022b; Yousaf & Yarovaya, 2022) to the emerging asset class of Real World Asset (RWA *hereafter*) tokens. As blockchain technology transforms financial markets, understanding the dynamic linkages between RWA and traditional commodities is essential for investors, portfolio managers and policymakers. By integrating RWA into the analysis, this study offers new insights into their interconnectedness with commodities, shedding light on diversification opportunities and risk transmission in this evolving asset landscape.

2.3 Hypothesis development

Tokenization of RWAs has emerged as a transformative innovation in financial markets, bridging traditional asset classes with blockchain-based technologies. By digitizing tangible assets such as real estate, commodities and artwork, tokenization enhances liquidity, reduces issuance and transaction costs and broadens investor access to high-value assets (Benedetti & Rodríguez-Garnica, 2023; Kim, 2020). Through fractional ownership, even small-scale investors can participate in markets that were once limited to institutional participants, improving diversification opportunities and reshaping portfolio construction strategies (Hines, 2021). The economic characteristics of tokenized RWAs suggest potential parallels with commodities. Commodities such as gold, oil and agricultural products have long served as hedging instruments due to their inflation-resistant properties and low correlation with equity markets (Bekiros *et al.*, 2017). Similarly, RWAs, particularly those backed by tangible cash-flow-generating assets, offer a blend of transparency, liquidity and perceived intrinsic value, positioning them as stabilizing forces in volatile markets (Xia *et al.*, 2022). Given these attributes, a logical link emerges between RWAs and commodities, where both asset classes serve complementary roles in mitigating risk and enhancing resilience during market disruptions.

Recent developments further underscore the importance of understanding the interconnectedness between these asset classes. RWAs, like commodities, are increasingly embedded in diversified portfolios, particularly during periods of macroeconomic uncertainty. As global financial conditions evolve, both markets are likely to be influenced by common factors such as interest rate fluctuations, geopolitical tensions and inflation expectations. Prior research has shown that digital assets, including NFTs and DeFi tokens, exhibit time-varying connectedness with traditional markets, with spillovers intensifying during crisis periods such as the COVID-19 pandemic and geopolitical shocks (Yousaf *et al.*, 2022a, b, c; Umar *et al.*, 2022; Abdullah *et al.*, 2023). This suggests that RWA tokens may also display dynamic linkages with commodities that vary across time and frequency domains. Accordingly, this study hypothesizes that RWA tokens and commodities exhibit both static and dynamic interconnectedness. Statistically, static relationships reflect the average or long-run level of connectedness between the two markets, while dynamic relationships capture how this interconnectedness evolves in response to economic events or shifts in market sentiment. These relationships are likely influenced by global uncertainty factors and amplified during periods of stress. By examining both dimensions, the study seeks to offer a more comprehensive understanding of the co-movement patterns and transmission mechanisms between tokenized and traditional real assets. Our hypothesis is as follows:

H1. There is a connectedness between the tokenization of RWAs and commodities.

3. Data and methodology

3.1 Methods

3.1.1 R^2-based time-frequency connectedness approach. Following the pioneering spillover framework introduced by Diebold and Yilmaz (2012, 2014), subsequent advancements have sought to refine and extend our understanding of return interdependencies among various assets. Noteworthy extensions include frequency-based models (Baruník & Křehlík, 2018), wavelet approaches (Antonakakis, Chang, Cunado, & Gupta, 2018a, Antonakakis, Gabauer, Gupta, & Plakandaras, 2018b), TVP-VAR models (Antonakakis, Cunado, Filis, Gabauer, & de Gracia, 2023) and TF-QVAR models (Chatziantoniou, Abakah, Gabauer, & Tiwari, 2022) and quantile VAR connectedness approach (Cunado, Chatziantoniou, Gabauer, de Gracia, & Hardik, 2023). However, challenges such as convergence issues, particularly when dealing with a higher number of variables and the occasional failure of the total connectedness index to converge to unity have been encountered. To address these limitations, Gabauer *et al.* (2023) introduced a model-free connectedness approach. This approach, rooted in the R^2 goodness-of-fit measure, offers an analytical upper limit for the total connectedness index, thereby overcoming convergence obstacles.

In this study, we use a novel R^2 based time-frequency connectedness approach, building upon the model-free connectedness framework introduced by Gabauer *et al.* (2023). In the context of RWA and commodities, the degree of interdependence between multiple financial assets is crucial because it allows for a detailed analysis of how these asset classes influence each other over time. The traditional connectedness models often assume static relationships, but the R^2 based method accounts for the time-varying nature of these relationships, making it more adaptable to the dynamic interactions in the tokenized asset markets. Moreover, it accounts for different investment horizons and provides a robust framework for analyzing risk transmission and interdependencies without relying on restrictive model assumptions. This innovative approach aims to provide a more detailed understanding of return spillovers, considering both short-term fluctuations and long-term trends, with the R^2 goodness-of-fit measure serving as a pivotal metric in assessing the dynamic linkages between RWA tokens and commodities. Our estimation process commences by decomposing time series data into different time frequencies through the utilization of a maximal overlapping discrete wavelet transform (MODWT), as put forth by Percival and Walden (2000).

The MODWT begin by considering the return series of asset $r[i]$ characterized by a length T, where T equals 2^J for a given integer J. Introduce low-pass filter $h_1[i]$ and high-pass filter $g_1[i]$, both defined by an orthogonal wavelet. In the initial stage, convolve $r[i]$ with $h_1[i]$ to yield the approximation coefficients $a_1[i]$ and concurrently convolve it with $g_1[i]$ to derive the detail coefficients $d_1[i]$. Notably, both $a_1[i]$ and $d_1[i]$ are of a length denoted as N at this first level of analysis.

$$a_1[i] = h_1[i] * s_1[i] = \sum_k h_1[i-k]s[k] \tag{1}$$

$$d_1[i] = g_1[i] * s_1[i] = \sum_k g_1[i-k]s[k] \tag{2}$$

Subsequently, we subject $a_1[i]$ to further filtration using a comparable scheme, albeit with adapted filters $h_2[i]$ and $g_2[i]$. These modified filters are derived through dyadic up-sampling of $h_1[i]$ and $g_1[i]$. This recursive process persists, extending the refinement of coefficients. As we iterate through $J = 1, 2, \ldots, J_0 - 1$, where J_0 is constrained to be less than or equal to J, we can systematically compute both the approximate and detailed coefficients, contributing to the ongoing evolution of the asset return characterization.

$$a_{j+1}[i] = h_{j+1}[i] * a_j[i] = \sum\nolimits_k h_{j+1}[i-k] a_j[i] \tag{3}$$

$$d_{j+1}[i] = g_{j+1}[i] * a_j[i] = \sum\nolimits_k g_{j+1}[n-k] a_j[j] \tag{4}$$

where, $h_{j+1}[i] = U(h_j[i])$ and $g_{j+1}[i] = U(g_j[i])$. Operator U facilitates up-sampling by introducing a zero between each pair of adjacent time-series elements. This process essentially involves expanding the temporal resolution of a given time series by doubling the number of data points through the insertion of zeros. We decompose our return series into $j = 6$ wavelet scales into short-term (D1 = 2–4 days and D2 = 4–8 days), medium-term (D3 = 8–16 days and D4 = 16–32 days) and long-term (D5 = 32–64 days and D6 = 64–128 days) frequency. By segmenting the data into short-term, medium-term and long-term frequencies, we can identify distinct patterns and spillover effects that may be obscured when analyzing the data as a whole. This approach allows for a more nuanced understanding of how market connections evolve over different time periods, accounting for the fact that financial markets respond differently to short-term shocks versus long-term trends. Moreover, it enables a clearer assessment of the impact of macroeconomic and geopolitical events on asset interdependencies at various timeframes.

Afterward, we delve into the main connectedness estimation process using the overall short-term (D2 = 4–8 days weekly investment horizon) and long-term (D6 = 64–128 days quarterly to bi-annual investment horizon) return series of the assets [1]. The R^2 connectedness approach functions as a null hypothesis, positing a scenario where lagged variables exert no influence on z_t (Gabauer *et al.*, 2023). In this context, the assumption is that the coefficients (B) would be zero, consequently causing the model to collapse, along with the subsequent collapse of its associated Generalized Forecast Error Variance Decomposition (GFEVD).

$$z_t = u_t z_t, u_t \sim N(0, \Sigma) \tag{5}$$

$$A_0 = I_k A_i = 0 \, i = 1, \ldots, p \tag{6}$$

$$\phi^{gen}_{i \leftarrow j} = \frac{\Sigma^2_{ij}}{\Sigma_{jj}\Sigma_{ii}} = \left(\frac{\Sigma_{ij}}{\sqrt{\Sigma_{jj}\Sigma_{ii}}} \right) = \rho^2_{ij} = R^2_{ij} \tag{7}$$

This metric remains consistent irrespective of the forecast horizon, labeled as H and essentially corresponds to the square of the Pearson correlation coefficient. This coefficient serves as a reflection of the R^2 goodness-of-fit measure, originating from a bivariate linear regression conducted between variable i and j. Consequently, it leads to the following equivalences: $R^2_{ii} = 1$ and $R^2_{ij} = R^2_{ji}$. To ensure normalization, the scaled GFEVD follows the normalization approach introduced Diebold and Yilmaz (2012), resulting in the following equation:

$$gSOT_{i \leftarrow j} = \frac{R^2_{ij}}{\sum_{l=1}^{k} R^2_{il}} \tag{8}$$

If the row sum for variable i converge to unity, it signifies that variable i can be accurately forecasted based on all other variables j and these j variables maintain orthogonality among themselves. This characteristic implies that the summation of bivariate R^2_{ij} does not equate to the R^2_i value in the context of multivariate linear regression. However, in scenarios where all variables j exhibit orthogonality with each other, the $gSOT_{ij}$ represents the relative R^2_i contribution that variable j imparts to variable i. Consequently, the interpretation of the total connectedness index (TCI) unfolds as the following equation:

$$TCI = 1 - \frac{1}{k}\sum_{i=1}^{k} gSOT_{i\leftarrow i} \quad (9)$$

$$= 1 - \frac{1}{k}\sum_{i=1}^{k} \frac{R_{ii}^2}{\sum_{l=1}^{k} R_{il}^2} \quad (10)$$

Since R_{ij}^2 consistently equals unity and the highest value of $\sum_{l=1}^{k} R_{il}^2$ is k, it implies that the TCI falls within the range of 0 and $\frac{k-1}{k}$.

Finally, the total directional connectedness (TO) and from others (FROM) and net total directional connectedness (NET) is measured as follows:

$$TO_i = \sum_{j=1, i\neq j}^{k} gSOT_{j\leftarrow i} \quad (11)$$

$$FROM_i = \sum_{j=1, i\neq j}^{k} gSOT_{i\leftarrow j} \quad (12)$$

$$NET_i = TO_i - FROM_i \quad (13)$$

Here, TO_i and $FROM_i$ denote the impact of variable i on all other variables and the collective impact of all other variables j on variable i, respectively. When $NET_i > 0\,(NET_i < 0)$, variable i is identified as a net transmitter (receiver) of shocks, indicating that it exerts a greater influence on other variables than it is influenced by them (or vice versa). This metric provides insights into the directional flow of influences among variables in the system.

3.1.2 Portfolio analysis method. We broadened the scope of our investigation by incorporating a thorough examination of portfolios, alongside our analysis of the interconnection analysis. Employing the DCC-GARCH model (Engle, 2002) facilitated the calculation of variances and covariances essential to this evaluation. Subsequently, we determined the best weights and hedge ratios utilizing the methodologies outlined by Kroner and Ng (2015) and Kroner and Sultan (1993). Through the application of these techniques, our objective was to offer an encompassing and pragmatic approach to enhancing risk management and maximizing returns within the dynamic landscape of technology industry tokens and equities.

3.2 Data

We have chosen five RWA tokens according to two specific criteria (Abakah *et al.*, 2024; Abdullah *et al.*, 2023) [2]. The first criterion is centered around the earliest launch date of the tokens, providing us with an extended time series for analysis. This criterion enables a more comprehensive examination of historical data, fostering a deeper understanding of the tokens' performances over time. The second criterion for token selection is grounded in higher market capitalization. This deliberate choice allows us to include prominent assets in our sample, ensuring the capture of significant market dynamics. Specifically, our selected tokens are Bytom (BTM), Maker (MKR), Polymath (POLY), Propy (PRO) and Synthetix (SNX).

In line with prior studies conducted by Enilov, Mensi, and Stankov (2023), Naeem *et al.* (2024) and Wang *et al.* (2023), our study focuses on five real-world commodity spot prices. Utilizing the S&P GSCI Spot Price Index as our benchmark, we specifically consider the following commodity indices: S&P GSCI Energy Spot Price Index (ENERGY), S&P GSCI Agriculture Spot Price Index (AGRICULTURE), S&P GSCI Livestock Spot Price Index

(LIVESTOCK), S&P GSCI All Metals Spot Price Index (METAL) and S&P GSCI Softs Spot Price Index (SOFTS).

Our selected sample period spans from March 14, 2018, to June 9, 2023, with the initiation date determined by the data availability of SNX. Throughout this timeframe, we retrieved the daily closing USD prices of RWA tokens from CoinMarketCap (https://coinmarketcap.com/) and the closing USD spot price indices of commodities from Datastream [3]. This chosen duration encompasses a multitude of significant economic events and financial upheavals, including the COVID-19 pandemic, the Russia-Ukraine war, the collapse of FTX and the Silicon Valley Bank crisis. By focusing on periods of heightened uncertainty and market volatility and a stable period, we can better capture the true dynamics of interconnectedness between RWA tokens and commodities under stress conditions. These events expose how markets respond to extreme shocks, providing crucial insights into potential investment strategies and risk management techniques that are highly pertinent during times of financial instability. This approach allows us to explore the resilience and vulnerability of these asset classes in real-world, tumultuous scenarios.

Figure 1 visually represents the normal and decomposed return series for all assets, revealing a consistent pattern of movement in both token and commodity categories. Complementing this visual analysis, Table 1 provides a comprehensive overview of the summary statistics for the return series. The results highlight a positive mean return for all assets throughout the sample period. Notably, the variance of PRO stands out at 138.963, signifying a higher level of variation in PRO's return compared to other assets. Skewness values indicate a positive skew for all token returns and a negative skew for all commodity returns. The Jarque and Bera test results suggest that all variables adhere to a fat-tailed distribution. Furthermore, the ERS unit-root test confirms the stationarity of all variables. In terms of Kendall correlation analysis, the majority of assets exhibit positive correlations in their returns, with the exception of energy, which shows some insignificant correlation.

4. Empirical results

4.1 Static connectedness results

We initiated our analysis of connectedness in the time-frequency domain by investigating static connectedness. Tables 2–4 present the outcomes of average connectedness, encompassing overall, short-term and long-term frequencies. The diagonal elements signify shocks associated with own-variance, while the off-diagonal elements signify the interactions between network variables. In the case of overall market conditions, Table 2 shows that LIVESTOCK exhibits the highest proportion of idiosyncratic shocks of 87.83%. The remaining errors are attributed to innovations in other variables within the network. The FROM column indicates shocks from other variables in the system, with MKR (45.25%) registering the highest shock received and LIVESTOCK (12.17%) receiving the lowest shocks from other assets in the network. Furthermore, the TO row illustrates the shock received from other variables in the system, with MKR (49.36) again recording the highest shock transmitted in normal frequency and LIVESTOCK (12.17%) transmitting the lowest amount of shock.

The NET row in our results delineates the outcomes for net directional transmission, where a positive value signifies a net transmitter of shocks and a negative value indicates a net receiver of shocks. Our findings reveal that MKR (4.11%) emerges as the primary net transmitter of shocks, while PRO (−3.90%) stands out as the primary net receiver. Examining the total connectedness index (TCI) in the normal frequency, we observe a value of 33.79%, indicating a relatively lower level of connectedness. This finding suggests that the movements and fluctuations in the returns of these assets exhibit a degree of independence from each other. A lower TCI implies that the shocks or variations in one asset class have a limited impact on the other, indicating a certain level of decoupling. This diminished TCI suggests a decoupling between RWA tokens and commodities, implying potential diversification benefits for

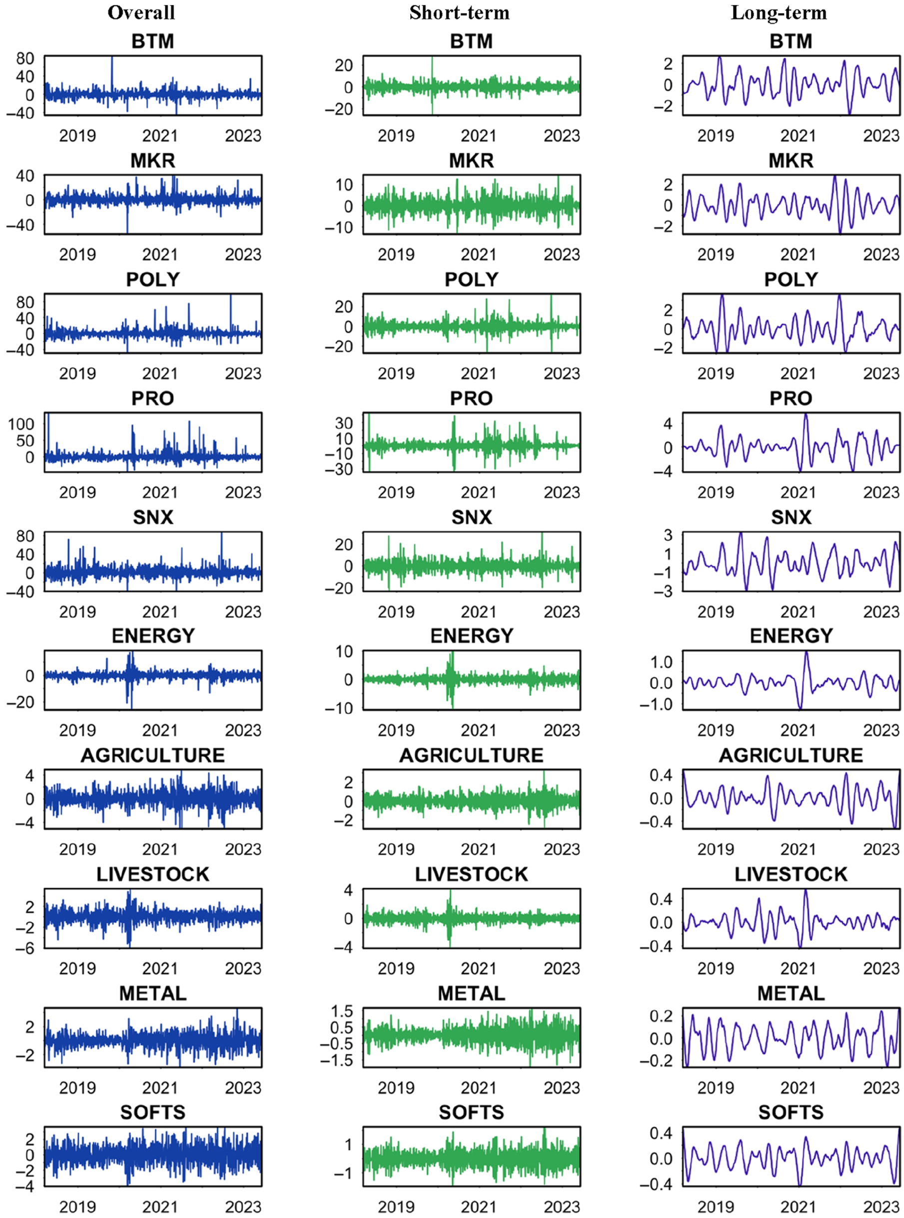

Figure 1. Historical return series. Source: Figure by authors

portfolios. This aligns with earlier studies that have similarly documented a lower level of connectedness between tokens and traditional assets in the context of various tokens (Abdullah *et al.*, 2023; Yousaf *et al.*, 2023a; Yousaf, Riaz, & Goodell, 2023c).

In the context of the short-term frequency, Table 3 displays that LIVESTOCK exhibits the highest proportion of idiosyncratic shocks at 80.19%. The FROM column indicates MKR (46.81%) has the highest shocks received, while LIVESTOCK (19.81%) receives the lowest

Table 1. Summary statistics

	BTM	MKR	POLY	PRO	SNX	ENERGY	AGRICULTURE	LIVESTOCK	METAL	SOFTS
Panel A: Descriptive statistics										
Mean	0.057	0.215	0.235	0.506	0.552**	0.046	0.031	0.031	0.018	0.035
Variance	52.945	45.512	75.15	138.963	95.02	6.793	1.356	1.222	0.856	1.258
Skewness	1.112***	0.523***	2.244***	3.706***	1.518***	−0.724***	−0.046	−0.328***	−0.051	−0.022
Ex.Kurtosis	17.091***	8.309***	22.848***	28.510***	9.971***	17.156***	1.911***	3.240***	1.726***	0.440***
JB	16919.595***	3995.241***	30881.415***	49427.588***	6188.111***	16883.906***	208.491***	622.359***	170.322***	11.126***
ERS	−11.957***	−12.151***	−15.706***	−16.016***	−5.818***	−15.399***	−10.737***	−12.703***	−9.416***	−12.303***
Q(20)	16.293*	20.851**	15.851*	18.681**	24.048***	30.099***	19.330**	32.855***	14.514	12.329
Q2(20)	12.808	76.884***	3.833	19.471**	15.575*	396.417***	302.922***	1514.120***	100.700***	84.000***
Panel B: Correlation analysis										
BTM	1.000***	0.350***	0.332***	0.250***	0.319***	−0.003	0.044**	0.064***	0.092***	0.058***
MKR	0.350***	1.000***	0.334***	0.247***	0.365***	0.032	0.063***	0.022	0.077***	0.055***
POLY	0.332***	0.334***	1.000***	0.221***	0.303***	0.043**	0.041**	0.046**	0.074***	0.074***
PRO	0.250***	0.247***	0.221***	1.000***	0.220***	0.006	0.028	0.017	0.069***	0.041**
SNX	0.319***	0.365***	0.303***	0.220***	1.000***	0.037**	0.070***	0.011	0.082***	0.063***
ENERGY	−0.003	0.032	0.043**	0.006	0.037**	1.000***	0.192***	0.056***	0.210***	0.212***
AGRICULTURE	0.044**	0.063***	0.041**	0.028	0.070***	0.192***	1.000***	0.072***	0.185***	0.374***
LIVESTOCK	0.064***	0.022	0.046**	0.017	0.011	0.056***	0.072***	1.000***	0.029	0.069***
METAL	0.092***	0.077***	0.074***	0.069***	0.082***	0.210***	0.185***	0.029	1.000***	0.214***
SOFTS	0.058***	0.055***	0.074***	0.041**	0.063***	0.212***	0.374***	0.069***	0.214***	1.000***

Note(s): Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; and ERS: Elliott, Rothenberg, and Stock (1996) unit-root test; ***,**,* denote significance at 1%, 5% and 10% significance level

Source(s): Table by authors

Table 2. Static connectedness results (overall)

	BTM	MKR	POLY	PRO	SNX	ENERGY	AGRICULTURE	LIVESTOCK	METAL	SOFTS	FROM
BTM	58.28	12.14	11.84	4.54	8.5	0.67	0.54	0.78	1.91	0.79	41.72
MKR	11.53	54.75	10.04	5.17	14.05	0.9	0.93	0.38	1.39	0.86	45.25
POLY	11.89	10.59	60	4.77	8.5	0.87	0.77	0.64	1.17	0.8	40
PRO	5.62	6.37	5.68	74.67	4.29	0.54	0.59	0.58	0.77	0.9	25.33
SNX	8.36	14.84	8.43	3.69	60.61	0.84	0.87	0.28	1.15	0.94	39.39
ENERGY	0.68	1.12	1.02	0.5	0.93	71.17	6.73	1.26	7.87	8.72	28.83
AGRICULTURE	0.63	1.07	0.89	0.58	0.88	6.35	63.88	1.94	5.35	18.43	36.12
LIVESTOCK	1.27	0.61	0.95	0.65	0.43	1.5	2.51	87.83	1.61	2.65	12.17
METAL	2.05	1.65	1.29	0.71	1.32	7.77	5.65	1.28	69.87	8.42	30.13
SOFTS	0.8	0.97	0.84	0.82	0.88	7.67	17.63	1.89	7.47	61.02	38.98
TO	42.83	49.36	40.97	21.43	39.79	27.1	36.23	9.03	28.68	42.5	337.92
Inc.Own	101.12	104.11	100.97	96.1	100.4	98.27	100.11	96.85	98.55	103.52	TCI
NET	1.12	4.11	0.97	−3.9	0.4	−1.73	0.11	−3.15	−1.45	3.52	33.79

Note(s): Results are based on R^2 model. FROM = spillover from other asset, TO = spillover to other asset, NET = net directional spillover, TCI = total connectedness index
Source(s): Table by authors

Table 3. Static connectedness results (short-term)

	BTM	MKR	POLY	PRO	SNX	ENERGY	AGRICULTURE	LIVESTOCK	METAL	SOFTS	FROM
BTM	56.91	11.72	11.48	4.14	8.34	1.32	1.85	1.81	1.43	1.02	43.09
MKR	11.02	53.19	9.08	6.51	13.75	1.15	1.59	1.05	1.23	1.43	46.81
POLY	11.72	9.71	58.84	5.12	7.96	1.04	1.44	1.37	1.28	1.52	41.16
PRO	4.75	7.89	5.68	69.75	4.06	1.4	1.33	1.25	1.17	2.71	30.25
SNX	8.04	14.37	7.6	3.71	59.37	1.81	0.95	0.72	2.06	1.37	40.63
ENERGY	1.32	1.42	1.2	1.37	2.11	67.41	7.14	1.48	7.55	9	32.59
AGRICULTURE	1.95	1.88	1.58	1.11	1.07	6.83	61.39	2.22	4.37	17.6	38.61
LIVESTOCK	2.74	1.56	2.13	1.52	1.04	1.84	2.75	80.19	2.76	3.48	19.81
METAL	1.64	1.47	1.61	1.19	2.42	8.12	4.77	2.42	67.93	8.43	32.07
SOFTS	1.08	1.59	1.72	2.39	1.45	8.08	16.66	2.54	7.16	57.34	42.66
TO	44.25	51.61	42.08	27.04	42.19	31.58	38.49	14.86	29.02	46.57	367.68
Inc.Own	101.16	104.8	100.92	96.79	101.55	98.99	99.88	95.05	96.95	103.9	TCI
NET	1.16	4.8	0.92	−3.21	1.55	−1.01	−0.12	−4.95	−3.05	3.9	36.77

Note(s): Results are based on R^2 model. FROM = spillover from other asset, TO = spillover to other asset, NET = net directional spillover, TCI = total connectedness index
Source(s): Table by authors

Table 4. Static connectedness results (long-term)

	BTM	MKR	POLY	PRO	SNX	ENERGY	AGRICULTURE	LIVESTOCK	METAL	SOFTS	FROM
BTM	28.75	13.56	7.36	8.11	10.33	8.97	6.25	3.13	7.1	6.44	71.25
MKR	11.91	24.34	11.48	7.88	10.79	6.82	9.55	3.36	4.84	9.03	75.66
POLY	7.64	12.54	29.27	11.4	9.63	5.28	7.74	3.69	5.55	7.26	70.73
PRO	7.44	8.34	11.41	30.93	7.35	8.44	5.86	5.99	6.76	7.48	69.07
SNX	10.61	11.81	9.69	7.16	30.05	5.2	8.03	2.73	6.25	8.47	69.95
ENERGY	10.31	8.41	5.45	9.13	6.17	31.7	5.21	6.19	11.1	6.33	68.3
AGRICULTURE	6.22	10.42	8.33	6.34	8.12	5.1	31.01	7.75	7.84	8.89	68.99
LIVESTOCK	3.7	4.71	4.92	7.08	3.78	7.41	8.47	43.38	6.67	9.87	56.62
METAL	7.9	6.39	6.02	6.76	6.45	11.73	8.37	5.77	31.84	8.77	68.16
SOFTS	6.74	9.48	7.36	7.11	9.18	5.51	9.36	8.21	7.7	29.34	70.66
TO	72.47	85.65	72.03	70.96	71.8	64.45	68.83	46.82	63.81	72.56	689.39
Inc.Own	101.22	109.99	101.3	101.89	101.86	96.15	99.84	90.2	95.64	101.9	TCI
NET	1.22	9.99	1.3	1.89	1.86	−3.85	−0.16	−9.8	−4.36	1.9	68.94

Note(s): Results are based on R^2 model. FROM = spillover from other asset, TO = spillover to other asset, NET = net directional spillover, TCI = total connectedness index
Source(s): Table by authors

shocks from other assets in the network. Additionally, the TO row indicates that MKR (51.61%) once again recorded the highest transmitted shocks in the short-term frequency, while LIVESTOCK (14.86%) transmitted the lowest amount of shock. The NET results reveal that MKR (4.80%) stands out as the primary net transmitter of shocks, while LIVESTOCK (−4.95%) emerges as the primary net receiver. Analyzing the TCI in the short-term frequency, we observe a value of 36.77%, indicating a relatively lower level of connectedness. This outcome is consistent with the overall market results, again suggesting that RWA tokens are decoupled from the commodity market.

In the long-term frequency, Table 4 indicates that LIVESTOCK has the highest own variance shock at 43.38%. In terms of shocks received from other assets in the network, MKR (75.66%) is recorded as having the highest, whereas LIVESTOCK (56.62%) receives the lowest. Furthermore, the TO row indicates that MKR (85.65%) once again has the highest transmission to others in the long-term frequency, while LIVESTOCK (56.62%) transmits the lowest amount of shock. The NET results disclose that MKR (9.99%) again emerges as the primary net transmitter of shocks, while LIVESTOCK (−9.80%) acts as the primary net receiver. The roles of transmission and reception for MKR and LIVESTOCK remain consistent across overall, short-term and long-term frequencies. The persistence of transmission and receiving patterns for MKR and LIVESTOCK across different time horizons underscores the enduring nature of their interconnected dynamics, with the long-term perspective revealing a more pronounced level of interdependence between the two assets. Evaluating the TCI in the long-term frequency revealed a comparatively higher value of 68.94%. This higher TCI in the long-term frequency signifies a heightened level of connectedness when compared to both overall and short-term frequencies. This result suggests that the shocks or variations in returns of RWA tokens and commodities exhibit a greater degree of mutual influence and dependence when observed over a more extended period. The increased connectedness in the long-term frequency could be attributed to various factors, including fundamental economic ties, shared market trends or sustained correlations between RWA tokens and commodities. This insight can inform investors about the potential co-movements and interdependencies between these assets, aiding in more informed decision-making for portfolio construction and diversification efforts.

In order to gain a more detailed understanding of the shock transmission mechanism, we present the results through a network connectedness plot. Figure 2 serves as a visual representation of the connectedness network, offering insights into the interdependencies between RWA tokens and commodities. In this visualization, the node color corresponds to the values of the spillover effect, providing a visual representation of the intensity of shocks. Arrows within the network illustrate the direction and strength of the shock spillovers, while the thickness and color of the edges further convey the magnitude and nature of these interconnected effects. Edge thickness serves as an indicator of the level of pairwise connectedness between markets, offering a quantitative measure of their interrelation. Under normal market conditions, our analysis indicates that RWA tokens exhibit connections primarily among themselves, with minimal transmissions observed from POLY to LIVESTOCK. A similar trend is observed in the short-term frequency, where RWA tokens demonstrate minimal connections, primarily with LIVESTOCK. In contrast, in the long-term frequency, a more comprehensive pattern of transmission emerges among RWA tokens and commodities. Notably, a significant proportion of shocks are transmitted from MKR to LIVESTOCK, METAL and ENERGY, highlighting a more pronounced and sustained interconnectedness over extended time horizons. This finding underscores the importance of considering different timeframes when assessing the transmission dynamics between RWA tokens and commodities, as the nature and extent of their connections vary across short, long and overall market conditions. Consistent with our findings, earlier studies conducted by Abdullah *et al.* (2023) and Yousaf *et al.* (2022a) have similarly documented a low level of connectedness among tokens and traditional assets. Their research aligns with our observations, indicating that the relationship between RWA tokens and commodities tends to be limited in terms of interconnectedness.

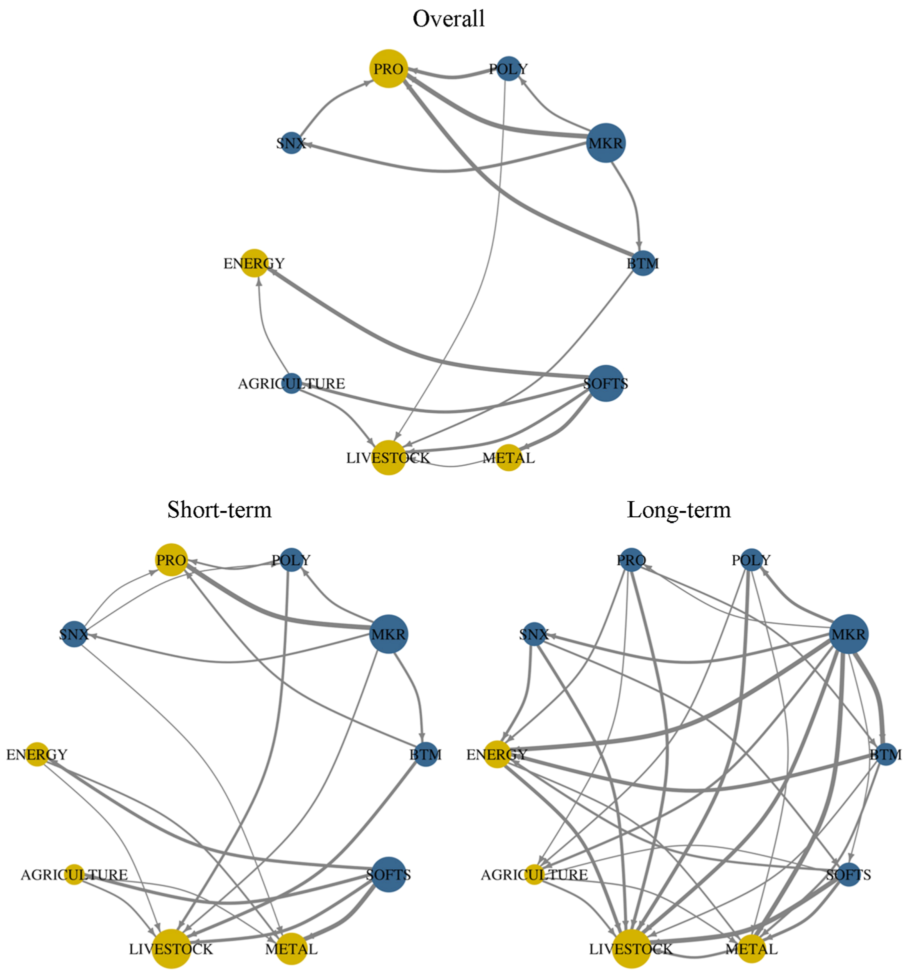

Figure 2. Connectedness network plots. Notes: Results are based on R^2 model. Source: Figure by authors

4.2 Dynamic connectedness results

The preceding analysis provides valuable insights, yet it is inherently static and does not account for time-varying evaluations. To delve deeper into the evolving dynamics and capture potential shifts over time, we transition toward a dynamic analysis. Figure 3 illustrates the outcomes of dynamic connectedness measures, with the shaded area depicting the evolution of the TCI in the overall market condition. The solid blue line and red dotted line represent long-term and short-term frequency TCI, respectively. The figure indicates that total connectedness varies between 25% and 80%, suggesting a dependence on events. Moreover, the results from the three distinct measures exhibit similar patterns, with notable peaks and troughs occurring around the same time intervals. Nevertheless, significant disparities emerge between long-term and short-term frequency, with the latter primarily driving system connectedness. Overall, these findings highlight the time-varying connectedness between RWA tokens and commodities, emphasizing its event dependency. Furthermore, the surge during COVID-19 is attributed to the economic downturn, contributing to increased uncertainty (Abakah *et al.*,

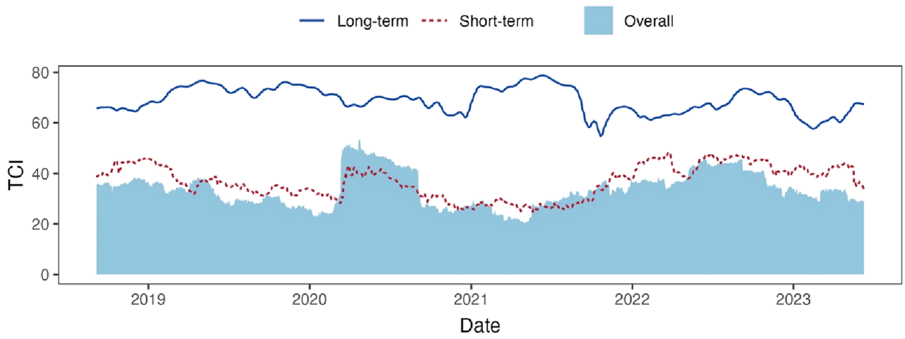

Figure 3. Dynamic total connectedness index. Notes: Results are based on a biannual (126 days) rolling window R^2 model. Source: Figure by authors

2023a, b). The peak in 2022 is linked to the Russia–Ukraine war, which disrupted global financial markets (Abakah *et al.*, 2024; Abdullah *et al.*, 2023).

In Figure 4, we explore the net directional dynamic connectedness, revealing whether a variable in the network functions as a net transmitter or net receiver. Positive (negative) values in the figure signify net transmitters (recipients) in the network and our findings illustrate that variables in the network assume different roles over time. The analysis indicates that AGRICULTURE, BTM, NKR and SOFTS consistently serve as net transmitters of return

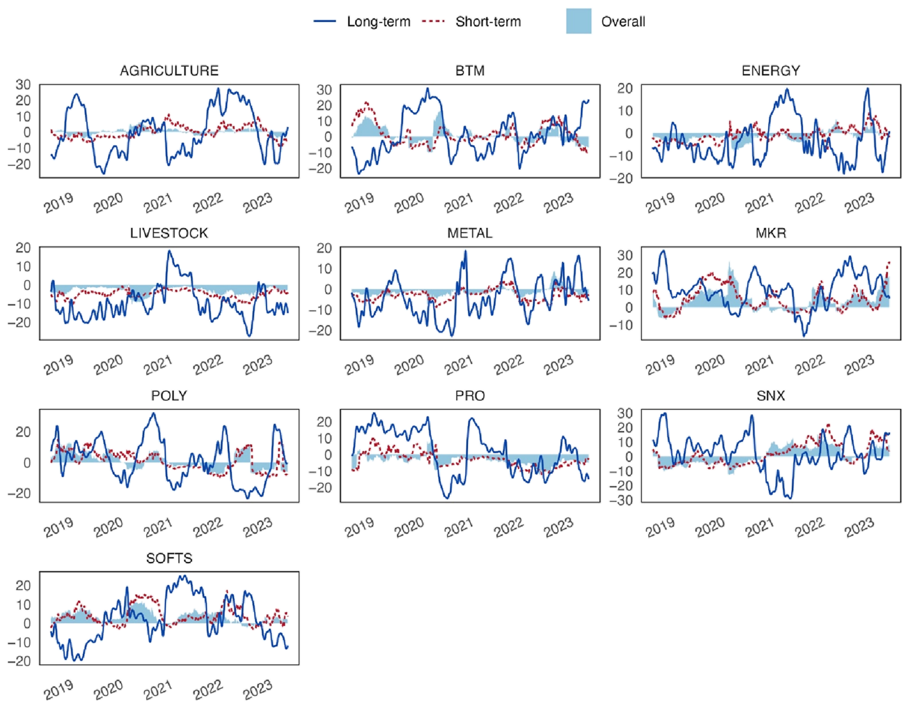

Figure 4. Dynamic net total directional connectedness. Notes: Results are based on a biannual (126 days) rolling window R^2 model. Source: Figure by authors

spillovers from other variables in the network. Additionally, ENERGY, LIVESTOCK, METAL and PRO tend to act as net receivers of return spillovers. Notably, long- and short-term frequency spillovers generally surpass overall and short-term frequency spillovers in magnitude. The shift between the dominance of short-term and long-term frequency return spillovers can be attributed to economic events. Further exploration of pairwise dynamic connectedness and net pairwise dynamic connectedness is detailed in Figures A2 and A3, respectively, supporting our earlier findings that RWA tokens are marginally connected with commodities, indicating potential portfolio benefits among them. Previous studies have also highlighted the lower connectedness in the case tokens and traditional assets (Abdullah *et al.*, 2023; Yousaf *et al.*, 2023a; Yousaf *et al.*, 2023c).

4.3 Robustness test results

In our initial analysis, we utilized 126-day rolling windows with the Pearson methodology. To enhance the robustness of our baseline results, we conducted additional tests using various rolling windows and methods. Specifically, for these robustness tests, we explored the Pearson, Spearman and Kendall methodologies, combined with rolling windows of 63, 189 and 252 days. The outcomes of these robustness tests are visually represented in Figure 5, illustrating multiscale connectedness. Notably, the results from these robustness tests substantiate our initial observations, demonstrating that the TCI fluctuates within the range of 25% to 80%. Furthermore, a consistent increase in TCI was observed during the COVID-19 period, reinforcing the reliability of our baseline conclusions. These collective findings underscore a moderate level of connectedness between RWA tokens and commodities.

4.4 Role of global uncertainty factors results

The preceding analysis clearly illustrates the existence of time-varying spillover between RWA tokens and commodities, particularly accentuated during economic events. However, these economic occurrences transmit risk to the market through diverse channels, encompassing stock market fear or stress, oil market fear or stress, economic policy uncertainty and geopolitical risk (Baker, Bloom, & Davis, 2016; Bekaert, Engstrom, & Xu, 2022; Caldara & Iacoviello, 2022). Consequently, in this section, our focus shifts to examining how uncertainties influence the connectedness between RWA tokens and commodities. To conduct this analysis, we utilize the Chicago Board Options Exchange's (CBOE) Crude Oil Volatility Index (OVX) as a proxy for oil market fear or stress, the CBOE Volatility Index (VIX) as a proxy for stock market fear or stress, the gold volatility index (GVZ) as a proxy for gold market fear or stress, the daily US Economic Policy Uncertainty Index (EPU) as a measure of US policy uncertainty and the risk aversion index (RAI) to capture investor sentiment [4]. We use a bivariate model to avoid multicollinearity issues as uncertainty factors are highly correlated.

The results presented in Table 5 highlight the outcomes related to uncertainty factors. Across all frequency TCI, a noteworthy positive association is observed between all uncertainty factors, except for GVZ in the short-term frequency, where the relationship is found to be insignificant. This implies that heightened levels of these uncertainty factors contribute to increased interconnectedness, potentially stemming from investor risk aversion behaviors and economic instability. Of particular interest is the observation that RAI exhibits the highest coefficient among all factors across all TCIs. This outcome suggests that risk aversion behaviors play a substantial role in the transmission of shocks from the token blockchain market to the commodity market. The significance of these factors underscores their potential impact on the spillover of shocks between these markets. These findings are in line with earlier studies that documented that uncertainty factors increase connectedness among financial assets (Abakah *et al.*, 2024; Abdullah *et al.*, 2023).

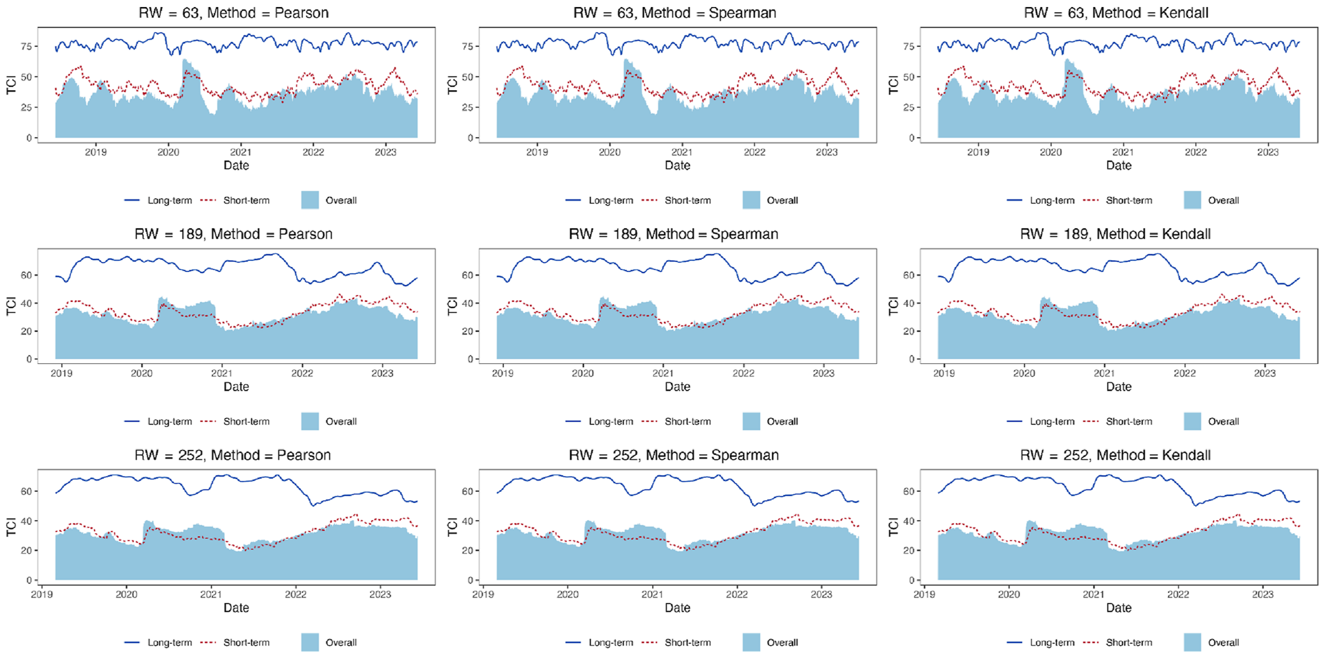

Figure 5. Robustness test results. Notes: Results are based on wavelet-based R^2 model. RW = Rolling window. Source: Figure by authors

Table 5. Role of uncertainty factors

Variables	(1) Overall (TCI)	(2) Short-term (TCI)	(3) Long-term (TCI)
Panel A: VIX			
VIX	0.444***	0.121***	0.657***
	(0.021)	(0.020)	(0.024)
Constant	24.076***	18.612***	27.803***
	(0.491)	(0.460)	(0.557)
R-squared	0.274	0.031	0.392
Adjusted *R*-squared	0.274	0.030	0.392
Panel B: OVX			
OVX	0.153***	0.058***	0.201***
	(0.007)	(0.006)	(0.008)
Constant	26.889***	18.645***	33.094***
	(0.361)	(0.336)	(0.436)
R-squared	0.285	0.062	0.324
Adjusted *R*-squared	0.285	0.061	0.323
Panel C: GVZ			
OVX	0.153***	0.058***	0.201***
	(0.007)	(0.006)	(0.008)
Constant	26.889***	18.645***	33.094***
	(0.361)	(0.336)	(0.436)
R-squared	0.285	0.062	0.324
Adjusted *R*-squared	0.285	0.061	0.323
GVZ	0.530***	−0.015	1.031***
	(0.039)	(0.034)	(0.042)
Constant	24.901***	21.520***	24.881***
	(0.682)	(0.594)	(0.742)
R-squared	0.135	0.000	0.333
Adjusted *R*-squared	0.134	−0.001	0.332
Panel D: GPR			
GPR	0.014***	0.025***	−0.013***
	(0.003)	(0.003)	(0.004)
Constant	32.166***	18.366***	43.759***
	(0.426)	(0.335)	(0.530)
R-squared	0.016	0.075	0.009
Adjusted *R*-squared	0.015	0.074	0.008
Panel E: EPU			
EPU	0.025***	0.001***	0.047***
	(0.002)	(0.001)	(0.002)
Constant	29.825***	21.068***	34.806***
	(0.328)	(0.290)	(0.357)
R-squared	0.155	0.001	0.350
Adjusted *R*-squared	0.155	−0.000	0.349
Panel F: RAI			
RAI	1.819***	0.373***	2.676***
	(0.138)	(0.119)	(0.167)
Constant	28.013***	20.087***	33.676***
	(0.483)	(0.417)	(0.581)
R-squared	0.128	0.008	0.179
Adjusted *R*-squared	0.127	0.007	0.179

Note(s): This table presents the results for the impact of global factors on the connectedness. Panels A to F shows the findings for VIX, OVX, GVZ, GPR, EPU and RAI as independent variable using respective TCI values as dependent variable estimated above section. All models are estimated using the OLS estimator with 1,193 observations. Standard errors are in parentheses. ***, **, * denote significance at 1%, 5% and 10% significance level

Source(s): Table by authors

4.5 Portfolio analysis results

Based on the earlier examination, it seems that there is a potential for diversifying portfolios between RWA tokens and commodities. Consequently, our attention now turns to the evaluation of portfolio weights and bivariate hedge ratios. The relevant statistics for the bivariate portfolio weights are presented in Table 6. The highest portfolio reaching 99%, between METAL and MKR implies that, in a $1 portfolio, 1 cent is allocated to MKR, while 89 cents are allocated to METAL. This highlights a significant emphasis on ENERGY within the portfolio, potentially due to perceived risk-return characteristics or other specific factors. The analysis further discloses that among the combinations of RWA tokens and commodities, BTM and ENERGY exhibit the highest weights at 11%. This signifies that in a portfolio comprising these assets, a substantial portion of the investment is assigned to ENERGY (89%), while BTM constitutes the remaining 11%. The elevated weight attributed to ENERGY suggests that it is perceived to possess favorable risk-return characteristics or other appealing attributes, making it an attractive investment choice. Allocating portfolio weights provides investors with an effective means of balancing their exposure to different assets, considering their individual risk profiles and expected returns.

Moreover, the hedge ratio, representing the average value of the hedging ratio, denotes the proportion of a short position in the second asset that can be used to hedge a $1 long position in the first asset. To illustrate, consider the example of PRO/LIVESTOCK. With an estimated hedging ratio of 0.16, it indicates that a $1 long position in PRO can be effectively hedged by investing $0.16 in LIVESTOCK as a short position. This implies that investors can potentially mitigate the downside risk associated with PRO by taking a short position in LIVESTOCK equivalent to 16% of the value of the long position in IPG. Hedging ratios offer insights into the potential advantages of diversification and risk management strategies within a portfolio. Through the application of suitable hedging techniques, investors have the potential to diminish their exposure to specific asset risks and improve the overall risk-adjusted returns of their portfolios. Our findings align with studies conducted by Abdullah *et al.* (2023) and Yousaf *et al.* (2022a), which identified significant opportunities for portfolio diversification between tokens and traditional assets.

5. Discussions

The empirical findings of this study offer valuable insights into the interconnectedness between RWA tokens and commodities, highlighting their implications for portfolio diversification and risk management. The static connectedness analysis shows limited spillovers between RWA tokens and commodities, with connections mostly within RWA. Minimal links, such as POLY to LIVESTOCK, suggest that these markets remain distinct, aligning with prior studies (Abdullah *et al.*, 2023; Yousaf *et al.*, 2022a). However, long-term frequency analysis reveals stronger transmissions, particularly from MKR to LIVESTOCK, METAL and ENERGY, highlighting the need for a multi-frequency perspective. The low static connectedness reflects RWA's emerging status and incomplete integration into commodity markets due to differences in market structures, regulations and investor bases (Yousaf *et al.*, 2022b).

The dynamic connectedness analysis shows significant time-varying spillovers between RWA and commodities, with total connectedness fluctuating between 25% and 80%, driven by events like the COVID-19 pandemic and the Russia–Ukraine conflict (Abakah *et al.*, 2023b; Abdullah *et al.*, 2023). These shocks increase interconnectedness, highlighting the role of external factors. Short-term spillovers dominate, reflecting quicker market reactions to shocks, consistent with previous studies on the responsiveness of digital assets (Abakah *et al.*, 2023a; Yousaf *et al.*, 2023a). The analysis also reveals how assets like AGRICULTURE and ENERGY act as transmitters or receivers of spillovers, offering insights into their dynamic behavior.

Table 6. Portfolio analysis results

Portfolios	Weights	Hedge ratios
AGRICULTURE/BTM	0.98	0.01
AGRICULTURE/ENERGY	0.84	0.15
AGRICULTURE/LIVESTOCK	0.46	0.15
AGRICULTURE/METAL	0.37	0.33
AGRICULTURE/MKR	0.98	0.02
AGRICULTURE/POLY	0.99	0.01
AGRICULTURE/PRO	0.99	0
AGRICULTURE/SNX	0.99	0.01
AGRICULTURE/SOFTS	0.52	0.54
BTM/AGRICULTURE	0.02	0.42
BTM/ENERGY	0.11	0.12
BTM/LIVESTOCK	0.01	0.63
BTM/METAL	0.01	1.14
BTM/MKR	0.44	0.56
BTM/POLY	0.68	0.38
BTM/PRO	0.76	0.21
BTM/SNX	0.73	0.29
BTM/SOFTS	0.02	0.51
ENERGY/AGRICULTURE	0.16	0.62
ENERGY/BTM	0.89	0.01
ENERGY/LIVESTOCK	0.17	0.24
ENERGY/METAL	0.07	0.9
ENERGY/MKR	0.89	0.03
ENERGY/POLY	0.94	0.02
ENERGY/PRO	0.96	0.01
ENERGY/SNX	0.95	0.02
ENERGY/SOFTS	0.13	0.69
LIVESTOCK/AGRICULTURE	0.54	0.14
LIVESTOCK/BTM	0.99	0.01
LIVESTOCK/ENERGY	0.83	0.05
LIVESTOCK/METAL	0.44	0.09
LIVESTOCK/MKR	0.98	0.01
LIVESTOCK/POLY	0.99	0.01
LIVESTOCK/PRO	0.99	0
LIVESTOCK/SNX	0.99	0
LIVESTOCK/SOFTS	0.56	0.13
METAL/AGRICULTURE	0.63	0.22
METAL/BTM	0.99	0.02
METAL/ENERGY	0.93	0.15
METAL/LIVESTOCK	0.56	0.07
METAL/MKR	0.99	0.02
METAL/POLY	0.99	0.01
METAL/PRO	0.99	0.01
METAL/SNX	0.99	0.01
METAL/SOFTS	0.66	0.27
MKR/AGRICULTURE	0.02	0.62
MKR/BTM	0.56	0.49
MKR/ENERGY	0.11	0.24
MKR/LIVESTOCK	0.02	0.37
MKR/METAL	0.01	1.05
MKR/POLY	0.73	0.36
MKR/PRO	0.8	0.2
MKR/SNX	0.82	0.36
MKR/SOFTS	0.02	0.58

(*continued*)

Table 6. Continued

Portfolios	Weights	Hedge ratios
POLY/AGRICULTURE	0.01	0.5
POLY/BTM	0.32	0.59
POLY/ENERGY	0.06	0.3
POLY/LIVESTOCK	0.01	0.66
POLY/METAL	0.01	1.23
POLY/MKR	0.27	0.63
POLY/PRO	0.64	0.24
POLY/SNX	0.58	0.38
POLY/SOFTS	0.01	0.81
PRO/AGRICULTURE	0.01	0.19
PRO/BTM	0.24	0.55
PRO/ENERGY	0.04	0.28
PRO/LIVESTOCK	0.01	0.16
PRO/METAL	0.01	0.96
PRO/MKR	0.2	0.6
PRO/POLY	0.36	0.4
PRO/SNX	0.44	0.36
PRO/SOFTS	0.01	0.51
SNX/AGRICULTURE	0.01	0.75
SNX/BTM	0.27	0.57
SNX/ENERGY	0.05	0.31
SNX/LIVESTOCK	0.01	0.11
SNX/METAL	0.01	1.23
SNX/MKR	0.18	0.8
SNX/POLY	0.42	0.47
SNX/PRO	0.56	0.27
SNX/SOFTS	0.01	0.83
SOFTS/AGRICULTURE	0.48	0.56
SOFTS/BTM	0.98	0.01
SOFTS/ENERGY	0.87	0.18
SOFTS/LIVESTOCK	0.44	0.16
SOFTS/METAL	0.34	0.43
SOFTS/MKR	0.98	0.02
SOFTS/POLY	0.99	0.01
SOFTS/PRO	0.99	0.01
SOFTS/SNX	0.99	0.01

Note(s): Results are based on the estimation of Kroner and Ng (2015) and Kroner and Sultan (1993) methodology

Source(s): Table by authors

The analysis of global uncertainty factors revealed a significant positive relationship with interconnectedness across all frequency TCIs, except for the GVZ index in the short-term frequency. This indicates that heightened risk aversion and economic instability amplify the transmission of shocks between RWA and commodities. The strong influence of the RAI index highlights the critical role of investor sentiment and behavioral biases in shaping market dynamics. These findings are consistent with prior studies (Abakah *et al.*, 2023a; Abdullah *et al.*, 2023), which document the impact of uncertainty factors on increasing connectedness in financial markets.

The portfolio analysis demonstrates the potential for diversification benefits between RWA and commodities, with distinct allocation strategies based on asset characteristics. For instance, the significant weight assigned to ENERGY in portfolios reflects its favorable risk-return profile, while assets like MKR and BTM provide complementary exposure.

The hedging ratio analysis further underscores the practical utility of these findings, enabling investors to effectively manage risks by offsetting positions in one asset with opposing positions in another. These results align with earlier research (Abdullah *et al.*, 2023; Yousaf *et al.*, 2022a) that identified diversification opportunities between blockchain-based assets and traditional financial instruments.

Overall, this study contributes to the literature by addressing gaps in understanding the interconnectedness of RWA with commodities. While earlier studies predominantly focused on cryptocurrencies, NFTs and DeFi (Ghosh *et al.*, 2023; Gunay *et al.*, 2023; Proelss *et al.*, 2023; Liu, 2023), this research extends the scope to include RWA, offering fresh perspectives on their dynamic relationships with traditional assets. The novel application of the R^2-based time-frequency connectedness approach provides a more nuanced understanding of these interactions, particularly in the context of global uncertainty and portfolio management.

6. Conclusions

This study explores the static and dynamic connectedness between RWA tokens and commodities across overall, short-term and long-term frequencies. Our comprehensive analysis of the connectedness between RWA tokens and commodities across various frequencies provides valuable insights into the dynamics of these markets. The static connectedness results reveal a detailed relationship, with a lower level of interconnectedness observed, particularly in the overall and short-term frequencies. However, a more pronounced interdependence surfaced in the long-term frequency, suggesting potential co-movements influenced by fundamental economic ties. The dynamic connectedness measures underscore the time-varying nature of interconnectedness, with heightened levels during economic events such as the COVID-19 pandemic and the Russia–Ukraine war in 2022.

The influence of global uncertainty factors, including stock market fear, oil market stress, economic policy uncertainty and geopolitical risk, further amplifies connectedness, highlighting the multifaceted channels through which economic occurrences transmit risk to the market. The positive associations observed between uncertainty factors and connectedness emphasize the role of investor risk aversion behaviors and economic instability in shaping the relationship between RWA tokens and commodities. Our portfolio analysis indicates potential diversification opportunities, with bivariate hedge ratios offering insights into effective risk management strategies within the portfolio. The emphasis on balancing exposure to RWA tokens and commodities aligns with previous studies that have identified significant opportunities for diversification between tokens and traditional assets.

The results of our study bear significant implications for various stakeholders in the financial landscape. For investors, the observed lower level of static connectedness, particularly in the overall and short-term frequencies, suggests potential diversification benefits between RWA tokens and commodities. Investors can strategically allocate their portfolios to capitalize on this limited interconnectedness and mitigate risks associated with market fluctuations. The heightened connectedness during economic events underscores the importance of staying vigilant and adapting portfolio strategies during periods of increased uncertainty. Portfolio managers can leverage the insights from our study to refine their diversification strategies and optimize risk-adjusted returns. The dynamic connectedness measures highlight the need for adaptive portfolio management, considering the time-varying nature of interconnected dynamics between RWA tokens and commodities. Portfolio managers may consider incorporating global uncertainty factors into their risk models to enhance the effectiveness of risk management strategies.

Regulators and policymakers can benefit from our findings to gain a deeper understanding of the evolving dynamics at the intersection of blockchain-based assets and traditional commodities. The observed connections during economic events emphasize the importance of monitoring these markets for potential systemic risks. Policymakers may consider adopting flexible regulatory approaches that accommodate the unique characteristics of RWA tokens while ensuring market stability. Furthermore, our results underscore the need for ongoing research and monitoring of the interconnectedness between emerging blockchain-based assets and traditional commodities. As these markets continue to evolve, policymakers and regulators should stay informed about the implications of economic events and global uncertainty factors on the dynamics of RWA tokens and commodities.

One limitation of this study is its focus on an unstable sample period, primarily centered around significant events like the COVID-19 pandemic, the Russia–Ukraine War, the FTX collapse and the Silicon Valley Bank crisis. While these events provide valuable insights into the interconnectedness of RWA tokens and commodities during times of financial stress, they may not fully capture normal market conditions. Future studies could expand on our findings by using alternative methodologies, such as event studies, to examine the specific effects of each event in greater detail, offering a more detailed understanding of their individual impacts on market dynamics.

Notes

1. For the estimation simplicity, we utilize overall, short- and long-term scales (D2 and D6). The same methodology can be applied consistently across all scales, ranging from D1 to D6 or beyond.
2. List of RWA available at: https://coinmarketcap.com/view/real-world-assets/.
3. Daily closing price series is illustrated in Figure A1.
4. Data source: OVX, VIX, and GVZ, = Datastream, EPU = https://www.policyuncertainty.com/, RAI = https://www.nancyxu.net/risk-aversion-index, and GPRI = https://www.matteoiacoviello.com/gpr.htm.

Supplementary material

The supplementary material for this article can be found online.

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