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Dynamic interactions between metaverse-related cryptocurrencies and traditional financial assets: evidence from a TVP-VAR model

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Abstract

Purpose – To explore the relationships between major metaverse-related cryptocurrencies and traditional financial assets, as well as their hedging capabilities over time.

Design/methodology/approach – The study period spans from 1 September 2021 to 31 January 2025. Using the time-varying parameter vector autoregressive (TVP-VAR) method, this study examines the dynamic relationships between Bitcoin and Ethereum, the ten most capitalised metaverse-related cryptocurrencies, and traditional financial assets. As a robustness measure, the DCC-GARCH model is used to calculate optimal portfolio weights, hedge ratios, and hedging effectiveness, providing a comprehensive evaluation of risk mitigation.

Findings – The results reveal that the relationships between assets intensify during periods of turmoil. Intra-market relationships are stronger than cross-market relationships, traditional markets offer more effective hedging and crypto markets exhibit greater variability when constructing hedged portfolios.

Originality/value – These findings provide a deeper understanding of this new technology and valuable practical implications for investors, regulators, researchers, and society.

Keywords Metaverse, Cryptocurrencies, TVP-VAR model, DCC-GARCH, Dynamic relationships, Decentralised finance

Paper type Research article

Introduction

Since its conception, the metaverse has captured the attention of investors, researchers, and society (Bouri *et al.*, 2024; Piñeiro-Chousa *et al.*, 2025). The digital world has transformed how people interact with technology, companies, and even with each other (Basty and Abidly, 2025; Naeem *et al.*, 2025; Vidal-Tomás, 2023). Nowadays, the concept of the metaverse is associated with the term "crypto-metaverse", as it integrates blockchain technology at its foundation (Vidal-Tomás, 2023). This technology improves traceability, security, and auditability (Klein *et al.*, 2018). Through metaverses, users can create, manage, and exchange digital assets such as non-fungible tokens (NFTs). The main payment systems are metaverse-related cryptocurrencies (Vidal-Tomás, 2023).

According to CoinMarketCap, the cryptocurrency market is valued at 3.88 trillion dollars as of 24 September 2025. This market includes different types of tokens such as decentralised

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finance (DeFi), NFTs, meme coins, and metaverse-related cryptocurrencies, each with a specific purpose (Ghorbel and Jeribi, 2021). For instance, DeFi replicates financial services on a blockchain using smart contracts, thereby generating new economic activities (Piñeiro-Chousa *et al*., 2022; Romero-Castro *et al*., 2025). This article defines metaverse-related cryptocurrencies as those specifically linked to immersive digital environments, selected from CoinMarketCap's metaverse category. Metaverse-related cryptocurrencies differ from NFTs in their uniqueness, which is relevant when analysing their integration with traditional assets.

Traditional financial assets form the basis of the global economy and are essential to understanding how emerging digital assets interact with the current financial system. To capture the behaviour of these traditional assets, this study includes three major US stock indices (Nasdaq Composite [NDX], S&P500 [SP], and VIX index [VIX]), four commodities (Brent crude oil [Brent], West Texas Intermediate [WTI], Gold, and Silver), and the ICE MSCI World Climate Change NTR Futures (ICE) as an environmental proxy. Three major US stock indices were selected because of their representativeness in the US market and their potential relationship with our sample (Ghorbel and Jeribi, 2021; Guo *et al*., 2024). Commodities allow for the analysis of the interaction between volatile assets and safe-haven assets (Alqaralleh and Canepa, 2022; Cheng *et al*., 2024; Foroutan and Lahmiri, 2024; Ghorbel and Jeribi, 2021). Finally, the high consumption of fossil fuels and climate change have intensified the focus on transitioning toward a greener economy. To reflect the growing importance of sustainability in investment decisions, this study includes the ICE as a proxy for environmental considerations (Basty and Abidly, 2025; Guo *et al*., 2024; Pérez Calderón *et al*., 2021).

The growing interconnectedness of financial assets has gained significant importance (Cheng *et al*., 2024; Diebold and Yilmaz, 2009; Zhang, 2025), because of several risks, such as shock transmission, increased volatility, and potential systemic threats (Brunnermeier, 2009; Cheng *et al*., 2024; Demir *et al*., 2018; Guo *et al*., 2024; Li *et al*., 2023). This strong connection is the result of various factors, such as globalisation (Cheng *et al*., 2024; Diebold and Yilmaz, 2014; Kearney and Lucey, 2004; Zhang, 2025), information flows (Zhang, 2025), technological advancements (Naeem *et al*., 2025), and increasingly similar investor behaviours (Bouri *et al*., 2024; Vieira, 2015). The integration of metaverse-related cryptocurrencies and conventional financial assets is evident, because companies and governments worldwide are adopting blockchain technology and cryptocurrencies in their initiatives. Major corporations such as Meta and Apple already view the metaverse as the future of human interaction (Frank and Rudolf, 2024; Piñeiro-Chousa *et al*., 2025).

Research on cryptocurrencies has grown over the past decade, with particular attention to their interconnections with other financial assets (Giudici and Abu-Hashish, 2019; Katsiampa, 2019; Yousaf and Yarovaya, 2022). The spillover effects between digital and traditional assets have been extensively investigated, with research emphasising the internal dynamics of the cryptocurrency market (Chowdhury *et al*., 2023; Guo, 2022; Malek *et al*., 2023), the capability of these assets as a safe haven or hedge (Akkus and Dogan, 2024; Cevik *et al*., 2022; Corbet *et al*., 2022; Li *et al*., 2023), the impact of macroeconomic policies (Demir *et al*., 2018), speculative bubbles within the metaverse, and even the relationship between these new assets and the environment (Abakah *et al*., 2023; Yousaf *et al*., 2022). However, traditional assets and their interactions with metaverse cryptocurrencies remain unexplored. Understanding the behaviour of these assets is crucial for designing investment strategies, managing risks, and formulating monetary policies.

Previous studies have explored this topic; however, none have addressed it from the same perspective. Some articles included MANA in their sample, although it has been classified as an NFT (Dowling, 2022; Yousaf *et al*., 2024). However, based on the formal definition of an NFT, MANA does not qualify. Additionally, although several studies have employed the Time-Varying Parameter Vector Autoregression (TVP-VAR) model, they focus on other asset relationships (Cheng *et al*., 2024; Foroutan and Lahmiri, 2024; Yousaf *et al*., 2024; Yousaf and Yarovaya, 2022). The most comparable study focuses on three metaverse-related cryptocurrencies (MANA, XTZ, and AXS) and their connections with commodities and clean energy assets (Basty and Abidly, 2025). To the best of our knowledge, no study is comprehensive and specifically related to metaverse-related cryptocurrencies. This research expands the current literature by analysing the ten largest metaverse-related cryptocurrencies by market capitalisation and by incorporating Bitcoin and Ethereum to capture the dynamics within the cryptocurrency ecosystem, thereby addressing a critical gap that would arise from omitting these dominant assets.

This study uses the TVP-VAR model of Antonakakis *et al*. (2020), which extends the connectedness framework of Diebold and Yilmaz (2009, 2012, 2014), and incorporates a Kalman filter with forgetting factors (Koop and Korobilis, 2014). This approach has been shown to be superior to other models in capturing the dynamic nature of financial spillovers (Antonakakis *et al*., 2020; Yousaf *et al*., 2024; Yousaf and Yarovaya, 2022). Many studies have attempted to analyse these relationships using copulas, Var or Wavelet techniques, but the predominant approach relies on the spillover proposed by Diebold and Yilmaz (2009, 2012, 2014). Nevertheless, this method suffers from arbitrarily chosen rolling window sizes, which can lead to erratic or flattened parameters and the loss of valuable observations (Antonakakis *et al*., 2020; Yousaf *et al*., 2024). The TVP-VAR stands out from previous models because it allows the estimation of total, pairwise, and net connectedness “from” and “to” the assets to each market (Antonakakis *et al*., 2020; Yousaf *et al*., 2023, 2024; Yousaf and Yarovaya, 2022). In addition, by not requiring an arbitrary window size, the model adapts much faster to economic events. This is particularly important because our dataset is composed of highly volatile assets (Antonakakis *et al*., 2020; Guo *et al*., 2024; Naeem *et al*., 2025). After the connectedness analysis, and in line with Yousaf *et al*. (2023), we use DCC-GARCH to compute optimal portfolio weights (Kroner and Ng, 1998), hedge ratios (Kroner and Sultan, 1993), and hedging effectiveness (Ederington, 1979), providing a comprehensive evaluation of risk mitigation.

This study contributes to the literature by addressing gaps on metaverse-related cryptocurrencies, providing new evidence of their interconnections, and highlighting their hedging capabilities. Furthermore, by incorporating more assets, we provide a perspective that extends beyond previous studies. This study can help investors, practitioners, and regulators make better decisions.

The remainder of this paper is organised as follows: Section 2 presents the literature review and hypotheses. Section 3 describes the data collection, cleaning, and descriptive statistics. Section 4 presents the methodology used. Section 5 and 6 present and discuss the results respectively. Finally, section 7 concludes the paper with the limitations of the study and suggestions for future research.

Literature review

The crypto-metaverse allows users to trade different types of assets using cryptocurrencies that enable secure and traceable transactions (Gupta *et al*., 2024; Vidal-Tomás, 2023). They are distinct from NFTs in their unique features (Basty and Abidly, 2025; Nunes *et al*., 2024; Xia *et al*., 2022; Yousaf *et al*., 2024). While the primary function of cryptocurrencies is to be used as a means of payment, NFTs can be effectively used as promotional devices to increase brand value (Cho *et al*., 2025), or even as souvenirs from a tourist destination (López-Cabarcos *et al*., 2026; Prados-Castillo *et al*., 2024). To operate in crypto-metaverse, it is essential to understand the behaviour and relationship that exists between metaverse-related cryptocurrencies and traditional assets.

Globalisation has driven the integration of financial markets and amplified their risks (Brunnermeier, 2009; Cheng *et al*., 2024; Demir *et al*., 2018; Guo *et al*., 2024; Kearney and Lucey, 2004; Li *et al*., 2023; Naeem *et al*., 2025). Although crises are unpredictable, their transmission mechanisms tend to be similar (Reinhart and Rogoff, 2008). Therefore, it is important to analyse the main actors or assets in the economy to delve into their temporal behaviour and evolution toward more integrated environments. Further exploration of the integration of crypto assets, especially those related to the metaverse, with traditional assets is crucial because of the increasing number of participants in this new environment. It is estimated that the cost of metaverse products will exceed one billion dollars in the coming years (Gupta *et al*., 2024).

The literature shows that cryptocurrency prices are highly correlated with each other, but exhibit low correlation with traditional assets (Giudici and Abu-Hashish, 2019). Nevertheless, these correlations tend to increase during periods of turmoil (Abakah *et al*., 2023; Demir *et al*., 2018, 2018; Li *et al*., 2023). Yousaf *et al*. (2022) explored renewable energy tokens and highlighted that fossil fuel markets act as net transmitters of return spillovers under normal conditions, whereas Brent and natural gas dominate during extreme market events. Guo (2022) and Malek *et al*. (2023) suggested that cryptocurrencies exhibit significant volatility and time-dependent risk profiles. This behaviour challenges the perception of cryptocurrencies as entirely decentralised and independent assets (Giudici and Abu-Hashish, 2019) reinforcing the need for this study. Chowdhury *et al*. (2023) suggested that DeFi and NFT assets display complex price dynamics with cross-correlations on different timescales. These findings highlight the complexity of the volatility and interconnectedness within the cryptocurrency ecosystem. At the same time, they highlight the need for the present study and the use of the TVP-VAR methodology to accurately capture the behaviour of these new assets. Based on the aforementioned studies, we formulated the following hypotheses.

H1. The total relationships among all assets intensify over time owing to the current market instability.

H2. Metaverse-related cryptocurrencies, Bitcoin and Ethereum, have stronger internal relationships than those with traditional financial assets.

These two hypotheses lead us to the next two. If the relationships between assets change over time, it is essential to investigate the possibility of using these new assets as hedging instruments. Katsiampa (2019) suggested that Ethereum can function as a hedge against Bitcoin. Expanding on this, Li *et al*. (2023) suggested that only meme coins act as a hedge for Bitcoin, whereas DeFi assets and smart contract tokens serve as safe havens during extreme market downturns. Havidz *et al*. (2024) suggested that NFTs can serve as hedges against traditional assets in times of turmoil. In line with this, Cevik *et al*. (2022) suggested that DeFi tokens create an effective hedging effect on gold and oil during periods of turmoil. Nevertheless, this contrasts with Corbet *et al*. (2022), who suggested stronger relationships between DeFi and Bitcoin in bear markets influenced by investor sentiment. This is in line with Piñeiro-Chousa *et al*. (2022), who suggested that Telegram chats influence Defi. Akkus and Dogan (2024) identified Ethereum and Chainlink as the central transmitters of volatility spillovers in cryptomarkets. Yousaf and Yarovaya (2022) added that NFTs and DeFi assets tend to decouple from traditional markets. This is in line with Piñeiro-Chousa *et al*. (2022), who found that DeFi tokens act as a safe haven during market downturns. Dyhrberg (2016) suggested that Bitcoin can hedge stocks. Nevertheless, this perspective contrasts with that of Klein *et al*. (2018), who concluded that Bitcoin does not serve as a safe haven for equity markets. In line with this, Basty and Abidly (2025) suggested that metaverse tokens show limited safe-haven behaviour against commodities and clean energy. These mixed findings highlight the need for further research into cryptocurrency hedging capabilities. These gaps led us to formulate the following hypotheses.

H3. Traditional assets maintain more stable optimal weights and hedge ratios over time, achieving higher average intra-market hedging effectiveness than cross-market hedging effectiveness.

H4. Metaverse-related cryptocurrencies generate time-varying hedge ratios and portfolio weights that are significantly more volatile than traditional assets.

Despite the extensive literature on the interaction between cryptocurrencies and traditional financial markets (Cevik *et al*., 2022; Dyhrberg, 2016; Piñeiro-Chousa *et al*., 2022; Yousaf and Yarovaya, 2022), as well as studies on the volatility dynamics and hedging properties of digital assets (Corbet *et al*., 2022; Katsiampa, 2019; Li *et al*., 2023), significant gaps remain regarding metaverse-related cryptocurrencies. Most previous research focused on Bitcoin, Ethereum, and DeFi assets (Akkus and Dogan, 2024; Dyhrberg, 2016; Klein *et al*., 2018), with limited attention paid to cryptocurrencies powering immersive virtual economies. Furthermore, while various econometric models have been used to analyse volatility and spillovers, few studies have examined the dynamic interdependencies between cryptocurrencies, traditional financial indices, commodities, and climate assets. In addition, most hedging analyses use static correlation frameworks, omitting the evolution of optimal portfolio weights and hedge ratios over time.

This study aims to fill these gaps by analysing the dynamic relationships between the two most representative cryptocurrencies, the ten most capitalised metaverse-related cryptocurrencies, and traditional assets, using TVP-VAR for connectedness and DCC-GARCH for time-varying hedging metrics.

Data

The dataset comprises the daily prices for 12 cryptocurrencies and eight traditional assets from 1 September 2021 to 31 January 2025. All data were collected in USD, except for stock indices. This sample period covers the most significant recent events, including the most recent boom and subsequent crash that led to the crypto-winter in late 2021 (Bouri *et al*., 2024), the subsequent recovery which peaked in early 2025, and the growing interest after Meta's rebranding in October 2021. This period included 1,249 observations to ensure robustness of the results.

The selected cryptocurrencies are Bitcoin, Ethereum, and the ten largest metaverse-related cryptocurrencies by market capitalisation according to CoinmarketCap as of 31 January 2025: Render (RNDR), Stacks (STX), Virtual Protocol (VIRTUAL), Sandbox (SAND), Floki (FLOKI), Decentraland (MANA), Axie Infinity (AXS), MultiversX (EGLD), ApeCoin (APE), and Zilliqa (ZIL). Bitcoin and Ethereum were included due to their status as the largest and most recognised cryptocurrencies. According to CoinmarketCap, these cryptocurrencies represented over 70% of the total cryptocurrency market as of 31 January. Omitting a comprehensive overview of the cryptocurrency market can lead to incomplete results.

The eight traditional assets included in the analysis are the three major US stock market indices (NDX, SP, and VIX), four commodities (Brent, WTI, Gold and Silver), and ICE as a proxy for climate change assets. NDX represents the technology sector, which is important for the development of the metaverse. SP covers the 500 largest US companies and represents nearly 80% of US stock market capitalisation (BenMabrouk *et al*., 2024). VIX is a well-known measure of market volatility. Commodities include Brent and WTI as global oil benchmarks (Chang *et al*., 2011), and Gold and Silver as precious metals (Alqaralleh and Canepa, 2022). The intrinsic value of commodities makes them potential candidates for hedging against other markets (Foroutan and Lahmiri, 2024). Oil is a vital resource for firms and a key component of everyday life (Cevik *et al*., 2022). Gold is predominantly used for investment, whereas silver is used for industrial applications (Alqaralleh and Canepa, 2022; Foroutan and Lahmiri, 2024). Finally, ICE is included to analyse the relationship between cryptocurrencies and environmental factors. However, the influence of economic activities on the environment remains indisputable (Pérez Calderón *et al*., 2021). Studies indicate that the energy consumption of cryptocurrencies has adverse environmental effects (Wiwoho *et al*., 2024), specifically, proof-of-work (PoW) algorithms such as Bitcoin (Guo *et al*., 2024). In addition, there is a growing focus on sustainable investment (Basty and Abidly, 2025; Piñeiro-Chousa *et al*., 2025). ICE was selected as a proxy because it includes data from 23 developed countries with large- and mid-cap companies that consider the opportunities and risks associated with transitioning to a low-carbon economy.

Different databases and websites were used to download data in CSV format. For historical cryptocurrency prices, the website "CoinMarketCap.com" was used. This website is widely recognised for providing reliable data. These price data are particularly suitable for empirical analysis because they are calculated from the weighted average of cryptocurrency prices across multiple exchanges, providing the aggregate market value of each asset (BenMabrouk *et al.*, 2024; Guo *et al.*, 2024; Li *et al.*, 2023). For NDX data, the website "Nasdaq" was employed. This website is a reliable and authoritative source of financial market data, known for its comprehensive coverage and accuracy. For daily VIX prices, data were downloaded from the Chicago Board Options Exchange (CBOE) website, which is the world's leading derivative network. For ICE data, SP and, commodities, the website "Investing.com" was used. These sources were selected because of their credibility and comprehensive coverage of financial market data.

The data downloads focused on the daily closing prices. For cryptocurrencies, which trade 24 hours a day, the closing price is the last price offered on that day. For traditional assets that do not trade on holidays and weekends, the closing prices from the last trading day were carried forward to non-trading days. This method ensured consistency, contributing to a more precise and robust analysis (Piñeiro-Chousa *et al.*, 2022).

After the data were selected and downloaded, they were reviewed and cleaned. APE and VIRTUAL were excluded from the sample because their launch dates in 2022 and 2023, respectively, were outside the start of the study period. This criterion aligns with that proposed by Yousaf and Yarovaya (2022). FLOKI was omitted because its prices were consistently near zero (less than 0.00001 cents). Once the data were cleaned and reviewed, and given that the TVP-VAR and DCC-GARCH models assume stationarity, the sample fluctuation was reduced through the logarithmic difference (Antonakakis *et al.*, 2020) as follows:

$$Ri_t = \ln(Xi_t) - \ln(Xi_{t-1})$$

Where Ri_t : are the returns at time t; Xi_t *and* Xi_{t-1} are the closing price and one-period lagged price, respectively.

Table 1 highlights the key descriptive statistics of the sample. The mean returns for all the series are close to zero, suggesting low average daily returns over the period. The maximum and minimum values reveal the extent of extreme price fluctuations, with the highest volatility

Table 1. Descriptive statistics

Series	Mean	Max	Min	Variance	Std_Dev	ADF test	ERS test
NDX	0.000256	0.072200	−0.057020	0.000149	0.012211	−11.601842	−16.740989
SP	0.000232	0.053953	−0.044199	0.000080	0.008926	−11.579023	−13.602412
Brent	0.000056	0.084287	−0.141083	0.000337	0.018355	−12.422152	−6.006286
WTI	0.000048	0.082612	−0.134360	0.000380	0.019500	−12.307080	−6.174531
Gold	0.000358	0.030889	−0.035158	0.000059	0.007664	−10.730473	−11.269943
Silver	0.000230	0.078267	−0.063397	0.000233	0.015250	−11.012013	−6.852916
ICE	0.000249	0.056410	−0.040175	0.000078	0.008835	−11.260065	−13.306453
VIX	0.000016	0.554110	−0.330681	0.003597	0.059973	−12.636679	−13.424787
BTC	0.000593	0.135764	−0.174053	0.000842	0.029015	−10.780520	−12.233621
ETH	−0.000121	2.213222	−2.176060	0.009016	0.094951	−11.816637	−19.063619
RNDR	0.001112	0.353640	−0.359141	0.004843	0.069592	−9.683482	−3.636753
STX	−0.000101	0.522607	−0.256948	0.003511	0.059255	−11.172343	−9.900193
SAND	−0.000519	0.565329	−0.289164	0.003588	0.059897	−9.811579	−14.865392
MANA	−0.000630	4.628628	−4.549432	0.037523	0.193710	−11.055289	−17.324096
AXS	−0.002095	0.394413	−0.270915	0.002874	0.053609	−10.223111	−13.807395
EGLD	−0.001430	0.323196	−0.251697	0.002260	0.047534	−11.186379	−9.503061
ZIL	−0.001412	2.210515	−2.176790	0.010731	0.103589	−11.236059	−6.723932

observed for cryptocurrency assets. The standard deviations confirm that cryptocurrencies exhibit significantly higher volatility than traditional financial assets.

To ensure the suitability of the TVP-VAR and DCC-GARCH estimations, stationarity was evaluated using the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981), and Elliott-Rothenberg-Stock tests (ERS) (Elliott *et al.*, 1996). Both tests indicate that the entire dataset is stationary at the 1%, 5%, and 10% significance levels. Therefore, the dataset is well suited for both methodologies.

Methodology

Research on the relationships between assets has a long tradition. Early portfolio theory, pioneered by Markowitz (1952), emphasised efficient portfolios by minimising risk through diversification. Sharpe (1964) introduced the concept of systematic risk. However, these models rely on restrictive and unrealistic assumptions (Sharpe, 1964). Sims (1980) advanced this field using a vector autoregressive (VAR) model. Engle (1982) developed an autoregressive conditional heteroscedastic (ARCH) model to capture time-varying volatility. Subsequently, Bollerslev (1986) proposed GARCH, which makes the model much more flexible with its lag structure, allowing for a better fit in explaining situations. Using the GARCH model, Engle *et al.* (1990) proposed the heat wave and meteor shower hypotheses to explain volatility transmission. Building on Engle *et al.* (1990), Diebold and Yilmaz (2009, 2012, 2014) created a framework using VAR to focus on variance decompositions and analyse the connectedness and contagion effects between markets. Nevertheless, these models have some fundamental shortcomings, such as the random selection of the rolling window and loss of observations. To overcome these limitations, Antonakakis *et al.* (2020) propose the TVP-VAR model. This approach is superior to other alternatives due to its ability to capture dynamic financial spillovers (Antonakakis *et al.*, 2020; Yousaf *et al.*, 2024; Yousaf and Yarovaya, 2022). Thus, TVP-VAR has been employed to capture time-varying crypto and traditional assets. This approach allows the variance-covariance matrix to be varied through a Kalman filter estimation with forgetting factors (Koop and Korobilis, 2014). Moreover, by assigning greater weight to recent observations in the estimation process and being less sensitive to outliers, it allows the examination of measures of dynamic connectedness for low-frequency data and limited time series data. The TVP-VAR model is written as follows:

$$\begin{array}{ll} \gamma_t = A_t z_{t-1} + \varepsilon_t & \varepsilon_t|\Omega_{t-1} \sim N(0, \Sigma_t) \\ vec(A_t) = vec(A_{t-1}) + \zeta_t & \zeta_t|\Omega_{t-1} \sim N(0, \Xi_t) \end{array}$$

With

$$Z_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{pmatrix} A'_t = \begin{pmatrix} A_{1t} \\ A_{2t} \\ \cdots \\ y_{t-p} \end{pmatrix}$$

where Ω_{t-1} represents all available information until t-1, γ_t and z_{t-1} represents $m \times 1$ and $mp \times 1$ vectors, respectively, A_t and A_{it} are $m \times mp$ and $m \times m$ dimensional matrices, respectively, ε_t is an $m \times 1$ vector, and ζ_t is an $mp^2 \times 1$ dimensional vector, whereas the time-varying variance-covariance matrices Σ_t and Ξ_t are $m \times m$ and $m^2p \times m^2p$ dimensional matrices, respectively. Moreover, $vec(A_t)$ is the vectorisation of A_t which is an $m^2p \times 1$ dimensional vector.

After estimating the TVP-VAR parameters, the model must be transformed into its vector moving average (VMA) to calculate the generalised impulse response functions (GIRF) and generalised forecast error variance decompositions (GFEVD). VMA can be written as follows:

$$\gamma_t = \sum_{j=0}^{\infty} B_{jt}\varepsilon_{t-j}$$

where B_{jt} is an $m \times m$ dimensional matrix.

This transformation is needed to calculate pairwise directional connectedness, net pairwise directional connectedness, total directional connectedness, and net total directional connectedness. The GIRFs (Ψij,t(H)) represent the responses of all variables j, following a shock in variable i. The GIRFs can be expressed as follows:

$$GIRF_t\left(H, \delta_{j,t}, \Omega_{t-1}\right) = E\left(\gamma_{t+H} \middle| e_j = \delta_{j,t}, \Omega_{t-1}\right) - E\left(\gamma_{t+J} | \Omega_{t-1}\right)$$

$$\Psi_{j,t}(H) = \frac{B_{H,t}\sum_t e_j}{\sqrt{\sum jj, t}} \frac{\delta_{j,t}}{\sqrt{\sum jj, t}} \; \delta_{j,t} = \sqrt{\sum jj, t}$$

$$\Psi_{j,t}(H) = \sum\nolimits_{jj,t}^{-\frac{1}{2}} B_{H,t} \sum\nolimits_t e_j$$

where vector e_j, of dimension $m \times 1$, represents a selection vector with a value of one in the j th element, and zero elsewhere $GFEVD(\widetilde{\Phi}_{ij,t}(H)$, captures the pairwise directional connectedness from variable j to variable i, measuring the contribution of variable j to the forecast error variance of variable i. These variance contributions are normalised such that each row sums up to one, meaning that the total forecast error variance of variable I is fully explained for all variables in the dataset. This is calculated as follows:

$$\widetilde{\Phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum_{j=1}^{m}\sum_{t=1}^{H-1} \Psi_{ij,t}^2}$$

With

$$\sum\nolimits_{j=1}^{m} \widetilde{\Phi}_{ij,t}(H) = 1 \text{ and } \sum\nolimits_{j=1}^{m} \widetilde{\Phi}_{ij,t}(H) = m$$

In line with the above formulation, the Total Connectedness Index (TCI) is introduced as

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \widetilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^{m} \widetilde{\Phi}_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1,i\neq j}^{m} \widetilde{\Phi}_{ij,t}(H)}{m} * 100$$

This connectedness approach shows how a shock in one variable spill over to other variables. The next formula shows how variable i transmits its shock to all other variables j. This formula is called Total Directional Connectedness to others and can be defined as

$$C_{i\rightarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{m} \widetilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^{m} \widetilde{\Phi}_{ji,t}(H)} * 100$$

The following formula shows how i receives shocks from all variables j. This formula is called Directional Connectedness from others and is defined as

$$C_{i \leftarrow j,t}(H) = \frac{\sum_{j=1, i \neq j}^{m} \widetilde{\Phi}_{ij,t}(H)}{\sum_{i=1}^{m} \widetilde{\Phi}_{ij,t}(H)} * 100$$

To calculate the Net Total Directional Connectedness, it is necessary to subtract the Total Directional Connectedness to others from the Total Directional Connectedness from others, which can be interpreted as the influence variable i on the analysed network and can be defined as

$$C_{i,t} = C_{i \rightarrow j,t}(H) - C_{i \leftarrow j,t}(H)$$

If $\boldsymbol{C_{i,t}}$ is positive, variable i has a greater influence on the network than the influence it receives. By contrast, if $\boldsymbol{C_{i,t}}$ is negative, variable i is driven by the network.

With Net Total Directional Connectedness, bidirectional relationships can be examined by calculating the net pairwise directional connectedness as

$$NPDC_{ij}(H) = \left(\widetilde{\Phi}_{jit}(H) - \widetilde{\Phi}_{ijt}(H) \right) * 100$$

Where variable *i* dominates (is dominated by) variable j if $NPDC_{ij}(H) > 0$ $(NPDC_{ij}(H) < 0)$

Following Yousaf *et al*. (2023), we employ the TVP-VAR framework to analyse dynamic connectedness, and use DCC-GARCH to estimate time-varying optimal portfolio weights, hedge ratios, and hedging effectiveness. This dual methodology ensures a robust measurement of both transmission and portfolio effectiveness. The Kroner and Ng (1998) model is used to calculate the optimal weight between two assets. The formula can be written as follows:

$$W_{ab,t} = \frac{\sigma_{b,t}^2 - \sigma_{ab,t}}{\sigma_{a,t}^2 - 2\sigma_{ab,t} + \sigma_{b,t}^2}$$

$$W_{ab,t} = \begin{cases} 0 \; if \; W_{ab,t} < 0 \\ W_{ab,t} \; if \; 0 \leq W_{ab,t} \leq 1 \\ 1 \; if \; W_{ab,t} > 1 \end{cases}$$

Where $W_{ab,t}$ represents the weight of asset *a* in a one-dollar portfolio of assets *a* and *b* at time *t*. This optimal weight is subject to a non-shorting constraint. Following Kroner and Sultan (1993), the dynamic hedge ratio at moment *t* can be written as

$$\widehat{\beta}_t = \frac{\widehat{\sigma}_{ab,t}}{\widehat{\sigma}_{b,t}^2}$$

Where $\widehat{\beta}_t$ denotes de optimal dynamic hedge ratio. This ratio can be computed as the conditional covariance between assets *a* and *b* to the conditional variance of asset *b* (both measured at time *t*).

Finally, hedging effectiveness (HE) was calculated according to Ederington (1979). This model allowed us to score and compare the effectiveness of different hedging portfolios. The higher the hedging effectiveness score, the greater the risk reduction. The formula can be written as follows:

$$HE = 1 - \frac{Var(R^*)}{Var(U)}$$

Where $Var(R^*)$ denotes the minimum variance of the hedged portfolio and $Var(U)$ denotes the variance of the unhedged portfolio, which in this case consists of a single asset.

Results

Figure 1 shows a persistent and constant increase in influence within the dataset. The initial peak corresponds to the Bitcoin all-time high in November 2021, followed by a sharp decline of more than seventy-seven percent in a year, giving way to the crypt winter. After reaching its lowest point, connectedness began to rise. The rebound in mid 2022 could have been due to several factors, including the Russian incursion into Ukraine in February 2022 and the collapse of the stablecoin TerraUSD (UST) in May 2022. The following spike emerged at the end of 2022, coinciding with the collapse of the FTX, one of the largest crypto exchanges. This peak persisted, possibly due to the regional banking crisis, with failures of the Silicon Valley Bank and First Republic Bank in March and May 2023. The latest spike in 2023 could be due to the Gaza conflict and the rise in inflationary fear. The latest peak in 2024–2025, could come from the US presidential election and the political crisis that emerged in South Korea at the end of 2024.

Figure 2 illustrates the net total directional connectedness of each asset over time. A positive (negative) value indicates that the asset is a net shock transmitter (receiver). Among traditional markets, the NDX, SP, and ICE have consistently emerged as net shock transmitters. Commodities tend to function as persistent net shock receivers. Among cryptocurrencies, Bitcoin (BTC) and SAND are consistent net transmitters of shocks. The behaviour of the other cryptocurrencies changed over time. ZIL remained the most persistent shock receiver.

Tables 2 and 3 present the average dynamic connectedness across datasets. The diagonal elements reflect the shocks of the assets, while the off-diagonal elements reflect the interactions among the variables. The “FROM” column indicates the shock received from the market, and the “TO” row shows the shock transmitter to the market. The TCI is 66.54%, suggesting that, on average, 66.54% of the shocks are attributed to the market. A closer examination reveals two distinct quadrants of influence in each table. The quadrants show a low cross-market connection, but a high intra-market connection. The lowest influence of traditional assets is observed for stock and commodities. BTC is the dominant shock transmitter, although its influence on traditional markets is notably weaker. ZIL has almost no

Figure 1. The dynamic of total return connectedness over time. Source: Authors' own work

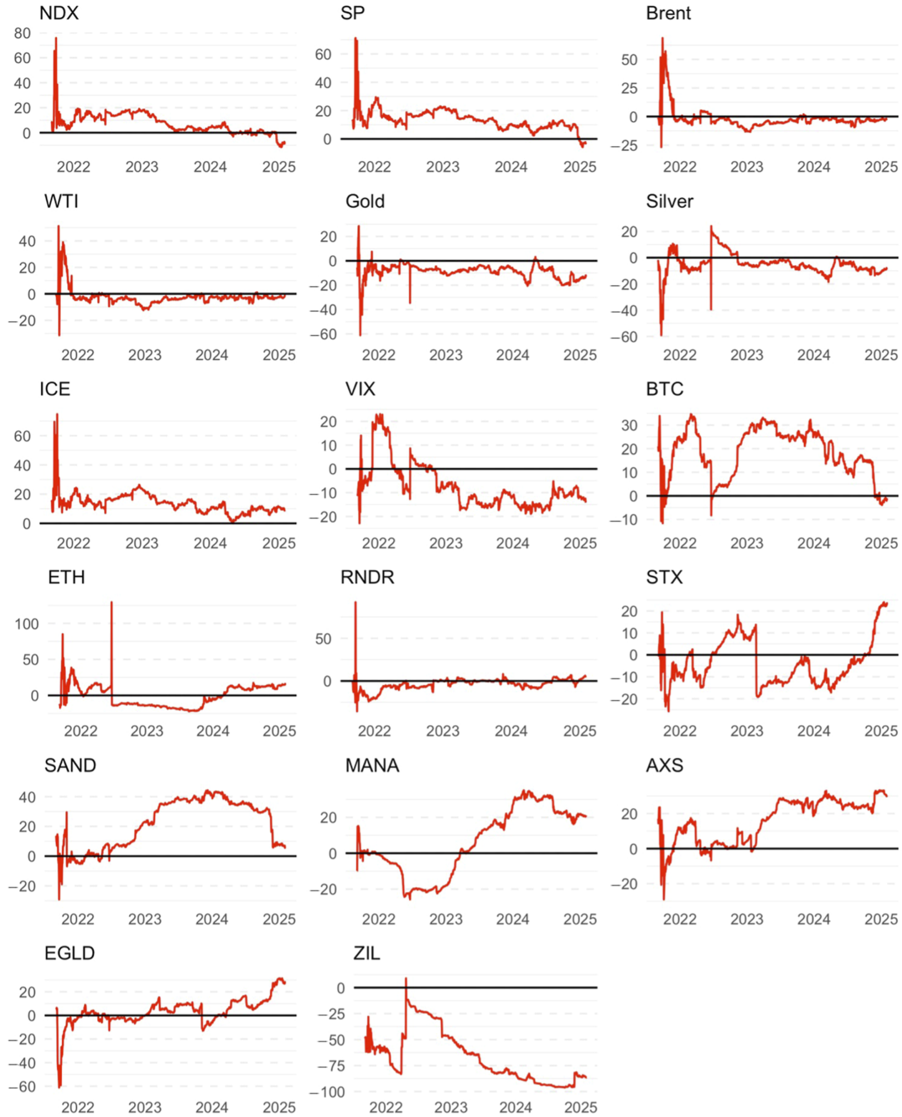

Figure 2. The net total directional connectedness over time. Source: Authors' own work

influence on the market. Tables 2 and 3 show the net average value of each asset. This approach helps us understand and evaluate an asset's capacity to either influence the market or be affected by it in general terms. Positive (shock transmitter) and negative (shock receivers) values can be observed. The most extreme values are found in crypto assets, with SAND and BTC emerging as the most influential transmitters of shock and ZIL as the strongest receiver. Moderate values are observed for traditional assets. Stock indices mainly act as transmitters, whereas commodities and the VIX primarily serve as receivers.

Figure 3 illustrates the net pairwise directional connectedness of the two largest Net Shock Transmitter (SAND and BTC) and the largest Net Shock Receiver (ZIL). We analyse the entire sample in Appendix A. Positive values indicate that the first asset listed in the name transmits

Table 2. Average dynamic connectedness table focus on traditional assets

Series	NDX	SP	Brent	WTI	Gold	Silver	ICE	VIX	FROM
NDX	25.25	22.53	0.57	0.54	1.02	1.66	21.71	11.63	74.75
SP	21.34	23.88	0.90	0.96	1.17	1.77	21.62	13.14	76.12
Brent	0.89	1.58	43.98	39.35	2.31	2.77	1.32	1.94	56.02
WTI	0.87	1.68	39.36	44.28	2.25	2.96	1.36	2.09	55.72
Gold	2.05	2.31	2.91	2.73	48.58	29.11	2.83	1.49	51.42
Silver	3.20	3.37	2.83	3.01	27.41	45.58	3.99	2.11	54.42
ICE	20.64	21.68	0.76	0.77	1.33	1.95	24.07	12.68	75.93
VIX	14.12	16.79	1.49	1.58	1.21	1.59	16.16	30.92	69.08
BTC	2.57	2.80	0.63	0.54	0.60	0.56	2.93	2.08	75.07
ETH	1.66	1.71	0.30	0.35	1.09	1.75	1.81	1.71	55.81
RNDR	2.89	2.87	0.70	0.54	0.38	0.59	2.88	2.29	68.96
STX	2.79	2.74	0.63	0.43	0.89	0.81	2.96	2.35	67.67
SAND	1.92	1.98	0.54	0.43	0.61	0.54	2.11	1.60	74.65
MANA	1.89	1.81	0.33	0.30	0.41	0.78	1.80	1.61	57.47
AXS	1.49	1.65	0.63	0.56	0.78	1.22	1.70	1.44	74.42
EGLD	2.08	2.09	0.43	0.37	0.55	0.59	2.37	1.96	70.77
ZIL	1.64	1.91	1.22	0.90	0.76	0.88	1.93	1.72	72.92
TO	82.05	89.51	54.23	53.35	42.77	49.53	89.49	61.85	TCI
NET	7.30	13.39	−1.79	−2.37	−8.65	−4.88	13.56	−7.22	66.54

Table 3. Average dynamic connectedness table focus on crypto assets

Series	BTC	ETH	RNDR	STX	SAND	MANA	AXS	EGLD	ZIL	FROM
BTC	24.93	8.47	8.32	9.31	10.71	5.94	10.91	8.53	0.19	75.07
ETH	10.63	44.19	4.85	4.82	7.54	4.11	7.90	5.17	0.41	55.81
RNDR	10.21	5.11	31.04	7.46	10.01	6.50	8.63	7.72	0.17	68.96
STX	11.90	4.89	7.62	32.33	8.21	5.39	7.71	8.05	0.28	67.67
SAND	10.45	5.36	7.74	6.08	25.35	10.36	14.80	9.96	0.16	74.65
MANA	6.50	3.36	5.74	5.00	12.06	42.53	9.03	6.66	0.17	57.47
AXS	11.24	5.99	6.93	6.08	15.41	8.32	25.58	10.81	0.16	74.42
EGLD	10.05	5.04	7.14	7.26	11.67	6.81	12.00	29.23	0.37	70.77
ZIL	8.80	5.75	6.26	6.05	9.86	7.41	9.87	7.97	27.08	72.92
NDX	2.54	1.53	2.15	2.15	1.86	1.48	1.41	1.70	0.25	74.75
SP	2.65	1.57	2.08	2.14	1.90	1.42	1.51	1.69	0.28	76.12
Brent	0.80	0.52	0.61	0.62	0.75	0.49	0.68	0.39	0.98	56.02
WTI	0.73	0.56	0.52	0.51	0.69	0.44	0.60	0.33	0.75	55.72
Gold	0.84	1.62	0.43	1.05	1.07	0.98	0.76	0.67	0.58	51.42
Silver	0.95	2.00	0.59	1.01	0.78	1.04	0.99	0.51	0.63	54.42
ICE	2.77	1.65	2.15	2.31	2.00	1.46	1.60	1.90	0.28	75.93
VIX	2.44	1.77	1.97	2.31	1.92	1.67	1.77	1.82	0.46	69.08
TO	93.49	55.20	65.11	64.15	96.43	63.83	90.18	73.88	6.12	TCI
NET	18.43	−0.62	−3.85	−3.51	21.78	6.36	15.76	3.11	−66.80	66.54

shocks to the second asset. This Figure highlights several key relationships. The crypto-winter causes a clear increase in spillovers. ZIL consistently appears as a strong receiver, whereas BTC dominates the cryptocurrency market and persistently transmits shocks. SAND, MANA, and AXS occasionally challenge BTC's dominance. BTC acts as a shy transmitter of shocks to commodities. After the initial peak, the connectedness between the traditional and cryptocurrency markets approaches low values close to zero.

For portfolio risk management and noise reduction, the 20 pairs with the highest hedge effectiveness were analysed. Hedge effectiveness is particularly relevant because higher

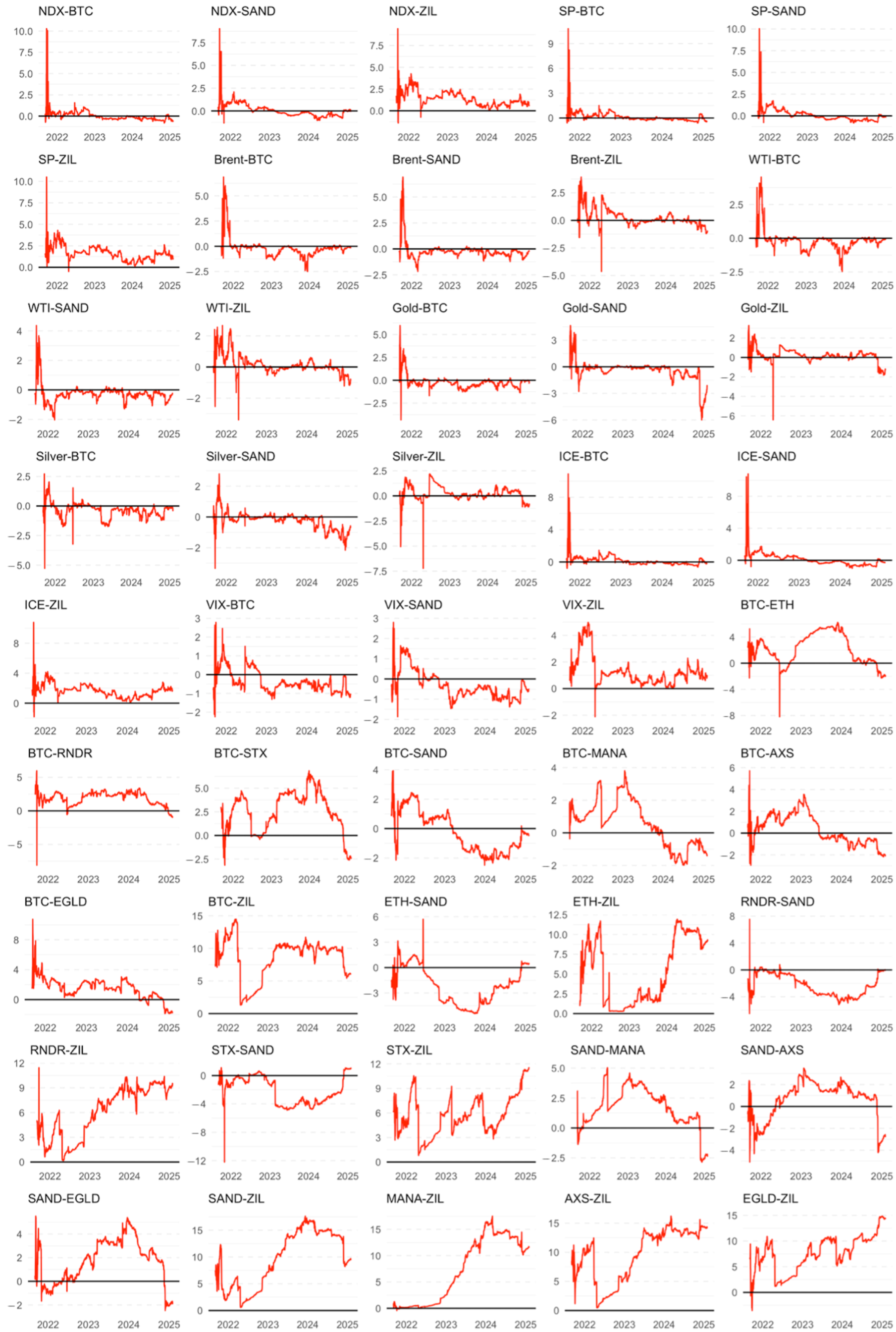

Figure 3. The net pairwise directional connectedness. Source: Authors' own work

values indicate stronger hedging potential and diversification opportunities (Chemkha *et al*., 2021). Table 4 presents the optimal portfolio weights, hedge ratios, and hedging effectiveness. Optimal weights range from 0 to 1, where zero means the investor should not hold the asset and one means the investor should hold everything in that asset. The optimal hedge ratio for the SP-ICE is 0.8858, indicating that the $1 position in the SP can be hedged with a short position in the ICE (Yousaf *et al*., 2023). Hedging effectiveness is particularly relevant because higher values indicate stronger hedging potential and diversification opportunities (Chemkha *et al*., 2021). The analysis focuses on the 20 most effective hedging pairs to highlight the strongest risk-mitigation relationships.

Figure 4 shows the dynamic hedge ratios of the 20 pairs with the highest average hedging effectiveness. Traditional markets exhibit stable ratios even during periods of stress. By contrast, metaverse-related pairs display extreme volatility. This high movement rate highlights the time-varying and unpredictable risk of exposure to metaverse-related cryptocurrencies.

Figure 5 illustrates the dynamic optimal weights for the 20 pairs with the highest average hedging effectiveness, limited to between zero and one. Traditional pairs maintain high stability and underscore the reliability of allocation strategies. Metaverse and cryptocurrency assets show high oscillations, demonstrating a greater need for rebalancing, driven by speculative sentiment.

Discussion

The main contribution of this study is to address gaps in the literature on metaverse-related cryptocurrencies by offering new evidence on their interconnections, highlighting their hedging capabilities, and examining their optimal weighting in a portfolio. The results show that intra-market relationships are stronger than cross-market relationships. Additionally, the analysis allows for the assessment of asset variability over time and the mitigation of risk.

Table 4. Optimal portfolio weights, optimal portfolio hedge ratio and hedging effectiveness

Pair	Optimal portfolio weights	Optimal portfolio hedge ratio	Hedging effectiveness
SP-ICE	0.82847034	0.8858113575	0.9063175099
NDX-SP	0.00000000	1.3273290472	0.9045714246
Brent-WTI	0.65284967	0.9200731187	0.8744255022
NDX-ICE	0.00310805	1.2103007280	0.8554082834
Gold-Silver	1.00000000	0.3904657189	0.5961609252
ICE-VIX	0.90030445	−0.1031677933	0.5451699499
SP-VIX	0.90434509	−0.0999073372	0.5449159192
SAND-AXS	0.50085669	0.8580278040	0.5318927141
NDX-VIX	0.87567928	−0.1274401047	0.4673802494
AXS-EGLD	0.29252451	0.7980273434	0.4455908927
BTC-SAND	0.96425768	0.4218888229	0.4310864570
BTC-AXS	0.96831835	0.4175586708	0.4257240802
BTC-STX	0.99150382	0.3873223158	0.4105495220
BTC-RNDR	0.98637649	0.2977160266	0.3560769601
SAND-EGLD	0.26869466	0.8505462136	0.3451403972
BTC-EGLD	0.82809126	0.4405062786	0.3385207804
RNDR-SAND	0.27839108	0.7438831598	0.3220029331
STX-AXS	0.39300939	0.6785050579	0.3181655077
RNDR-EGLD	0.17667608	0.8233682028	0.3078708675
RNDR-AXS	0.28119082	0.7120405658	0.3075921216

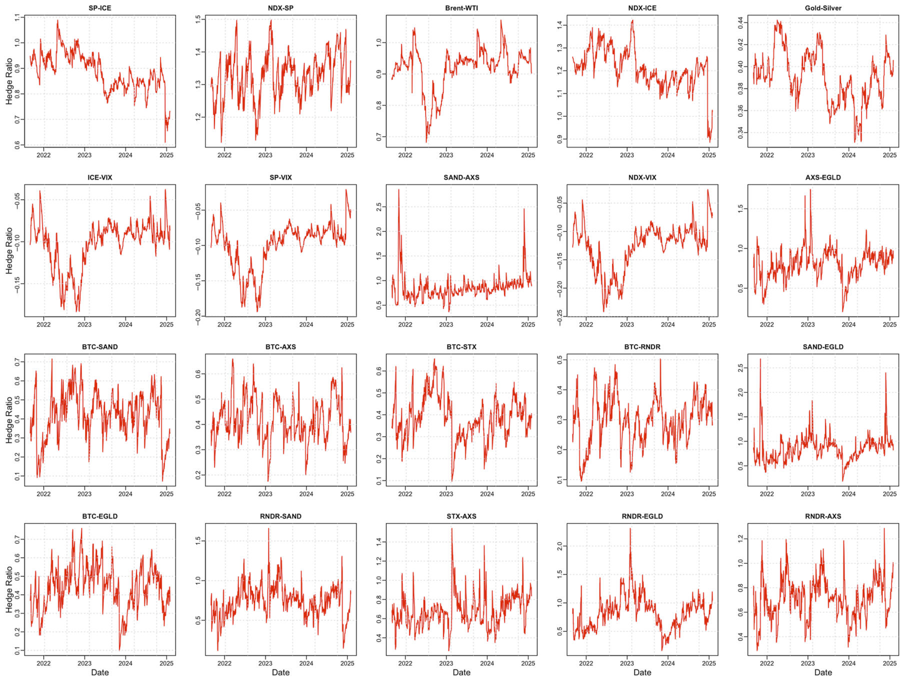

Figure 4. The dynamic hedge ratios for the 20 pairs with the highest average hedging effectiveness over the time. Source: Authors' own work

These contributions expand the connectivity literature and provide a solid foundation for risk management, regulatory design, and sustainable investment strategies.

Figure 1 shows a persistent and constant increase in influence within the dataset. Figure two and three reinforces this conclusion by showing an increase in connection strength in early 2022, coinciding with crypto-winter. These results demonstrate how market turmoil temporarily intensifies the spillover effects across markets, thereby supporting hypothesis one. These results are consistent with the literature, suggesting that the interrelationships between different asset classes increase during economic turmoil (Abakah *et al.*, 2023; Demir *et al.*, 2018; Li *et al.*, 2023).

Figure 2 shows the high (low) variability in the behaviour of crypto assets (traditional assets), which suggests specific intra-market behaviour. The results in Tables 2 and 3 reinforce the hypothesis of stronger intra-market behaviour by revealing clear structural segmentation. Again, Figure 3 shows the dominance of BTC within the cryptocurrency market, while showing a shy transmitter of shocks to traditional assets. The lack of stable transmission from crypto (traditional assets) to traditional assets (crypto) confirms the limited cross-market integration, reinforcing the formation of a distinct crypto ecosystem with intra-cluster relationships. These results confirm Hypothesis 2, and are in line with those of Giudici and Abu-Hashish (2019), Basty and Abidly (2025), Yousaf and Yarovaya (2022), and Havidz *et al.* (2024), who suggest that crypto assets are not typically correlated with traditional markets. Bitcoin's dominance contrasts with Akkus and Dogan (2024), who identify Ethereum as the primary transmitter of spillovers in the crypto market. This underscores the need for further research to identify the primary players.

Table 4 shows how crypto (traditional) assets are highly hedging effective in crypto (traditional) markets. This reflects strong intra-market capacity, confirming Hypothesis 3 and reinforcing Hypothesis 2. Figure 5 shows how traditional pairs maintain high stability,

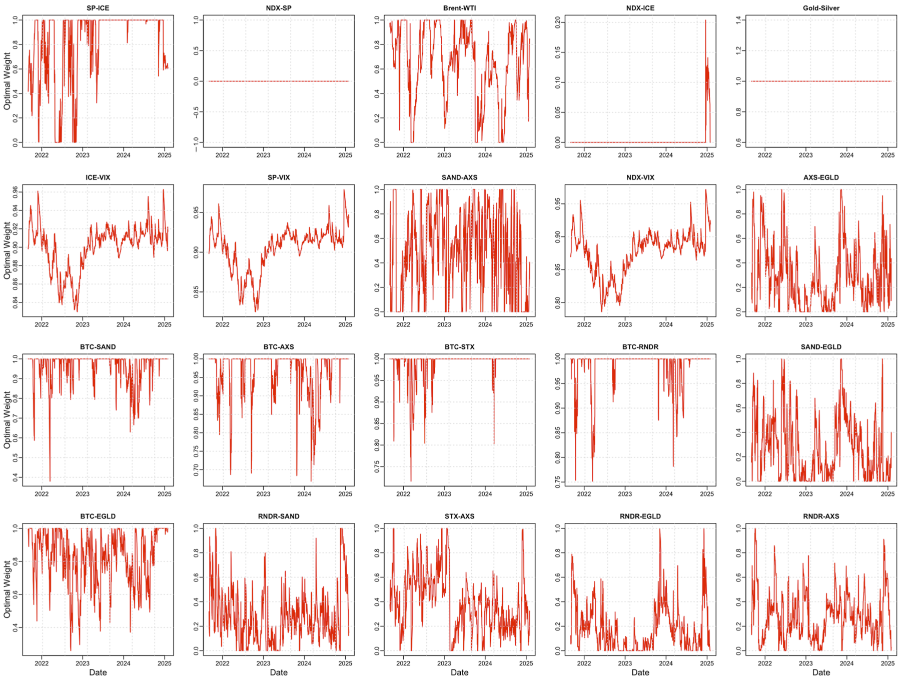

Figure 5. Illustrates the dynamic optimal weights for the 20 pairs with highest average hedging effectiveness, constrained between zero and one, over the time. Source: Authors' own work

underscoring reliable allocation strategies within conventional markets and reinforcing Hypothesis 3. These results are consistent with the literature on possible hedges within the crypto market (Katsiampa, 2019; Klein *et al*., 2018; Li *et al*., 2023), but contrast with Dyhrberg (2016) and Cevik *et al*. (2022), who find effective hedges between crypto and stocks.

Figure 4 shows how traditional (crypto) markets exhibit more (less) stable ratios over time, confirming Hypothesis 4. This high movement rate highlights the time-varying and unpredictable risk of exposure to metaverse-related cryptocurrencies. The spikes in assets in early 2022 reinforce the first hypothesis. Figure 5 demonstrates a greater need for rebalancing portfolios composed of crypto assets driven by speculative sentiment, reinforcing Hypothesis 4. These results are consistent with those of previous studies, confirming the high volatility of cryptocurrencies and their time-dependent risk profiles (Guo, 2022; Malek *et al*., 2023).

The intensification of total connectedness during market turmoil, identified by the TVP-VAR analysis in Figure 1, is corroborated by the DCC-GARCH findings. Specifically, dynamic hedge ratios and optimal portfolio weights exhibit high volatility spikes at the end of 2022 and the beginning of 2023, specifically across market combinations, reflecting transmission under stress periods. Similarly, the cluster of Metaverse, Bitcoin, and Ethereum assets supported by Hypothesis 2 is corroborated by the DCC-GARCH analysis. Hedges within the same market are better than those across markets. This dual methodology, combining TVP-VAR and DCC-GARCH, enhances the reliability of Hypotheses 1 and 2 while providing a foundation for the hedging analysis in Hypotheses 3 and 4.

We also evaluate the hedging potential of metaverse-related crypto assets and traditional assets. The intra-crypto-hedge and weight ratios show higher volatility than traditional pairs. Despite this effect, the optimal hedging strategies are found to be intra-market, even in volatile markets, such as the crypto market. Specifically, crypto market assets (traditional assets) serve as more effective hedges for other crypto assets (traditional assets) than for traditional markets (crypto markets). Time-varying dynamics illustrate stable weights and hedge ratios in traditional markets, even under stress, whereas metaverse pairs require frequent rebalancing owing to speculative sentiment. The DCC-GARCH serves as a robustness measure for the TVP-VAR.

Conclusions, limitations, and research implications and opportunities

Based on integration theory, this study provides a comprehensive analysis of the dynamic relationships between traditional financial assets and metaverse-related cryptocurrencies. The sample period covers both the bull market and turmoil periods. The results show variable behaviour throughout the analysed period, with the cryptocurrency market exhibiting greater volatility. The findings reveal that during periods of turmoil, all assets exhibit a growing relationship. This finding confirms Hypothesis 1. The results indicate that the TCI stands at 66.54%, indicating that 66.54% of the shocks are explained by the market as a whole (Yousaf and Yarovaya, 2022). Nevertheless, intra-market relationships are stronger than cross-market relationships. This finding confirms Hypothesis 2. This limited integration suggests that systemic risks to the real economy remain contained. Nevertheless, due to the high volatility of cryptocurrencies, the development of effective hedging strategies is necessary.

To validate these results and test robustness, we apply DCC-GARCH to compute the optimal portfolio weights (Kroner and Ng, 1998), hedge ratios (Kroner and Sultan, 1993), and hedging effectiveness (Ederington, 1979). The DCC-GARCH findings corroborate the intensification of total connectedness during market turmoil. Simultaneously, the results show that crypto assets (traditional assets) serve as more effective hedges for other crypto assets (traditional assets) than traditional markets (crypto markets). In addition, the time-varying dynamics illustrate stable (frequent rebalancing) optimal weights and hedge ratios in traditional markets (cryptocurrency assets), confirming Hypotheses 3 and 4. This dual methodology, which combines TVP-VAR and DCC-GARCH, improves the reliability of the results and contributes to new findings.

This study addresses gaps in the literature on metaverse-related cryptocurrencies by offering new evidence of their interconnections and highlighting their hedging capabilities and makes several valuable contributions. First, it clarifies the relationships between assets, offering a comprehensive understanding of total and net directional connectivity and the connections between them. Second, regarding portfolio risk management, we analyse the hedging capacity of all assets and their optimal weights in a portfolio. These contributions not only expand the literature on connectedness but also provide a robust foundation for risk management, regulatory design, and sustainable investment strategies.

The results offer valuable insights for entrepreneurs, investors, researchers, society, and regulators. For entrepreneurs and investors, this study helps improve understanding of the risks associated with the metaverse and supports the development of effective hedging strategies. This is a starting point for researchers, as there is limited research on metaverse-related cryptocurrencies. This research is vital because the metaverse may become a key player globally owing to the trend toward digitalisation. The impact could extend beyond digitalisation and reach the real economy. Understanding the risks in this environment in a practical rather than purely theoretical manner is essential for society to make informed decisions. Society allows users to better understand the risks before participating. For regulators, this study clarifies risk transmission between traditional and digital markets. Although the risk between markets is currently contained, it can change in the future. Therefore, real-time monitoring by regulators is necessary to try to prevent, as far as possible, a systemic contagion that could spread to the real economy. It also gives regulators time to create legislation, since we are in an early stage of development but with growth potential.

The main limitation of this study was its small sample size. Although this study used one of the largest datasets on metaverse-related cryptocurrencies to date, a larger sample could offer deeper insights. Additionally, using a single TVP-VAR model is a limitation that was addressed through a robustness check using the DCC-GARCH model.

Future research could incorporate alternative modelling approaches or higher-frequency data to provide a deeper understanding of individual asset dynamics. Additionally, a larger sample size would allow for a better understanding of the metaverse environment. Another research direction would be to consider not only payment methods but also other assets and actors within the metaverse and how they are connected.

Supplementary material

The supplementary material for this article can be found online.

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