Research in International Business and Finance 68 (2024) 102190

Contents lists available at ScienceDirect

Research in International Business and Finance

journal homepage: www.elsevier.com/locate/ribaf

Full length Article

FinTech and fan tokens: Understanding the risks spillover of digital asset investment

Matteo Foglia [a,*], Giampiero Maci [b], Vincenzo Pacelli [c]

[a] *Department of Economics and Finance, "Aldo Moro" University of Bari, Italy*
[b] *Department of Economics, University of Foggia, Italy*
[c] *Ionian Department in "Legal and Economic Systems of the Mediterranean: Society, Environment, Cultures", "Aldo Moro" University of Bari, Italy*

A R T I C L E I N F O

JEL classification:
G10
G11
G14

Keywords:
FinTech
Fan token
Emerging technologies
Football clubs
Risk spillover
Digital asset investment

A B S T R A C T

Digital asset investment represents a new class of assets to invest in. In recent months, fan tokens have been among the most popular digital assets among football clubs and investor fans. Therefore, understanding the dynamics and spillover effects between these new and traditional assets is essential for risk management. In this study, we use daily data covering November 2020 and December 2022 to examine the mean and volatility risks spillover between the stock market and the fan token ones. Using the VAR-BEEK-AGARCH model and wavelet frequency analysis, we are able to identify the sender and receiver characteristics of the risks between the two assets. Our results show that volatility spillovers are more persistent in the long run, suggesting a strong interdependence between the stock market and fan tokens. Our empirical findings can be helpful for portfolio managers and investors.

1. Introduction

Cryptocurrency, FinTech applications, and blockchain technologies are revolutionising the financial system (Feyen et al., 2021; Carlini et al., 2022; FSB, 2022). Indeed, in recent years, investors have been turning to alternative assets such as Digital Asset Investment (DAI) to diversify their portfolios from traditional investments such as stocks, bonds, and funds. A specific category of DAI is the fan tokens. Fan tokens are a digital asset gaining popularity among football fans and cryptocurrency investors (Scharnowski et al., 2021; Demir et al., 2022). These tokens give holders a say in club decisions through interactive polls, access to numerous offers and promotions, but also pre-emption rights in the purchase of tickets for matches. They serve as a link between the clubs and their fan base. Hence, they can allow for greater fan engagement and participation in club-related decisions. This can increase fan loyalty and give clubs valuable feedback on important decisions.

From a financial point of view, the fan token is a digital asset (cryptocurrency) issued by football clubs which provides "access to an encrypted ledger of voting and membership rights ownership" (Demir et al., 2022). Fan tokens are typically issued on blockchain platforms. Their value can be influenced by the sports performance of the club, the changes in the club's management or ownership, and financial market conditions. On the one hand, football clubs are issuing fan tokens to bring new income streams and allow more participation and engagement with fans. On the other hand, football clubs seek to tokenise stocks of their club to be traded in digital assets markets. The issuance of fan tokens allows clubs to create new revenue streams by selling tokens directly to fans and using the tokens as a form of currency within the club's ecosystem. Furthermore, this type of tokenisation can lead to more liquidity in

* Corresponding author.
E-mail addresses: matteo.foglia@uniba.it (M. Foglia), giampiero.maci@unifg.it (G. Maci), vincenzo.pacelli@uniba.it (V. Pacelli).

https://doi.org/10.1016/j.ribaf.2023.102190
Received 17 May 2023; Received in revised form 31 October 2023; Accepted 23 November 2023
Available online 30 November 2023
0275-5319/

the shares and allow smaller investors to buy shares more easily. This approach might increase the club's visibility and valuation in financial markets.

As per the data provided by Fan Market Cap,[1] the current count of fan tokens has reached 82, and their collective market capitalisation exceeds $244 million. However, the literature on this crypto innovation as an emerging alternative investment class still needs to be expanded. Despite the growing interest from users and the increasing number of clubs issuing fan tokens, relatively little research has been conducted on this emerging market, i.e., digital asset investment (e.g., Ersan et al., 2022; Demir et al., 2022; Mazur and Vega, 2023). Indeed, understanding the flow of information between the two markets is crucial for financial market stability (Azar et al., 2022), and such knowledge would provide a comprehensive understanding of how the two markets are related from a risk perspective (OECD, 2022). In this study, we attempt to fill this gap by providing a detailed financial analysis of fan tokens and their relationship with the financial market. The paper aims to study the risk spillover between fan tokens and stock prices of four football clubs, i.e., Juventus FC (JUV) and AS Roma (ASR) from Italy and Galatasaray (GAL), and Trabzonspor (TRA) from Turkey. Following Ersan et al. (2022), we selected these clubs because they are the only ones that are listed in the financial market and, at the same time, emit fan tokens. Our objective is to explore whether the two financial asset classes are correlated, i.e. whether they transmit risks to each other. We aim to answer these questions: *Are there spillover effects between the two asset classes? Is the risk of one asset transferred to the other? How can we manage risk from a portfolio perspective?*

One question we need to ask ourselves is, *why should the prices of fan tokens influence stock markets* (and *viceversa*)? As an instrument in the cryptocurrency market, fan tokens can show co-movement with other asset classes. Fan tokens and stock prices should be inherently correlated. More precisely, we assume a positive linkage between them, in that an increase in the price of the fan token. Thus, positive fan sentiment should encourage people to invest in that company, thus potentially increasing equity prices (Maci et al., 2020; Scharnowski et al., 2021; Mazur and Vega, 2023). Indeed, in the case of fan tokens, the sentiment effect may be the dominant factor in determining the price. This effect can be explained by the fact that fan token investors are more driven in their investment choices by the clubs' sports performance (winning, losing) than by the analysis of corporate fundamentals. On the flip side, sports performance could significantly influence the sentiment of fan token investors, causing the financial market to react (Demir et al., 2022).

We use a three-step empirical strategy to investigate the fan token-stock market nexus. First, we utilise a VAR-BEKK-AGARCH model (Engle and Kroner, 1995) to estimate and examine spillover effects in both the mean and variance between the two assets. This method allowed us to comprehend how "bad" news in one market spreads to the other. Second, we employ a wavelet frequency analysis (Torrence and Compo, 1998) to explore the interrelationships between the two markets, identifying short- and long-term nexus at the frequency level. Third, we perform a portfolio analysis to provide a detailed overview of the investment strategy between the two assets.

Our article offers three main contributions to the literature. *First*, we contribute to the sparse literature on fan tokens (Scharnowski et al., 2021; Demir et al., 2022; Ersan et al., 2022; Vidal-Tomás, 2023; Mazur and Vega, 2023). Studying these new asset classes offers new evidence for understanding financial markets' evolution, especially in the current FinTech era. Indeed, according to OECD (2022), and FRB (Azar et al., 2022) reports, understanding the relationship between these traditional and token assets is of critical importance to the stability of financial markets. Therefore, in this research, we offer fresh empirical evidence for this nexus. *Second*, in this study, the presence of spillovers in mean and volatility between fan token assets and the stock market is explored. Reference recent literature (Umar et al., 2022; Yousaf et al., 2023a,b; Umar et al., 2023) shows the existence of spillovers between tokens and stocks. However, we are the first to investigate such effects in the fan token context. We find asymmetric spillover effects, showing how "bad" news in the token market affects the dynamics of stock prices. We provide solid evidence of dependence between these markets at different time scales. *Third*, by incorporating fan tokens into an optimal portfolio view, our paper sheds further light on the interrelation of this new asset class with a traditional asset class, such as equities. Our findings have implications for football clubs wishing to raise capital and for investors and traders in the digital asset and equity markets.

1.1. Motivations of the study

Why do we analyse fan tokens? In this article, to understand the transformative potential of digital asset investments (DAIs) in modern financial systems, we focus our analysis on fan tokens due to their distinctive nature and the unique blend of sociocultural and financial dynamics. While other forms of DAIs are also significant, the compelling combination of fan tokens' interactive engagement, fan loyalty cultivation, and their role as a bridge between football clubs and their supporters provides an opportunity for comprehensive exploration.

The emergence of fan tokens represents a unique and evolving asset class that offers distinctive features and characteristics, setting it apart from traditional financial assets. Fan tokens have garnered substantial attention due to their accessibility to retail investors and fans, contributing to their increasing popularity in sports and entertainment. These characteristics provide the fan token market with speed and accessibility, which have the potential to transform the relationship between sports clubs, fans, and investors. However, as with any innovative financial instrument, fan tokens also bring forth a set of challenges and risks that need careful consideration. One of the most significant concerns is the absence of comprehensive regulatory oversight in the fan token market, rendering these markets more susceptible to fraudulent activities. In the lack of robust regulations, fan token markets can become fertile ground for various forms of market manipulation, echoing some of the challenges witnessed in the broader cryptocurrency

[1] https://www.fanmarketcap.com/

market (Lopez-Gonzalez and Griffiths, 2023). Manipulative practices such as pump-and-dump schemes and front-running tactics can compromise the integrity of the fan token market, leading to unfair advantages for some participants while disadvantaging others (Azar et al., 2022; Nassr, 2021; Nghiem et al., 2021). Furthermore, their decentralised nature, often built on blockchain technology, contributes to the complexity of regulating and monitoring these digital assets. The absence of standardised regulations and oversight frameworks in the fan token sector can impact the transparency of the price discovery process, making it challenging for fan investors to assess the accuracy of market prices.

The rise of fan tokens and their impact on the financial sector raises important questions regarding their potential implications for financial market stability. On the one hand, football clubs are adopting fan tokens as a source of new revenue streams while also expanding opportunities for fan participation and interaction (Demir et al., 2022). On the other hand, these clubs are moving towards tokenizing portions of their stocks, opening up the possibility of trading on digital asset markets. By issuing fan tokens, clubs are creating new revenue streams by directly offering tokens to fans and using them as a new form of currency within the club's ecosystem. However, this democratisation of ownership, on the one hand, has the potential to create new opportunities for investors; on the other one, it can pose risks to the stability of the financial system (Azar et al., 2022; OECD, 2022; Lopez-Gonzalez and Griffiths, 2023). It is crucial to recognise that fan tokens are part of the broader trend of digitalisation and tokenization that is transforming various sectors of the economy, including finance. As these digital assets continue to evolve, it is essential to strike a balance between fostering innovation and safeguarding market stability. By examining the mechanics and implications of fan tokens in comparison to other DAIs, we aim to uncover the complex interplay between technology, finance, and sports culture, shedding light on why fan tokens have captured the attention of investors and passionate football fans uniquely.

2. Related literature

The digital asset panorama is expanding rapidly, with various types of tokens and cryptocurrencies gaining importance. This literature review delves into the emerging field of digital assets, mainly focusing on Non-Fungible Tokens (NFTs), Decentralised Finance (DeFi), and Fan Tokens. We explore their dynamic interactions with traditional financial assets and the existing body of research on these digital assets.

2.1. NFTs and DeFi

NFTs have emerged as a distinctive digital asset class representing ownership of specific items, artworks, or collectables. Several research analysed their connection with traditional financial assets and their potential utility as diversification tools (Umar et al., 2023). Aharon and Demir (2022) found that NFTs are independent of the shocks affecting traditional financial assets, suggesting their diversification potential. Dowling (2022) suggested that NFTs might serve as low-correlation assets, providing an alternative to the often more volatile cryptocurrencies. Moreover, Umar et al. (2022) found that NFTs effectively absorbed risk during the COVID-19 pandemic, further underscoring their potential diversification benefits. A different view is shown by Ghosh et al. (2023) From a return and volatility perspective, the authors show the presence of a heavy fat-tail of NFT, suggesting their market instability and extreme price movements. The authors find that the safe-haven property of NFT is refuted.

Focusing on the DeFi segment, Yousaf et al. (2022) found that DeFi assets have limited interdependence with currency markets, which intensified during the initial phase of the COVID-19 pandemic. Ante (2022) found that active NFT wallets responded negatively to Ethereum price shocks, unveiling both short-term and long-term relationships within the NFT market. Maouchi et al. (2022) explored various aspects of the NFT market, including risk-return profiles and pricing dynamics. Their findings pointed towards NFTs as unique assets with the potential to outperform traditional financial assets, More recently, Corbet et al. (2023) tested the existence of bubbles on cryptocurrency based on DEFI platforms. The authors underlined how the DeFi market should be viewed as a separate asset class from conventional cryptocurrencies.

A growing area of research involves the exploration of the interrelations between NFTs and DeFi. These studies delve into how these digital assets interact with each other and their potential role within diversified investment portfolios. Dowling (2022) and Vidal-Tomás (2022) used wavelet analysis to systematically investigate the co-movements between NFT assets and other financial assets. Karim et al. (2022) and Umar et al. (2022) emphasised the critical need to analyse the volatility spillover effects between DeFi tokens, NFTs, and conventional assets, thereby shedding light on the potential risks and benefits associated with DeFi. By wavelet-based quantile causality, Qiao et al. (2023) study the risk spillover between cryptocurrency, decentralised finance and non-fungible tokens. The authors show how these markets are highly connected. Their findings are confirmed by Ugolini et al. (2023), which study the relationship between different DeFi, cryptocurrency, stock, and safe-haven assets.

2.2. Focus on fan token

Fan tokens represent a distinctive category of digital assets, bridging the worlds of sports and finance. Some recent studies have explored specific aspects of the fan token market. For instance, Scharnowski et al. (2021) examined the characteristics of fan tokens assets. Their results show how these assets are speculative and linked to classic cryptocurrencies. Another study by Demir et al. (2022) analysed the impact of soccer game results on the prices of fan tokens associated with soccer teams. The authors find that football match outcomes can significantly affect token prices. Ersan et al. (2022) used the time-varying parameter vector autoregression (TVP-VAR) framework to investigate the return connectedness between fan tokens and football stocks. The authors discover that the token market transmitted return spillovers to the equity market. Recently, Vidal-Tomás (2023) and Mazur and Vega

(2023) conducted research on the fan token market using different methodologies such as wavelet analysis, panel regression, and a real-time bubble detection approach to explore the characteristics of this market. Their findings suggest that the cryptocurrency world significantly influences the fan token market.

Despite the progress made by previous papers, the research on the fan token-stock nexus is still in an early state. This literature review underscores the significance of ongoing research in the digital asset space, especially concerning NFTs, DeFi, and fan tokens. These assets embody unique opportunities and challenges, and their interactions with traditional financial markets have far-reaching implications for portfolio diversification and risk management. As digital asset evolves, understanding the relationship between these assets and their broader financial context becomes indispensable for investors, regulators, and market participants.

3. Empirical strategy

Our empirical strategy is based on three steps. First, we employed a VAR-BEKK-AGARCH model (Engle and Kroner, 1995) to estimate and investigate spillover effects in mean and variance between the two assets. This methodology allowed us to understand how "bad news" in one market spread to the other. Second, we use wavelet frequency analysis (Torrence and Compo, 1998) to investigate the relational dynamics between the two markets, identifying short- and long-run relationships at the frequency level. Finally, we can offer a detailed picture of the investment strategy between the two assets through portfolio analysis.

3.1. VAR-BEKK-AGARCH framework

To investigate the spillover effect between the stock market and token one, we compute the VAR-BEKK-GARCH model (Engle and Kroner, 1995). Our approach involves utilising a model that estimates the conditional mean and conditional volatility functions of complex, multi-dimensional relationships. Therefore, this model enables us to examine volatility spillovers between the stock and token markets. Following the literature (Mensi et al., 2014; Katsiampa, 2019), we add VAR(1) into the conditional mean function to improve our forecasts' accuracy. The mean equation of our model is defined as follows:

$$r_t = \mu + \varepsilon_t \qquad \varepsilon_t = \sqrt{h_t \epsilon_t} \quad \epsilon_t \sim iid \tag{1}$$

where r_t shows the vector of the stock and fan token returns, μ is the vector mean of the return series parameters, while the ϵ_t is the $N \times 1$ residual vector with a conditional covariance matrix H_t.

To account the leverage effect, i.e., the "bad news" shocks, we use the asymmetric AGARCH specification. Hence, the conditional variance equation follows a BEKK-AGARCH(1,1) process. The conditional covariance matrix of the asymmetric VAR(1)-BEKK-AGARCH(1,1) model is given as:

$$H_t = C'C + A'\varepsilon_t\varepsilon_t' A + B' H_{t-1} B + D'\eta_{t-1}\eta_{t-1}' D \tag{2}$$

where C is the lower triangular constant coefficient matrix, while A, B and D are the coefficient matrices. The elements of matrix A measure past square errors in the current conditional variances, i.e. the effects of shocks on volatility (ARCH effect). The elements of matrix B show how past conditional variances influence current levels of volatility (GARCH effect). Finally, the elements of D capture the asymmetric effects of negative shocks, where η_t is defined as ϵ_t if ϵ_t is negative and zero otherwise. The off-diagonal elements of the A, B, and D matrices capture spillover effects between the two markets.

3.2. Wavelet coherence analysis

The wavelet analysis approach possesses two main compelling characteristics. In particular, it is a technique that allows for the decomposition of time-series variables in both the time and frequency domains, which provides insight into how variables may interact differently on distinct time scales. Additionally, the methodology can detect disruptions in the system, thereby aiding in identifying points where the temporal regime may shift.

The wavelet methodology begins by identifying the mother wavelet, namely:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\frac{t-\tau}{s} \qquad s, \tau \in \mathbb{R} \quad s \neq 0 \tag{3}$$

where s is the scaling factor, τ denotes the location parameter, and $\frac{1}{\sqrt{s}}\psi$ is the normalisation constant. Hence, following Goupillaud et al. (1984), we can specify the cross-wavelet (CW) transform for two variables (x and y) as follows:

$$W_{xy}(\tau, s) = W_x(\tau, s)W_y^*(\tau, s) \tag{4}$$

According to Torrence and Compo (1998), we can define the wavelet coherence (WC) between x and y, i.e,

$$R^2(\tau, s) = \frac{|S(s^{-1}W_{xy}(\tau, s))|^2}{S(s^{-1}|W_x(\tau, s)|)^2 S(s^{-1}|W_y(\tau, s)|)^2} \tag{5}$$

where S denotes the smoothing mechanism. $R^2(\tau, s)$ shows the wavelet coherence whose value ranges from zero to one. A value near zero indicates no correlation between variables, while a value closer to one suggests a strong dependence. The statistical significance of wavelet coherence and cross-spectra is determined by Monte Carlo simulation.

Finally, to investigate the positive and negative correlation between two-time series (stock and fan token market in our case), we use the wavelet coherence phase differences technique, i.e.,

$$\rho_{xy}(u,s) = \tan^{-1}\left(\frac{\Im\left\{S(s^{-1}W_{wy}(\tau,s))\right\}}{\Re\left\{S(s^{-1}W_{wy}(\tau,s))\right\}}\right) \tag{6}$$

where $\Im$ is the imaginary and $\Re$ is the real part of the smooth power spectrum. Arrows are used to indicate the phase correlations. When the arrows point to the right, it means that the two-time series are in phase, indicating a positive correlation. On the other hand, if the arrows point to the left, it implies that the two-time series are in anti-phase, indicating a negative correlation.

3.3. Portfolio strategy approach

We employ the dynamic conditional correlation (DCC) framework (Engle, 2002) to perform the hedging strategy analysis. This model enables us to estimate conditional covariances (h) that are useful in implementing dynamic portfolio strategies. To hedge a long position in one (i) asset (stock), we can utilise a short position in a (j) second asset (fan token). According to Kroner and Sultan (1993), we can determine hedge ratios between these two assets by the following method:

$$\beta_{ijt} = \frac{h_{ijt}}{h_{jjt}} \tag{7}$$

Further, we compute the optimal portfolio weights for stock market and fan token ones, hence:

$$w_{ji,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}} \tag{8}$$

$$w_{ij,t} = \begin{cases} 0, & \text{if } w_{ij,t} < 0 \\ w_{ij,t}, & \text{if } 0 \leq w_{ij,t} \leq 1 \\ 1, & \text{if } w_{ij,t} > 1 \end{cases} \tag{9}$$

where $w_{ij,t}$ is the weight of first asset in a 1$ dollar portfolio of two assets at time t. $h_{ij,t}$ denotes the conditional covariance between assets i and j, while $h_{ii,t}$ ($h_{jj,t}$) represents the conditional variance of asset i (j). For a definition, the weight of the second asset is equal to $1 - w_{ij,t}$.

4. Data

Our sample consists of four football clubs, namely Juventus FC (JUV) and AS Roma (ASR) from Italy, Galatasaray (GAL) and Trabzonspor (TRA) from Turkey. We selected these football clubs as they are the only ones that issue fan tokens and are listed on financial markets.[2] Following Demir et al. (2022), we collected publicly available token prices from www.coinmarketcap.com, while we extracted daily stock prices from Datastream. Based on the fan token data availability, our daily data runs from November 2020 to December 2022. The empirical analysis is based on daily returns computed as the log-differencing of the daily closing prices of each series. Table 1 reports the summary statistics of our sample. Based on the descriptive statistics, we can note that ASR exhibits the highest volatility values in both markets. The Kurtosis values indicate that none of the series has Gaussian distributions, which is confirmed by the Jarque–Bera test. Additionally, the results of the Elliott, Rothenberg & Stock (ERS) test do not provide evidence of a unit root, i.e., the stationarity requirement of VAR modelling is satisfied.

In Table 2, we report the market capitalisation, the trading volume and the volume over market capitalisation (V/MC) for both traditional stock markets and related fan tokens. The V/MC ratio measures liquidity and trading activity relative to market capitalisation. A higher V/MC ratio indicates more trading activity and liquidity in the market size. Looking at the table, we can observe that fan tokens often have relatively small market capitalisation compared to more traditional financial assets. This characteristic can create challenges regarding price informativeness and market stability, including practices like pump-and-dump schemes, where prices are artificially inflated and then quickly deflated (Dowling, 2022). However, if we focus on the V/MC ratio for fan tokens, it is significantly higher than that of traditional stocks. This means that fan tokens tend to have higher trading activity compared to their market capitalisation than conventional stocks. As evidenced by the report of OECD (2023), although the capitalisation of the digital market is relatively smaller than that of the traditional market, the daily turnover of token-asset trading turnover is 4%–5% of the conventional market capitalisation, four times the equivalent figure of the U.S. stock market. Therefore, rather than focusing on capitalisation, it is important also to consider trading volumes. We find that in the mean, the volume/market capitalisation ratio of the fan token market is 4 times the respect of football stock (492% vs 10%). This document shows how the growth of the digital market, thus the associated risks, may affect the traditional market more and more in these years. When fan tokens experience high trading activity and price volatility, they can spill over into other assets, including related traditional stock, through several channels:

- Attention and awareness: As fan tokens gain media attention and high trading volumes, investors and traders might take notice. This increased awareness can lead to more interest in football clubs (Lopez-Gonzalez and Griffiths, 2023).

[2] We omitted S.S. Lazio in our sample because the time series of its fan tokens starts in 2021.

Table 1
Descriptive statistics.

	Mean	S. Dev.	Kurtosis	Jarque–Bera	ERS
FanToken					
JUV FT	−0.147	46.67	16.190***	8494.812***	−8.635***
ASR FT	−0.036	72.81	31.218***	31269.217***	−9.780***
GAL FT	0.004	55.97	25.121***	20270.694***	−12.343***
TRA FT	−0.001	46.29	33.948***	37717.365***	−11.864***
Stock market					
JUV ST	−0.088	7.125	9.481***	2942.122***	−9.853***
ASR ST	0.033	42.268	23.478***	17707.627***	−5.142***
GAL ST	0.092	10.612	5.961***	1163.849***	−4.849***
TRA ST	0.078	12.386	3.340***	360.046***	−5.729***

Notes: The Table presents summary statistics for our sample, including results from the Jarque–Bera statistic, which tests the null hypothesis of normal distribution, as well as the ERS unit root test developed by Elliott, Rothenberg, and Stock.

*** indicates rejection of the null hypothesis at the 1% significance level.

Table 2
Digital Vs Traditional market snapshot.

	Market cap			Trading volume			Volume/Market cap		
	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min
FanToken									
JUV FT	11.97	29.27	3.63	76.68	406.54	3.21	695%	3070%	16%
ARS FT	8.95	25.69	3.41	63.63	357.41	1.91	801%	7814%	44%
GAL FT	18.69	57.16	7.03	35.48	495.98	1.81	195%	1954%	18%
TRA FT	7.53	19.84	3.67	22.51	146.19	3.62	277%	1650%	87%
Aggregate	11.78	24.31	4.69	49.57	258.76	6.01	492%	2269%	93%
Stock Market									
JUV ST	914.87	960.44	866.92	37.05	253.52	7.33	4%	29%	1%
ARS ST	279.22	279.22	279.22	46.85	581.54	1.71	17%	208%	1%
GAL ST	262.56	433.61	175.49	17.58	117.25	0.53	9%	67%	0%
TRA ST	184.49	218.11	124.99	15.72	85.575	1.22	10%	68%	1%
Aggregate	410.28	450.56	385.04	29.31	164.34	4.81	10%	59%	1%

Notes: The Table shows the summary statistics of market capitalisation, trading volume and the volume/market cap ratio at football firms and aggregate levels. Market capitalisation and trading volume are in millions of USD.

- Sympathetic moves: When fan tokens associated with a particular football team experience significant price movements, it can have a sympathetic impact on the related traditional stocks. Fan investors may believe the fan token movements reflect broader market sentiment and financial performance.
- Investor behaviour: Traders and investors often exhibit herding behaviour, following the crowd or trends. If they see significant trading activity in fan tokens, they might buy or sell traditional stocks associated with the same sports clubs, expecting similar price moves (Maouchi et al., 2022; Boido and Aliano, 2023; Vidal-Tomás, 2023).

Hence, in this research, we aim to investigate the direction of these risk spillover effects.

5. Empirical findings

5.1. Mean and volatility spillover

In Table 3, we report the estimation results, namely the conditional variance and residual of the VAR(1)-BEKK-AGARCH(1, 1) model. Table 4 shows the summary, namely the direction of spillovers.

The main feature of the VAR-BEEK-AGARCH model is that it allows us to study spillover effects in the mean in the variance and the asymmetric component. Therefore, we can decompose spillover effects into positive and negative shocks. This decomposition allows us to investigate how past negative information from one market can influence the other. Focusing our attention on mean spillover, we find that the coefficient ϕ_{21}, which captures the price spillover effects between the two markets, is significant for all football clubs. This means the price spillover goes from the fan token market to the stock market. Moreover, we find a bilateral effect for the company GALA. These results are in line with the study of Ersan et al. (2022), which find that each asset is the primary transmitter of return spillovers to themselves and that tokens are the main transmitters of shocks to equities.

The spillover results are summarised in Table 4. From a preliminary analysis, we find that spillovers can be unidirectional or bidirectional depending on whether we consider the price (mean), volatility (variance) or asymmetric spillovers. The diagonal elements of matrices A, B, and D capture the volatility effects specific to a market. The results show that the diagonal coefficients of matrix A (a_{11} and a_{22}), i.e. the ARCH component, are all highly statistically significant. On the other hand, we observe that the

Table 3
Estimations results of VAR(1)–BEKK–AGARCH(1,1).

	JUV	ASR	GAL	TRA
Mean equation				
Φ_{FT}	0.002	0.011	−0.025	−0.037
	(0.068)	(0.149)	(0.096)	(0.111)
ϕ_{11}	−0.095**	−0.143**	−0.085*	−0.071*
	(0.047)	(0.073)	(0.049)	(0.040)
ϕ_{12}	0.008	0.048	0.039***	−0.003
	(0.011)	(0.023)	(0.014)	(0.018)
Φ_{ST}	−0.199	−0.183	−0.575*	−0.220
	(0.156)	(0.200)	(0.297)	(0.168)
ϕ_{21}	0.159***	0.051**	0.141**	0.176***
	(0.053)	(0.021)	(0.070)	(0.046)
ϕ_{22}	0.033	−0.142**	0.041	0.058
	(0.041)	(0.068)	(0.0501)	(0.041)
Variance equation				
c_{11}	1.251***	4.57***	0.859***	2.499***
	(0.157)	(0.653)	(0.228)	(0.222)
c_{21}	0.474**	0.154	1.993*	0.047
	(0.240)	(0.215)	(1.219)	(0.305)
c_{11}	2.511***	1.609***	2.692***	−0.001
	(0.254)	(0.402)	(0.753)	(0.259)
a_{11}	0.724***	0.709***	0.401**	0.677***
	(0.103)	(0.086)	(0.082)	(0.059)
a_{12}	0.031	0.054	0.179	−0.118
	(0.107)	(0.050)	(0.120)	(0.841)
a_{21}	0.038***	0.001	−0.011	0.013
	(0.012)	(0.160)	(0.018)	(0.014)
a_{22}	0.515***	0.527***	0.833***	0.444***
	(0.067)	(0.087)	(0.193)	(0.062)
b_{11}	0.429***	−0.161	0.879***	−0.172
	(0.067)	(0.133)	(0.049)	(0.185)
b_{12}	0.127*	0.103**	0.217*	0.406***
	(0.007)	(0.084)	(0.120)	(0.109)
b_{21}	−0.003	0.008	0.014	−0.011
	(0.084)	(0.054)	(0.016)	(0.026)
b_{22}	0.742***	0.860***	0.465***	0.874***
	(0.036)	(0.041)	(0.150)	(0.032)
d_{11}	−0.863***	0.273	−0.081	−0.343**
	(0.132)	(0.173)	(0.095)	(0.160)
d_{12}	0.454***	−0.014	−0.084	−0.254
	(0.107)	(0.045)	(0.091)	(0.165)
d_{21}	0.094**	0.316**	0.049*	0.278**
	(0.038)	(0.134)	(0.030)	(0.153)
d_{22}	0.441***	0.027	0.232	0.079
	(0.109)	(0.068)	(0.189)	(0.076)
Goodness-of-fit				
Log-likelihood	−4130.47	−911.13	−4307.45	−4333.93
AIC	8302.94	9864.27	8656.90	8709.86
SBC	8400.48	9961.81	8754.44	8807.41

Notes: AIC and SBC are the Akaike and Schwartz information criteria, respectively.
* denote statistical significance at the 10% level.
** denote statistical significance at the 5% level.
*** denote statistical significance at the 1% level.

Table 4
Summary spillover.

Spillover	JUV	ASR	GAL	TRA
Mean	FT → ST	FT → ST	FT ↔ ST	FT → ST
Variance	ST ↔ FT	ST → FT	ST → FT	ST → FT
Asymmetric component	FT ↔ ST	FT → ST	FT → ST	FT → ST

Notes: ST is the Stock market, while FT denotes the Fan Token market. The arrows show the spillover direction.

diagonal coefficients of the B matrix, i.e. the GARCH component, are all significant b_{22} coefficients. In contrast, the b_{11} coefficients are significant for JUVENTUS and GALATASARAY. These results suggest how conditional volatility is determined by past information on index values, especially in the short term (ARCH effect). Furthermore, we can see that in most cases, the ARCH coefficients are relatively more significant than the corresponding GARCH coefficients. This indicates that past shocks have a stronger influence on conditional volatility than long-term information.

Volatility spillover effects between markets are captured by the off-diagonal coefficients of the matrices A, B and D. The coefficient of a_{21} is statistically significant at the 1% level for JUVENTUS. This result suggests that fan token has significant short spillover shock effects on Juventus' stock. Focusing on the long-run volatility spillover (b_{12} and b_{21}), we find that the b_{12} coefficients are significant at the 10% and 5% level, respectively, implying one-sided volatility spillover effects between the stock market and the fan token market. This result shows how the risk of the stock market is transmitted to the fan token market. Finally, we focus on the coefficients of the D matrix. These coefficients estimate asymmetric leverage effects between markets. We find mainly one-sided spillover effects, i.e. from the fan token market to the stock market (d_{21}). We find how negative information from the fan token market can affect a shock in the stock market. These findings indicate that more bad news is transmitted to the other market, suggesting that the dependence between the two markets differs depending on whether we consider the mean (return) or risk component.

Overall, the results suggest how negative shocks in the same or other markets induce a significant volatility reaction. Therefore, investors, to reduce portfolio risk, should pay more attention to the volatility imparted by the two markets, especially during downside market conditions.

5.2. Wavelet coherency findings

In this section, we use the wavelet coherence (WC) analysis to explore the behaviour of returns and volatility spillovers. Figs. 1–2 display the WC results. The cross-wavelet coherence plots show the correlations between the time series at different time scales. The intervals in the vertical axis, 0-16, 16-64 and 64-256, represent the short-, medium- and long-term frequency scales, while the horizontal axis represents time. The cone of influence (white line) indicates correlations at the 5% significance level. The colour indicates the degree of correlation: low coherence (blue) and high coherence (red). Therefore, regions with warmer (colder) colours represent regions with significant (low) dependence. The arrows reveal information about the lead–lag relationship in time–frequency space. In-phase connections, i.e. positive (negative) co-movements, are indicated by arrows pointing to the right (left).

Fig. 1 illustrates the link between stock and fan token returns, respectively. As we can observe, the figure documents a significant positive relationship (right-hand arrows) between the two markets, especially in the short term (2–16 days). This suggests that investors cannot take advantage of adequate diversification opportunities in portfolios in the short term. For GALATASARAY, there is evidence of significant spillovers from June 2021 to June 2022.

Focusing on the volatility transmission between the two markets (Fig. 2), we find that co-movements between the series are more persistent in the medium and long term (32–128 days). The islands of hot colour mainly occur starting in June 2021. However, we note how the results are not homogeneous over time. There are periods of in-phase and out-of-phase, indicating that the pairs are positively and negatively correlated for most wavelets. On the other hand, the vertical direction of the arrows depends on the pair considered and the holding period and time. However, we can note, also in the volatility case, a major positive relationship between the two markets. This result documents the transmission of risk, hence the existence of a contagion effect between the two assets.

All wavelets capture significant events associated with football results and the crypto world. Some of the main events include: the announcement of the European Super League (April 2021); the 'Launchpads' programme in December 2021, which states that Fan tokens introduced on Binance can be traded like any other cryptocurrency (Scharnowski et al., 2021); breach of the break-even rule known as financial fair play (FFP) for AS Roma and Trabzonspor (June 2022); the Juventus FC capital gains issue (December 2022). In summary, our findings suggest that the volatility spillover is more persistent in the long run, confirming the results obtained with the VAR-BEKK-AGARCH model. This result can be explained by the spillover effects of volatility between markets, mainly due to the passing of information between markets by rebalancing portfolios containing different assets (Fleming et al., 1998; Baumöhl et al., 2018). The new information that causes volatility can be specific to one market and spill over to the other or be common to both markets and act indirectly through the passing of volatility from one market to another. The results add new information to the evidence of a time dependency between the two assets reported by Ersan et al. (2022) and Scharnowski et al. (2021). In fact, our empirical analysis shows how the two markets transmit mean and risk spillovers at different time scales. Therefore, the results are potentially interesting for traders operating over different investment horizons.

5.3. Portfolio analysis

From the wavelet analysis, we learned that the correlations between returns and volatilities between the two assets are variable over the sample period. Furthermore, from the estimation of the VAR-BEKK-AGARCH model, we found that there are also clear volatility spillover effects. This implies that investors' portfolios are vulnerable to these uncertainties. Therefore, this section investigates the relationship between the stock market and fan tokens from a portfolio diversification and risk management viewpoint. First, we compute the dynamic conditional correlation (DCC), and second, we use the DCC model results to build an optimal portfolio diversification strategy. We calculate two alternative diversification strategies, namely the optimal hedge ratio (HR) and the optimal portfolio weight (PW), using the results of the DCC framework.[3]

[3] For the sake of brevity, we do not report the estimation results of the DCC model. However, they are available upon request.

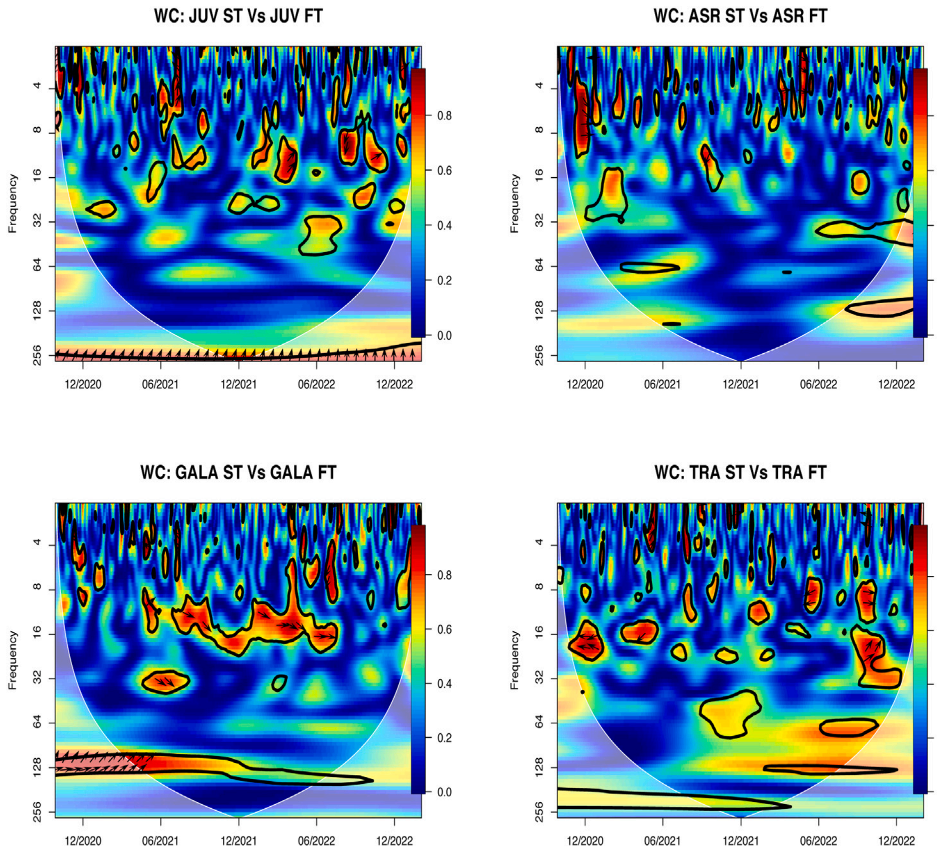

Fig. 1. Returns Wavelet coherency.
Notes: The plots show the wavelet coherence diagram between the stock market and fan token returns. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

In Fig. 3, we depict the optimal hedging ratios. Our portfolio consists of a long position in equities and a short position in fan tokens. The figure shows that the optimal hedge ratios are time-varying for all four football clubs. Generally, when the market trend is stable, the hedging ratio is stable, whereas if there is substantial market fluctuation, it increases. We observe how all the HR indicate an increase in coverage costs during the beginning of 2022. In Table 5, we show the summary statistics of the hedge ratios. As we can see, the average hedging ratios vary widely in the cost of using the fan token to hedge equities. Moreover, the average hedge ratios are the highest for JUVENTUS and GALATASARAY stocks. This result suggests that hedging these companies with the Fan token price is the most expensive compared to the other firms. This result is confirmed by the standard deviation. Indeed, when the hedge ratio volatility is high, it leads to a greater expense for hedging as investors will need to adjust their portfolios more frequently (Belhassine and Karamti, 2021). The Table shows that a $1 long position in JUVENTUS FT can be hedged on average for 24 cents with a short position in JUVENTUS ST. On the other hand, a long position of $1 in JUVENTUS ST can be covered on average with 0.4 cents with a short position in JUVENTUS FT. Finally, we can observe that ASR ST/ASR FT and ASR FT/ASR ST show negative average values. This result suggests that long or short positions should be taken in each asset pair.

Fig. 4 plots the dynamics of the portfolio weights, while the descriptive statistics are presented in Table 6. The optimal portfolio weights also exhibit evident volatility over time. We can observe periods in which the incidence tends towards values less than 0.5 and periods in which it tends towards 1. Looking at Table 6, the highest average portfolio weight is between JUVENTUS ST and JUVENTUS FT, with values of 0.83. This indicates that for a $1 portfolio, 83 cents should be invested in the stock market and 17 cents in fan tokens. TRA ST/TRA FT represents the lower average portfolio weight, indicating that 0.68 cents should be invested in TRABZONSPOR ST, while 32 cents should be invested in the token market. Overall, our portfolio analysis suggests that by incorporating optimal hedge ratios into their portfolio management, investors can aim for risk-adjusted returns. For example, during periods of higher market volatility, they may increase their short positions in fan tokens to reduce exposure to stock market risk while potentially benefiting from price movements in fan tokens. Moreover, the analysis suggests that fan tokens can be used as a satellite component in an investment portfolio, allowing investors to balance their core holdings in traditional stocks with more dynamic and potentially higher-yield fan tokens. While football stocks may serve as a more stable, long-term investment, fan tokens may introduce opportunities for short-term speculation. However, investors should recognise that football clubs' stocks and fan tokens are both inherently risky investments due to their susceptibility to factors like team performance and market sentiment (Ersan

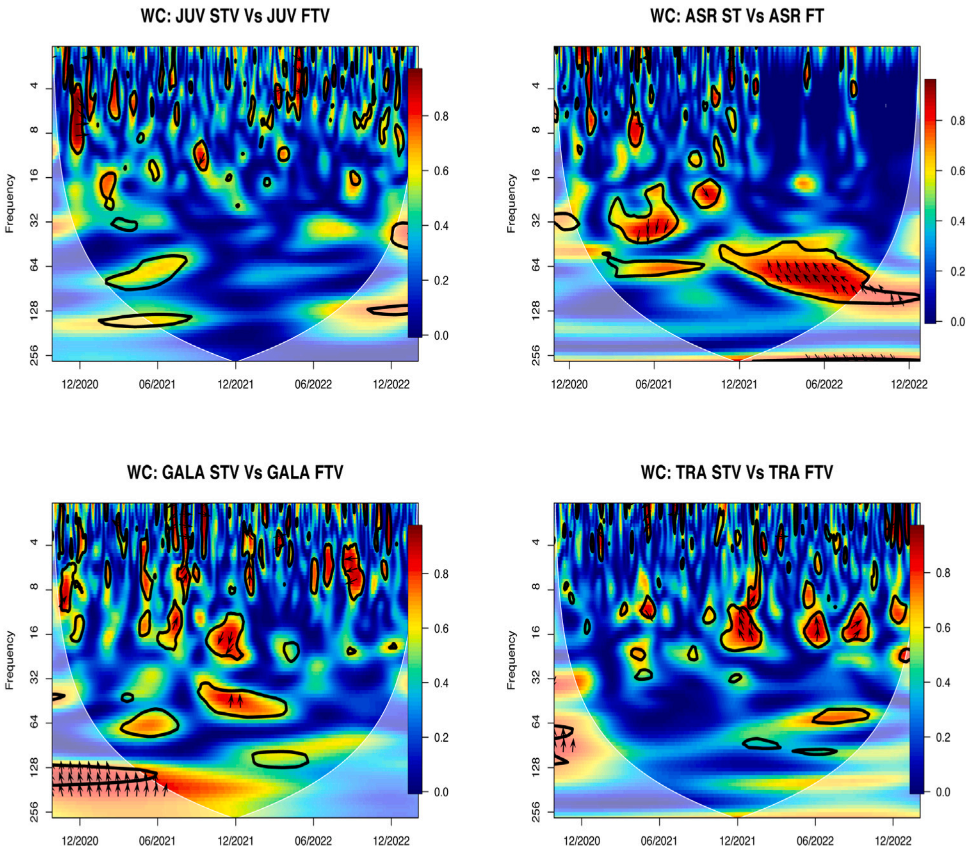

Fig. 2. Variance Wavelet coherency.
Notes: The plots show the wavelet coherence diagram between the stock market and fan token volatility returns. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5
Hedge ratio (long/short) summary statistics.

	Mean	Std.Dev.	5%	95%
JUV ST/JUV FT	0.04	0.05	0.00	0.13
ASR ST/ASR FT	−0.03	0.04	−0.08	0.01
GALA ST/GALA FT	0.03	0.04	0.00	0.09
TRA ST/TRA FT	0.02	0.04	−0.02	0.08
JUV FT/JUV ST	0.24	0.19	0.04	0.55
ASR FT/ASR ST	−0.09	0.15	−0.27	0.04
GALA FT/GALA ST	0.13	0.22	−0.02	0.40
TRA FT/GALA ST	0.05	0.15	−0.06	0.17

Notes: This Table presents the summary statistics of optimal hedge ratios when stock assets are hedged using fan tokens.

et al., 2022; Scharnowski et al., 2021). As evidenced by the VAR-BEKK-AGARCH analysis, there is a high level of interdependence between these two financial assets. This result suggests that investors holding stocks and fan tokens in their portfolio may experience higher risk than expected due to risk spillover effects. The results of this analysis can help market participants make adequate and reasonable asset allocation decisions, especially in the current context of the FinTech revolution.

5.4. Discussion about financial sector and the digital ecosystem

Digital assets have recently captured significant attention for their potential to transform various sectors. However, the rise of blockchain and non-fungible tokens (NFT) also brings with it several risks that could have a significant impact on financial markets. This section explores these risks and their potential impact on the financial sector. One particular category of digital assets is fan tokens, which generate interest from both football clubs and investors. On the one hand, these digital assets are designed to create a deep connection between football clubs and their fan base (engagement). Indeed, they grant access to exclusive club content, allow

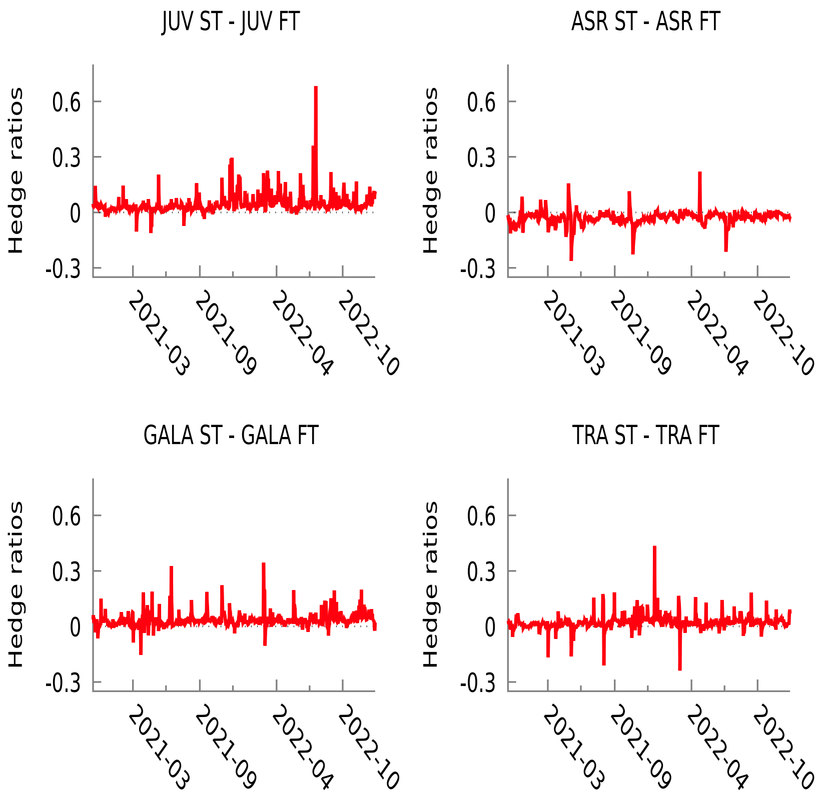

Fig. 3. Hedge ratios dynamics.
Notes: Time series plot of time-varying optimal hedge ratios. It is computed from the DCC model. Long (stock market) and short (fan token).

Table 6
Portfolio weight summary statistics.

	Mean	Std.Dev.	5%	95%
JUV ST/JUV FT	0.83	0.18	0.40	0.99
ASR ST/ASR FT	0.69	0.22	0.26	0.95
GALA ST/GALA FT	0.74	0.19	0.32	0.97
TRA ST/TRA FT	0.68	0.18	0.32	0.96

Notes: This Table presents the summary statistics of optimal portfolio weight for a $1 portfolio composed of stock market and fan tokens.

owners to participate in interactive surveys, and earn rewards such as tickets and digital badges (Demir et al., 2022). On the other hand, they can be considered an investment asset as they are, in effect, cryptocurrencies (Scharnowski et al., 2021). The main risks associated with these new forms of financial assets can be summarised as follows:

1. *Price volatility*. Fan tokens are subject to significant price volatility. They are traded on cryptocurrency exchanges, where prices can fluctuate widely (OECD, 2022).
2. *Liquidity risks.* These assets may not be traded on all cryptocurrency exchanges as they are relatively new. Investors who cannot swiftly or fairly sell their tokens may be exposed to liquidity issues as a result.
3. *Market risks.* Fan tokens are subject to market risks. The football team's performance, the player's popularity, and changes in the regulatory environment are just a few examples of the many variables that might affect demand for these assets. These risks may impact the value of the tokens, i.e., the investors' returns.
4. *Bubble risk*. There is the potential for excessive speculation could result in asset prices that are inflated and do not correspond to their true value (Maouchi et al., 2022; Boido and Aliano, 2023; Vidal-Tomás, 2023).
5. *Lack of regulation* (Azar et al., 2022). At the moment, there are no specific regulations governing fan tokens. Because of the lack of regulation, it may be challenging for investors and fans to understand the risks associated with these financial assets. Also, a lack of explicit regulation may open the door to dishonest practices like *pump-and-dump* schemes (Dhawan and Putniņš, 2022; Nghiem et al., 2021).

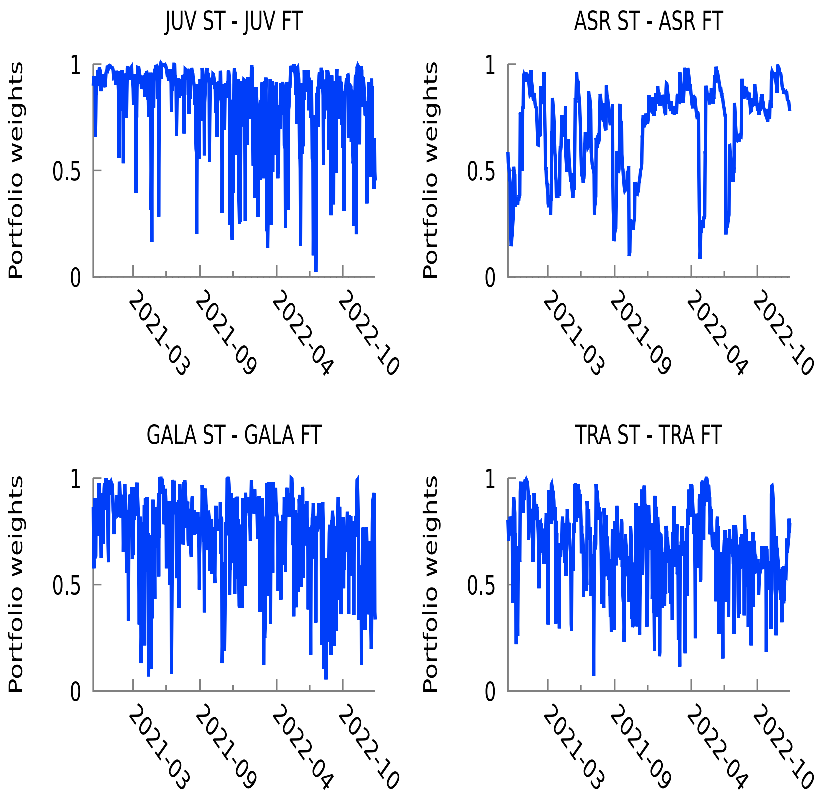

Fig. 4. Portfolio weight dynamics. *Notes:* Time series plot of time-varying portfolio weights. It is computed from the DCC model.

Our empirical analysis sheds light on the spillover risks between the returns and risks of the stock market and fan tokens. In fact, according to the Azar et al. (2022), traditional and digital financial markets are highly interconnected. First, our results show the existence of significant volatility spillovers between the stock market and fan token one. On the one hand, we find that stock market shocks have a lasting impact on fan token returns; on the other hand, we show how bad news in the fan token market spread to the financial one (Table 3). This indicates a high level of interdependence between these two financial assets. This result suggests that investors holding stocks and fan tokens in their portfolio may experience higher risk than expected due to these spillover effects. Second, we find that the four football clubs in our sample exhibit different patterns of spillover effects between the stock market and fan token returns. For example, JUVENTUS FC shows a higher two-way volatility interconnection effect between the stock market and fan tokens (Table 4) than the other clubs. In fact, the portfolio analysis finds that an ideal optimal portfolio composition would be that of the most 30% invested-in fan tokens for TRABZONSPOR (Table 6). These results suggest that investors should be aware of the potential risks associated with fan token investments. Hence, our findings have important investment and portfolio management implications and can help investors make more informed investment decisions. While fan tokens offer a new way for football clubs to engage with their fans and provide investors with a new asset class in which to invest, they also carry significant risks. Investors should carefully assess the risks associated with these assets before investing. Furthermore, regulators should consider implementing regulations to ensure transparency, protect investors and minimise the risks associated with volatility spillovers.

6. Conclusion

The emergence of digital asset investments due to the FinTech revolution has created a new class of assets for investors, namely, fan tokens. This new asset has become increasingly popular among football clubs and investors (Demir et al., 2022; Ersan et al., 2022). Hence, understanding the interplay and spillover effects between these new and traditional assets is crucial for effective risk management. Therefore, this paper investigates the mean (return) and risk spillovers between the stock market and fan tokens.

For this purpose, we employed the VAR-BEEK-AGARCH model, the wavelet frequency analysis, and the portfolio management strategy to identify the risk transmission between the two assets. We found evidence of a significant risk spillover between the two assets. Moreover, our findings suggest that the long-term volatility spillovers are more meaningful, indicating that the stock market and fan tokens are highly interdependent. This finding provides insight into the behaviour of investors in the market for fan tokens and sheds light on the role that fan tokens play in the larger ecosystem of football club investments.

Our results have important implications for investment and portfolio management. Investors considering diversifying their portfolios with fan tokens should be aware of the potential risks and the extent of the spillovers between them and the stock market.

Additionally, football clubs may find our findings helpful in designing fan token strategies and assessing their risks. Our research contributes to the recent literature on digital asset investment and provides valuable insights for both investors and football clubs.

The main limitation of this work refers to our dataset. Our sample is limited to four football clubs, which may not be representative of the broader population of football clubs. However, despite this limitation, we believe that our findings have important implications for football clubs and investors. Fan tokens can revolutionise how football clubs interact with their fans and provide a new avenue for investment. Future researchers can, based on these results, explore the impact of fan tokens on other aspects of football club operations, such as revenue streams, fan engagement, and brand loyalty. Besides, future development of this research could incorporate liquidity-weighted risk measures of markets, such as liquidity-adjusted VaR. Including liquidity risk could improve understanding of the dynamics between conventional and digital markets.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

We wish to thank participants of the 4th International Conference CGRM 2023, March 23–24, at Copernico Repubblica, Rome (Italy), for their very helpful comments and suggestions. The authors have received funding from the European Union - NextGenerationEU under the program ''MUR-Fondo Promozione e Sviluppo - DM 737/2021'' managed by the University of Bari Aldo Moro (reference: S47 - Verso una gestione integrata e prospettica del rischio sistemico attraverso modelli di 'explainable artificial intelligence' (XAI)'' – CUP H99J21017600006 – Principal Investigator: Prof. Vincenzo Pacelli). The usual disclaimer applies.

References

Aharon, D.Y., Demir, E., 2022. NFTs and asset class spillovers: Lessons from the period around the COVID-19 pandemic. Finance Res. Lett. 47, 102515.
Ante, L., 2022. The non-fungible token (NFT) market and its relationship with Bitcoin and Ethereum. FinTech 1 (3), 216–224.
Azar, P.D., Baughman, G., Carapella, F., Gerszten, J., Lubis, A., Perez-Sangimino, J.P., Scotti, C., Swem, N., Vardoulakis, A., Rappoport W, D.E., 2022. The financial stability implications of digital assets. FRB New York Staff Report, (1034).
Baumöhl, E., Kočenda, E., Lyócsa, Š., Vỳrost, T., 2018. Networks of volatility spillovers among stock markets. Physica A 490, 1555–1574.
Belhassine, O., Karamti, C., 2021. Volatility spillovers and hedging effectiveness between oil and stock markets: Evidence from a wavelet-based and structural breaks analysis. Energy Econ. 102, 105513.
Boido, C., Aliano, M., 2023. Digital art and non-fungible-token: Bubble or revolution? Finance Res. Lett. 52, 103380.
Carlini, F., Del Gaudio, B.L., Porzio, C., Previtali, D., 2022. Banks, FinTech and stock returns. Finance Res. Lett. 45, 102252.
Corbet, S., Goodell, J.W., Gunay, S., Kaskaloglu, K., 2023. Are DeFi tokens a separate asset class from conventional cryptocurrencies? Ann. Oper. Res. 322 (2), 609–630.
Demir, E., Ersan, O., Popesko, B., 2022. Are fan tokens fan tokens? Finance Res. Lett. 102736.
Dhawan, A., Putniņš, T.J., 2022. A new wolf in town? Pump-and-dump manipulation in cryptocurrency markets. Rev. Finance 27 (3), 935–975.
Dowling, M., 2022. Is non-fungible token pricing driven by cryptocurrencies? Finance Res. Lett. 44, 102097.
Engle, R., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J. Bus. Econom. Statist. 20 (3), 339–350.
Engle, R.F., Kroner, K.F., 1995. Multivariate simultaneous generalized ARCH. Econometric Theory 11 (1), 122–150.
Ersan, O., Demir, E., Assaf, A., 2022. Connectedness among fan tokens and stocks of football clubs. Res. Int. Bus. Finance 63, 101780.
Feyen, E., Frost, J., Gambacorta, L., Natarajan, H., Saal, M., et al., 2021. Fintech and the digital transformation of financial services: implications for market structure and public policy. BIS Pap..
Fleming, J., Kirby, C., Ostdiek, B., 1998. Information and volatility linkages in the stock, bond, and money markets. J. Financial Econ. 49 (1), 111–137.
FSB, 2022. FinTech and market structure in the COVID-19 pandemic. Implications for financial stability. Technical Report, Financial Stability Board, Basel, Switzerland.
Ghosh, B., Bouri, E., Wee, J.B., Zulfiqar, N., 2023. Return and volatility properties: Stylized facts from the universe of cryptocurrencies and NFTs. Res. Int. Bus. Finance 65, 101945.
Goupillaud, P., Grossmann, A., Morlet, J., 1984. Cycle-octave and related transforms in seismic signal analysis. Geoexploration 23 (1), 85–102.
Karim, S., Lucey, B.M., Naeem, M.A., Uddin, G.S., 2022. Examining the interrelatedness of NFTs, DeFi tokens and cryptocurrencies. Finance Res. Lett. 47, 102696.
Katsiampa, P., 2019. An empirical investigation of volatility dynamics in the cryptocurrency market. Res. Int. Bus. Finance 50, 322–335.
Kroner, K.F., Sultan, J., 1993. Time-varying distributions and dynamic hedging with foreign currency futures. J. Financial Quant. Anal. 28 (4), 535–551.
Lopez-Gonzalez, H., Griffiths, M.D., 2023. Gambling-like features in fan tokens. J. Gambl. Stud. 1–18.
Maci, G., Pacelli, V., D'Apolito, E., et al., 2020. The determinants of stock prices of European football clubs: An empirical analysis. Int. J. Econ. Finance Manag. Sci. 8 (5), 168.
Maouchi, Y., Charfeddine, L., El Montasser, G., 2022. Understanding digital bubbles amidst the COVID-19 pandemic: Evidence from DeFi and NFTs. Finance Res. Lett. 47, 102584.
Mazur, M., Vega, M., 2023. Football and cryptocurrencies. J. Altern. Invest.
Mensi, W., Hammoudeh, S., Nguyen, D.K., Yoon, S.-M., 2014. Dynamic spillovers among major energy and cereal commodity prices. Energy Econ. 43, 225–243.
Nassr, I.K., 2021. Understanding the tokenisation of assets in financial markets. Technical Report, OECD.
Nghiem, H., Muric, G., Morstatter, F., Ferrara, E., 2021. Detecting cryptocurrency pump-and-dump frauds using market and social signals. Expert Syst. Appl. 182, 115284.
OECD, 2022. Why Decentralised Finance (DeFi) Matters and the Policy Implications. Technical Report, OECD Paris.

OECD, 2023. Crypto-assets and decentralised finance. Technical Report, OECD Paris.

Qiao, X., Zhu, H., Tang, Y., Peng, C., 2023. Time-frequency extreme risk spillover network of cryptocurrency coins, DeFi tokens and NFTs. Finance Res. Lett. 51, 103489.

Scharnowski, M., Scharnowski, S., Zimmermann, L., 2021. Fan tokens: Sports and speculation on the blockchain. Available at SSRN 3992430.

Torrence, C., Compo, G.P., 1998. A practical guide to wavelet analysis. Bull. Am. Meteorol. Soc. 79 (1), 61–78.

Ugolini, A., Reboredo, J.C., Mensi, W., 2023. Connectedness between DeFi, cryptocurrency, stock, and safe-haven assets. Finance Res. Lett. 53, 103692.

Umar, Z., Polat, O., Choi, S.-Y., Teplova, T., 2022. Dynamic connectedness between non-fungible tokens, decentralized finance, and conventional financial assets in a time-frequency framework. Pac.-Basin Finance J. 76, 101876.

Umar, Z., Usman, M., Choi, S.-Y., Rice, J., 2023. Diversification benefits of NFTs for conventional asset investors: Evidence from CoVaR with higher moments and optimal hedge ratios. Res. Int. Bus. Finance 65, 101957.

Vidal-Tomás, D., 2022. The new crypto niche: NFTs, play-to-earn, and metaverse tokens. Finance Res. Lett. 47, 102742.

Vidal-Tomás, D., 2023. Blockchain, sport and fan tokens. J. Econ. Stud.

Yousaf, I., Abrar, A., Goodell, J.W., 2023a. Connectedness between travel & tourism tokens, tourism equity, and other assets. Finance Res. Lett. 53, 103595.

Yousaf, I., Nekhili, R., Gubareva, M., 2022. Linkages between DeFi assets and conventional currencies: Evidence from the COVID-19 pandemic. Int. Rev. Financ. Anal. 81, 102082.

Yousaf, I., Pham, L., Goodell, J.W., 2023b. Interconnectedness between healthcare tokens and healthcare stocks: Evidence from a quantile VAR approach. Int. Rev. Econ. Finance 86, 271–283.