Blockchain, sport and fan tokens

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Abstract

Purpose: This paper provides a thorough examination of Socios.com, a blockchain platform that integrates token sales with the fan experience in the sports industry. Our study focuses on three key aspects: the performance, bubble phenomenon, and dynamics of fan tokens. We aim to address important questions that may concern potential supporters and investors. Might sports fans incur financial losses due to their team loyalty? Is the fan token market just a passing trend? Are fan tokens driven by the behaviour of the cryptocurrency market?

Design/methodology/approach: Our analysis involves several methodologies. We evaluate the short- and long-term performance of fan tokens by computing first-day and buy-and-hold (abnormal) returns. We also employ the PSY real-time bubble detection method to investigate the presence of bubble phenomenon in the fan token market segment. Finally, we examine the potential dependences between fan tokens, Chiliz, and the cryptocurrency market (represented by the CCi30 index) using both Pearson/Kendall correlations and the wavelet coherence approach.

Findings: Our study presents three notable contributions to the existing literature. First, we demonstrate that investing in fan tokens to support one's favourite sports teams can lead to financial losses, whereas traders can potentially outperform the market by investing in Chiliz. Second, we state that fan tokens were a short-lived trend, as evidenced by their decline in value after the bubble burst in 2021. Third, our findings indicate that the fan token market was influenced by the cryptocurrency market and Chiliz during periods of market downturns.

Originality: To the best of our knowledge, this is the first paper to conduct a comprehensive analysis of the performance, bubble phenomenon, and dynamics of the fan token market segment, along with the exclusive on-platform currency, Chiliz.

Keywords: Chiliz · Fan token · Cryptocurrency · Sport

JEL: G10 · G11 · G40

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1 Introduction

Since Bitcoin was created by Nakamoto (2008), the blockchain has opened a range of new business possibilities, providing the basis for developing peer-to-peer platforms in order to exchange information, assets and digitised goods without any kind of intermediation (Aste et al., 2017). Consequently, scholars, companies and policy-makers have examined its potential application in very different sectors and fields, such as agri-food (Antonucci et al., 2019), health care (Angraal et al., 2017), logistics (Pournader et al., 2020), gaming (Vidal-Tomás, 2022a), education (Chen et al., 2018), metaverse (Vidal-Tomás, 2023), sharing economy (Fiorentino and Bartolucci, 2021) and regulatory compliance (Gozman et al., 2020).

In this paper, we focus on the application of blockchain in the sport and entertainment industry, which already includes more than 60 blockchain companies divided into seven market segments: sports betting, club and league management, fantasy sports, health and personal integrity, ecosystem development, collectives and memorabilia and talent investment (Carlsson-Wall and Newland, 2020). The second largest market segment, with more than 10 companies, is club and league management, whose main objective is to help clubs improve their fan engagement strategies. Within this group of blockchain companies, we focus on Chiliz/Socios.com, as it combines the fan experience with the sale of tokens through its own exchange and exclusive on-platform currency, namely, Chiliz. In particular, with this digital currency, supporters can buy virtual tokens of their favourite sports team (fan tokens, hereafter), through the Chiliz platform and Socios.com website or mobile application, in exchange for rewards and involvement in certain club decisions.[1] Moreover, sports teams can raise funds without the need for traditional intermediaries. This feature is particularly appealing for clubs, given the drastic decrease in sports teams' sales after the COVID-19 outbreak.[2]

Interestingly, the popularity of this blockchain company increased since 2021 [see Fig. (1)], with a growing list of prestigious international partners, such as FC Barcelona (football), Heretics (gaming), UFC (fighting), Aston Martin Cognizant (motorsport), Punjab Kings (cricket), Boston Celtics (basketball) and Davis cup (tennis).[3] Therefore, we could expect that (i) some supporters will engage with their sports team through fan tokens, and (ii) traders will regard fan tokens and Chiliz as an alternative kind of digital asset in which to invest.[4] Indeed, as a result of the growing popularity of fan tokens, scholars shed some light on the attributes of this novel form of cryptocurrency. Ersan et al., 2022 examined the dynamic connectedness among the fan tokens and their corresponding stocks using the TVP-VAR approach. They observed that these two asset classes are independent of each other, with a decreasing connectedness over time. Demir et al. (2022) assessed the impact of football match results on token prices of the clubs. Their results showed that fan token prices are affected by football clubs' match results, specially

[1]For instance, supporters can participate in polls related to the warm-up entrance song, fan-designed messages for the dressing room or team bus designs, among other club decisions.

[2]According to Telegraph (Morgan, 2021), some of Europe's top soccer clubs have obtained 150 million pounds ($204 million).

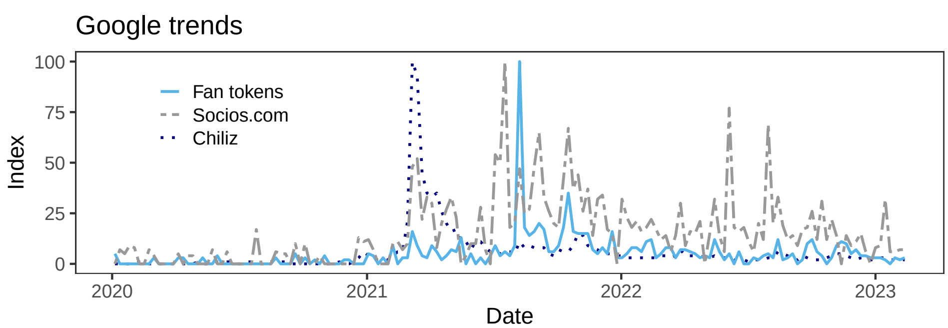
[3]See https://www.socios.com/socios-partners/.

[4]The increasing interest in fan tokens is also observed with the new service provided by Binance, as it allows its users to buy new fan tokens (e.g. S.S. Lazio), which are not included in the Chiliz exchange platform. Moreover, LaLiga and Socios.com announced an agreement in which Socios.com became a Global Fan Engagement Partner of Spain's top tier football league (LaLiga, 2021).

during matches in the UEFA Champions League tournament. Scharnowski et al. (2021) analysed the main stylised facts of fan tokens, showing that they are highly speculative and in many aspects resemble cryptocurrencies. Given the novelty of these new assets, there are still important unresolved questions for potential supporters and investors. Might sports fans incur financial losses due to their team loyalty? Is the fan token market just a passing trend? Are fan tokens and Chiliz driven by the behaviour of the cryptocurrency market?

Within this context, the main aim of this paper is to answer previous questions by analysing the performance, bubble phenomenon and dynamics of these new digital assets. To do so, first, we analyse their short- and long-term performance by computing first-day and buy-and-hold (abnormal) returns. Second, we assess the existence of bubble phenomenon through the PSY real-time bubble detection method. Finally, we examine the possible dependences between fan tokens, Chiliz and the cryptocurrency market, represented by the CCi30 index, using Pearson/Kendall correlations and the wavelet coherence approach.

Figure. 1: Google searches for "Fan tokens", "Socios.com", and "Chiliz". An index equal to 100 indicates the maximum popularity during the analysed period. Source: Author's own creation/work.



2 Data

For the purpose of this paper, we use cryptocurrency prices from the Coinmarketcap database, which is defined as a reliable data source (see Vidal-Tomás, 2022b). More specifically, we analyse Chiliz and 52 fan tokens between 23 April 2020 and 01 January 2023, given that the first trading day of the first fan token (Juventus FC) occurred on 23 April 2020.[5] Moreover, we also use the CCi30 index as the cryptocurrency market capitalization-weighted benchmark (see, e.g., Manahov, 2020). Thus, we can also analyse the performance and dynamics of fan tokens and Chiliz in relation to the behaviour of the crypto-market.

For all the price time series, we compute daily log-returns, whose descriptive statistics are shown in Table 1 and Fig. (2). We also calculate a fan token equally-weighted index to assess the general behaviour of these crypto assets, as reported in Fig. (3). Interestingly, we can observe that Chiliz is characterised by a higher mean than the CCi30 index. However, focusing on fan tokens, Fig. (2) and Fig. (3) show negative results, given the negative

[5]The list of fan tokens is included in the Appendix.

mean and poor progression of the fan token index [see also Table (1)]. Indeed, since the Juventus FC token was released on 23 April 2020, the fan token index has experienced a reduction in value amounting to 87%.

Table 1: Descriptive statistics of daily log-returns for the CCi30 index, Chiliz, fan token index, and all the fan tokens (in the median). Source: Author's own creation/work.

	Observations	Mean	Std.Dev.	Skewness	Kurtosis	Min.	Max.
CCi30	983	0.0007	0.0433	-1.0659	6.4035	-0.3474	0.1957
Chiliz	983	0.0028	0.0768	1.2085	13.5240	-0.4570	0.7153
Fan token index	983	-0.0020	0.0634	-1.0418	13.2794	-0.5887	0.3687
Fan tokens (Median)	505	-0.0033	0.0742	0.0388	12.5455	-0.4250	0.4715

Figure. 2: Descriptive statistics of daily log-returns for the entire sample of fan tokens. Source: Author's own creation/work.

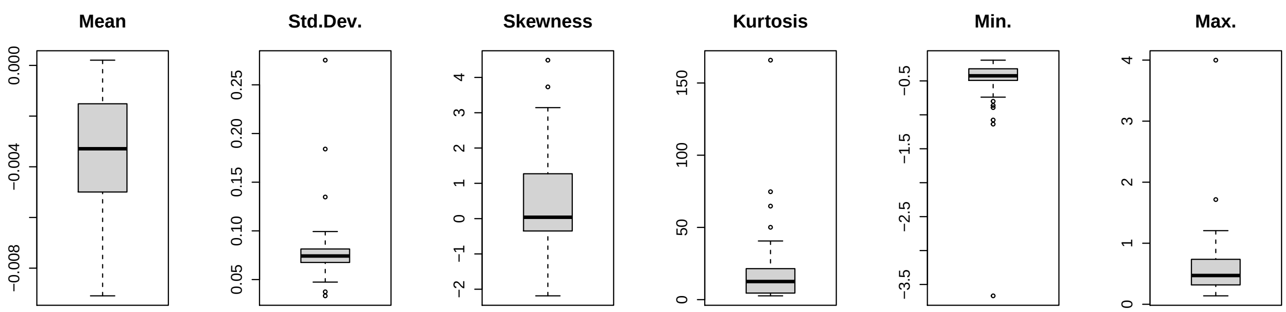
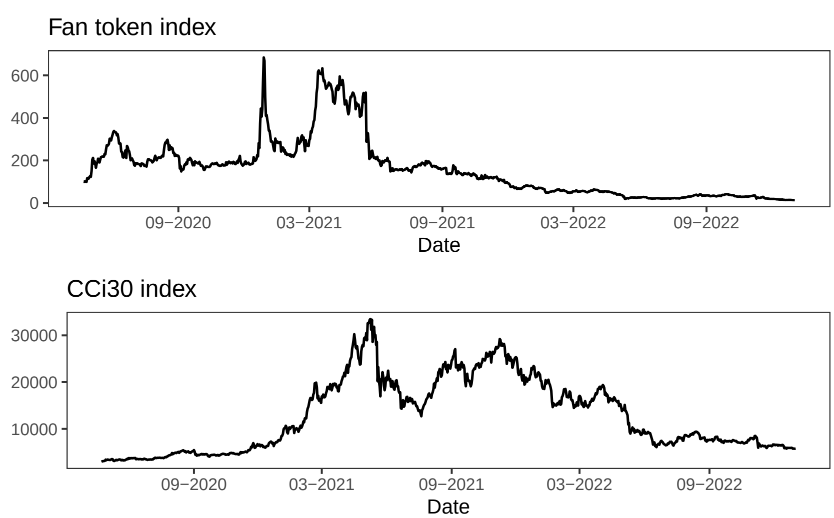


Figure. 3: Fan token index and CCi30 index. Source: Author's own creation/work.



3 Methodology

3.1 Performance: first-day and buy-and-hold (abnormal) returns

To analyse the short- and long-run performance of fan tokens, we use average first-day and average buy-and-hold returns, respectively. Following Momtaz (2019) and Vidal-Tomás (2023), the former are calculated as the sum over all fan tokens i of the closing and opening price difference over the opening price of the first-day of trading, after the fan token offering (FTO), divided by the number of fan tokens n:

$$\overline{R} = \frac{1}{n}\sum_{i=1}^{n}\frac{P_{i,1} - P_{i,0}}{P_{i,0}}, \tag{1}$$

where $\overline{R}$ is the average first-day returns, $P_{i,1}$ denotes closing prices and $P_{i,0}$ represents opening prices.

To analyse the long-term performance, we compute average buy-and-hold returns ($\overline{BHR}$), which are defined as Eq. (1) but replacing $P_{i,1}$ for the closing price after the focal holding period ($P_{i,\tau}$):

$$\overline{BHR}_\tau = \frac{1}{n}\sum_{i=1}^{n}\frac{P_{i,\tau} - P_{i,0}}{P_{i,0}}, \tag{2}$$

where the holding period is denoted by τ. For the purpose of this paper, we consider the following holding periods: (i) 1 week, (ii) 1 month, (iii), 3 months, (iv) 6 months, (v) 9 months, (vi) 1 year, and (vii) all the sample period since the FTO.

In order to also analyse the performance of Chiliz in the long run, we compute $BHR_{Chiliz,\tau} = (P_{Chiliz,\tau} - P_{Chiliz,0})/P_{Chiliz,0}$, where $P_{Chiliz,0}$ is 23 April 2020, i.e. we start the Chiliz analysis when the first fan token was introduced in the market. We do not consider the first-day return in this case, as its first trading day was on 7 February 2019, when supporters and traders could not buy fan tokens.

Finally, to examine their performance compared to the entire cryptocurrency market, we calculate first-day abnormal returns and buy-and-hold abnormal returns by adjusting $\overline{R}$, $\overline{BHR}_\tau$ and $BHR_{Chiliz,\tau}$ with a market capitalization-weighted benchmark. In other words, average first-day abnormal returns, $\overline{AR}$, average buy-and-hold abnormal returns, $\overline{BHAR}_\tau$ and buy-and-hold abnormal returns for Chiliz, $BHAR_{Chiliz,\tau}$ are defined as $\overline{R}$, $\overline{BHR}_\tau$ and $BHR_{Chiliz,\tau}$ less the market return, which is represented by the CCi30 market capitalisation index:

$$\overline{AR} = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{P_{i,1} - P_{i,0}}{P_{i,0}} - \frac{P_{CCi30,1} - P_{CCi30,0}}{P_{CCi30,0}}\right], \tag{3}$$

$$\overline{BHAR}_\tau = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{P_{i,\tau} - P_{i,0}}{P_{i,0}} - \frac{P_{CCi30,\tau} - P_{CCi30,0}}{P_{CCi30,0}}\right], \tag{4}$$

$$BHAR_{Chiliz,\tau} = \frac{P_{Chiliz,\tau} - P_{Chiliz,0}}{P_{Chiliz,0}} - \frac{P_{CCi30,\tau} - P_{CCi30,0}}{P_{CCi30,0}}, \tag{5}$$

where $P_{CCi30,0}$ is the same day as $P_{i/Chiliz,0}$.

3.1.1 Bubble phenomenon: Backward Sup Augmented Dickey-Fuller test (BSADF) test - PSY method

We use the methodology proposed by Phillips and Shi (2020), namely Backward Sup Augmented Dickey-Fuller test (BSADF) test, also known as PSY real-time bubble detection method, to analyse the presence of bubble phenomenon (see, e.g. Deng et al., 2017 and Pan, 2020).

With the PSY method, it is possible to identify explosive price behaviour in financial markets through sup ADF tests applied on a backward expanding sample sequence.[6] More specifically, this technique is based on an ADF model specification but uses flexible time window in its implementation to consider time-varying dynamics and structural breaks. The null hypothesis of the PSY test captures normal market behaviors and states that prices follow a martingale process with a mild drift function,

$$y_t = g_T + y_{t-1} + u_t, \tag{6}$$

where $g_T = kT^{-\gamma}$ (with constant $k, \gamma > 1/2$, and sample size T) captures any mild drift that could exist in prices. The regression model chosen by Phillips and Shi (2020) is

$$\Delta y_t = \mu + \rho y_{t-1} + \sum_{j=1}^{p} \phi_j \Delta y_{t-j} + v_t, \tag{7}$$

where the regression error v_t follows $v_t \overset{i.i.d}{\sim} \left(0, \sigma^2\right)$. The p lag terms of Δy_t consider potential serial correlation, and is selected by BIC. The regression model nests the null hypothesis as a special case with $\mu = g_T$ and $\rho = 0$. The ADF statistic is the t-ratio of the least squares estimate of ρ. The main feature of this methodology is that the recursive evolving algorithm allows real-time identification of explosive periods while also allowing for the presence of multiple structural breaks. In other words, the PSY procedure computes the ADF statistic recursively from a backward expanding sample sequence, considering r_1 and r_2 as the start and end points of the regression sample. Consequently, the ADF statistic calculated for this period is denoted by $ADF_{r_1}^{r_2}$. Following the nomenclature proposed by Phillips and Shi (2020), the end point of all the samples is $r_2 = r^{\dagger}$ while the start point r_1 can change within a plausible range, $\left[0, r^{\dagger} - r_0\right]$, where r_0 is the minimum window, and equal to $r_0 = 0.01 + 1.8/\sqrt{T}$. The PSY statistic is the supremum (Sup) taken over the values of all the ADF statistics in the entire recursion, i.e.

$$PSY_{r^{\dagger}}\left(r_0\right) = \sup_{r_1 \in [0, r^{\dagger} - r_0], r_2 = r^{\dagger}} \left\{ADF_{r_1}^{r_2}\right\} \tag{8}$$

[6] In this paper, we use the BSADF/PSY test. Alternatively, it could be possible to use the generalised SADF test (GSADF), which is an ex post statistic used for analysing a given data set for bubble behaviour. However, given that the PSY test can be used by traders to detect bubbles in real time, we employed this method to underline the possible speculative strategies.

Phillips and Shi (2020) defined the origination/termination date of a bubble as the first observation whose backward sup ADF statistic exceeded/fell below the critical value. Therefore, the estimated origination and termination dates (denoted by $\hat{r}_e$ and $\hat{r}_f$) are then given by:

$$\begin{aligned} \hat{r}_e &= \inf_{r^\dagger \in [r_0,1]} \left\{ r^\dagger : PSY_{r^\dagger}\left(r_0\right) > cv_{r^\dagger}\left(\beta_T\right) \right\}, \\ \hat{r}_f &= \inf_{r^\dagger \in [\hat{r}_e,1]} \left\{ r^\dagger : PSY_{r^\dagger}\left(r_0\right) < cv_{r^\dagger}\left(\beta_T\right) \right\}, \end{aligned} \tag{9}$$

where $cv_{r^\dagger}\left(\beta_T\right)$ is the $100\left(1-\beta_T\right)$ critical value of the $PSY_{r^\dagger}\left(r_0\right)$ statistic, and β_T takes values 1%, 5%, 10%, i.e. 99%, 95% and 90% critical value.

3.2 Dynamics

3.2.1 Pearson and Kendall correlations

To obtain an initial picture of the connections between CCi30/Chiliz – fan tokens, and CCi30 – Chiliz, we compute the Pearson correlation, which is the most common measure for studying the similarity between assets' dynamics (see, e.g., Francés et al., 2018 and Nava et al., 2018). Moreover, for robustness purposes, we also compute the Kendall correlation (Kendall, 1938), as it is appropriate for time series that are short and non-normal (Aste, 2019).[7]

3.2.2 Wavelet coherence approach

In addition to the Pearson and Kendall correlations, we also use the wavelet coherence approach with the continuous wavelet transform to analyse the co-movement between time series, both in time and frequency domain (see, e.g. Caferra and Marcello Falcone, 2022, Santorsola et al., 2022, Sharif et al., 2020, Bkedowska-Sójka et al., 2022). According to Torrence and Compo (1998), the cross wavelet transform of two time series of returns x_t and y_t is defined by means of the continuous wavelet transform $W_n^x(u,s)$ and $W_n^y(u,s)$, as follows:

$$W_n^{x,y}(u,s) = W_n^x(u,s) * W_n^y(u,s), \tag{10}$$

where u is associated with the location, s with the scale and $*$ denotes the complex conjugate. This measure identifies areas in the time-frequency domain where returns show a high common power. In other words, it shows the local covariance between the time series at each scale.

Having computed the cross wavelet transform, the wavelet coherence, which captures the co-movement between

[7] The correlation coefficient ranges from -1 to 1, i.e., from a negative perfect correlation to a positive perfect correlation. A value of 0 implies that there is no correlation between the time series.

two time series in the time-frequency domain, is defined as:

$$R^2(u,s) = \frac{|S(s^{-1}W^{xy}(u,s))|^2}{S(s^{-1}|W^x(u,s)|^2)S(s^{-1}|W^y(u,s)|^2)}, \quad (11)$$

where S is a smoothing operator over time as well as scale, and $0 \leq R^2(u,s) \leq 1$ (Rua and Nunes, 2009). Values close to 0 indicate the absence of correlation, while values close to 1 indicates a high correlation. Nevertheless, unlike the standard correlation coefficient, the wavelet squared coherence is restricted to positive values. As a consequence, it is not possible to identify properly positive and negative co-movements. To overcome this issue, we employ the phase difference proposed by Torrence and Compo (1998) that allows us not only to distinguish between positive and negative co-movements but also to shed some light on the causal relationships between time series. Wavelet coherence phase difference is defined as:

$$\psi_{x,y}(u,s) = tan^{-1}\left(\frac{\Im\{S(s^{-1}W^{xy}(u,s))\}}{\Re\{S(s^{-1}W^{xy}(u,s))\}}\right), \quad (12)$$

where $\Im$ and $\Re$ are the imaginary and real parts of the smoothed cross-wavelet transform, respectively. In the figures that report the wavelet coherence analysis, arrows indicate phase differences, which underlines the synchronization between the two series. On the one hand, arrows pointing to the right (left) indicate time series that are in-phase (out of phase); that is, they are positively (negatively) correlated. On the other hand, arrows pointing upward indicate that the first time series leads the second; whereas downward pointing arrows indicate that the second time series is leading the first.

4 Empirical results

4.1 Performance

In Table (2), we report the performance of Chiliz over the long run. Interestingly, we observe that Chiliz has increased its value by about 1434%, underlining the interest of traders and supporters in this new platform and currency. We can relate this positive performance to the fact that Chiliz is the exclusive on-platform currency, and supporters and traders must use and buy Chiliz to purchase any new fan token. In other words, as new fan tokens are offered, supporters buy new Chiliz tokens, giving rise to an increase in demand and price. BHAR reports an increase in value by about 1333%, even when deleting the effect of the market represented by the CCi30 index. Therefore, we conjecture that (i) supporters will not suffer from a decrease in value when buying Chiliz tokens with the purpose of purchasing any fan token, and (ii) traders can even outperform the cryptocurrency market. However, to observe this favourable outcome in the future, we need to assume that new fan tokens will be released over time due to the growing interest of sports enthusiasts, which will give rise to the corresponding increase in Chiliz's demand. Moreover, following Carlsson-Wall and Newland (2020), supporters and traders must also consider that Chiliz's dominance in the sport industry could end with the entrance of new competitors, which is a possible reality given the new service provided by Binance related to fan tokens.

Table 2: Long-run performance of Chiliz. Source: Author's own creation/work.

Chiliz	1 week	1 month	3 months	6 months	9 months	1 year	Entire sample
BHR	0.1269	0.4491	0.8189	0.6214	1.9716	94.1197	14.3448
BHAR	-0.0621	0.2851	0.4900	0.0461	-0.5986	85.0610	13.3332

Focusing on the performance of all the available fan tokens, we report in Table 2 and Fig. (3) that these assets are characterised by positive short-run and negative long-run performance. As a result, despite potentially observing favorable performance during the first trading day, supporters will ultimately experience a significant decline in the value of their fan tokens. More specifically, in the median, fan tokens lost the 79.86% of their initial value. Only 3 tokens (5.77% of the sample), obtained a positive performance since their release. These tokens are FC Barcelona (38.15%), OG (25.05%), and Juventus FC (21.09%). Hence, it can be asserted that sports fans will incur financial losses by supporting their preferred sports team. Interestingly, we only identify a positive performance, on average, for certain holding periods (6 months, 9 months and 1 year), given the existence of positive outliers, such as FC Barcelona. Given this outcome, sports enthusiasts should consider the cost of supporting their team through this kind of crypto asset.

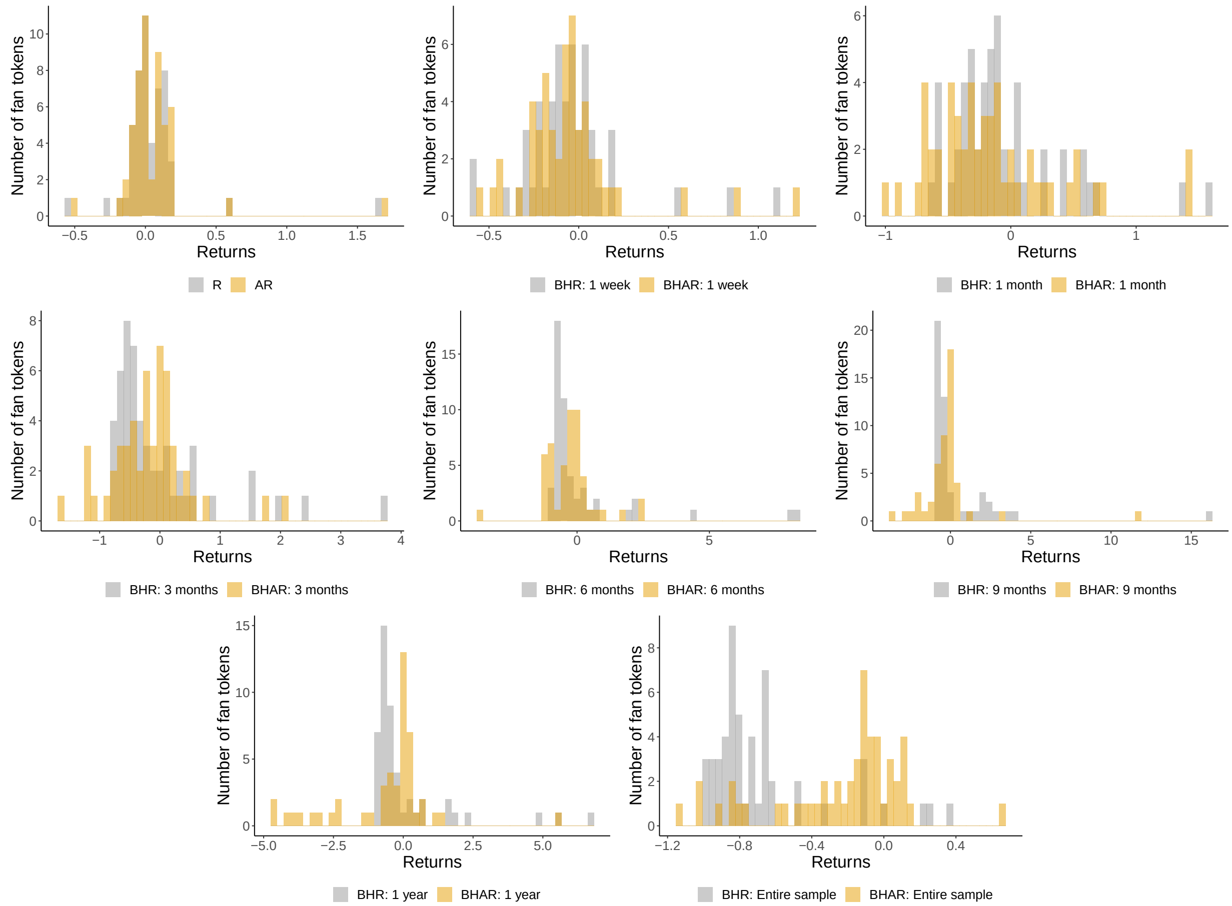
Finally, from a financial perspective, we show that traders cannot use fan tokens to outperform the cryptocurrency market, given the negative results reported by $\overline{BHAR}$. Specifically, the fan token market segment exhibited a negative performance, falling 23.79% below the CCi30 index. In fact, a mere 23.08% of fan tokens outperformed the CCi30 index.

Table 3: Short and long-run performance of fan tokens. Source: Author's own creation/work.

$\overline{R}$	1 day
Mean	0.0525
Median	0.0038
% of tokens: > 0	0.5385
$\overline{AR}$	1 day
Mean	0.0621
Median	0.0152
% of tokens: > 0	0.5577
Fan tokens	52

$\overline{BHR}$	1 week	1 month	3 months	6 months	9 months	1 year	Entire sample
Mean	-0.0456	-0.0590	-0.0216	0.1415	0.3450	0.0864	-0.6683
Median	-0.0632	-0.1550	-0.3469	-0.5633	-0.5233	-0.5519	-0.7986
% of tokens: > 0	0.3462	0.3077	0.3269	0.2400	0.2653	0.2500	0.0577
$\overline{BHAR}$	1 week	1 month	3 months	6 months	9 months	1 year	Entire sample
Mean	-0.0492	-0.1591	-0.1725	-0.2896	-0.1986	-0.6272	-0.2379
Median	-0.0784	-0.2371	-0.1419	-0.2719	-0.1957	-0.0739	-0.1241
% of tokens: > 0	0.3077	0.2500	0.3462	0.2600	0.3265	0.4583	0.2308
Fan tokens	52	52	52	50	49	48	52

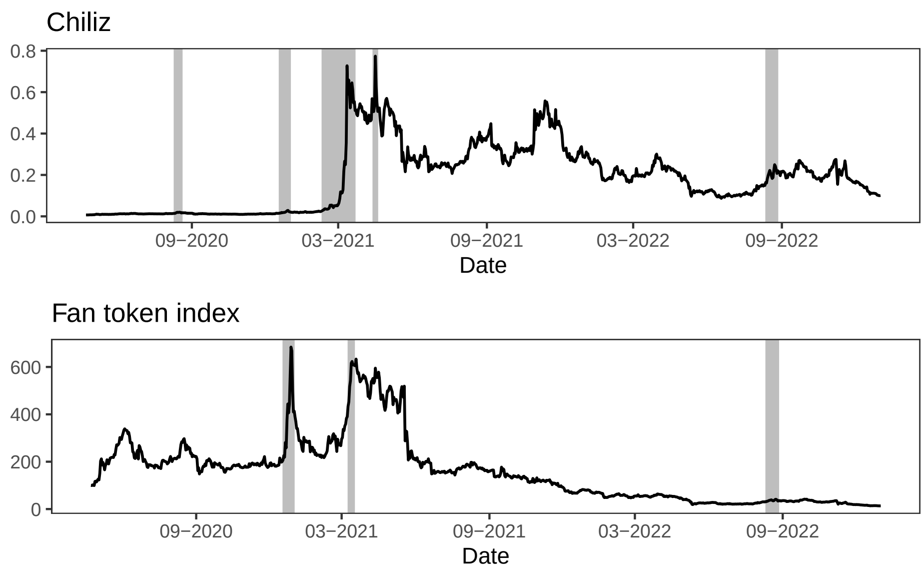
Figure. 4: Histogram of first-day (abnormal) returns (R & AR), and buy-and-hold (abnormal) returns (BHR & BHAR) for the entire sample of fan tokens. Source: Author's own creation/work.



4.2 Bubble phenomenon

Fig. (5) shows the time intervals during which the PSY real-time bubble indicator identifies the occurrence of bubble phenomenon in both the fan token index and Chiliz, at the 1% significance level. We observe that the main bubbles in this market segment are detected towards the conclusion of 2020 and commencement of 2021, coinciding with the increase in prices in the entire cryptocurrency market during the same period [see CCi30 in Fig. (3)]. Subsequently, we observe a negative trend in both Chiliz and the fan token index. Specifically, since reaching their peak prices, Chiliz and the fan token index experienced a decrease in value of 86% and 98%, respectively. In contrast to the fan token index, which has lost 87% of its value since the first fan token was released, Chiliz has been able to maintain a positive long-term performance, as indicated in Table (2) with an increase in value of 1434%. As previously mentioned, we can attribute this positive performance to the exclusive use of Chiliz as the on-platform currency, ensuring a minimum demand for this token. However, we can also deduce that Chiliz do not exhibit an increasing demand over time, as evidenced by its poor performance since 2021. Therefore, given the burst of the bubble in 2021, we hypothesize that fan tokens were merely a transient trend, and supporters are not inclined towards this type of cryptocurrency asset any longer. To observe in the future a positive trend in Chiliz and fan token prices, it will be necessary to attract more supporters to this crypto niche.

Figure. 5: Chiliz/fan token index prices (black line) and bubbles detected by the BSADF/PSY method at the 1% significance level (grey areas). Source: Author's own creation/work.



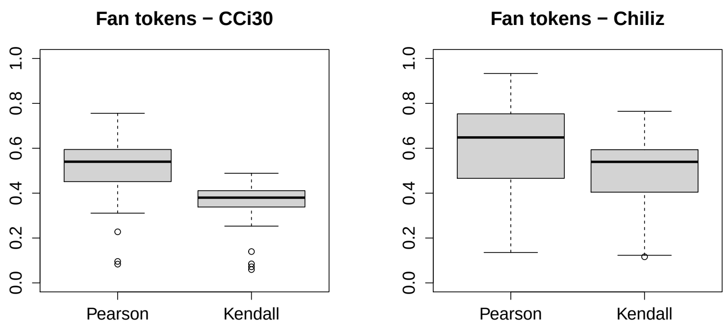
4.3 Dynamics

4.3.1 Pearson and Kendall correlations

We evaluate the behavior of the fan token market by calculating Pearson and Kendall correlations for the CCi30–Chiliz pair, whose coefficients are 0.6001 and 0.4903, respectively. Consequently, we cannot state that a strong co-movement exists between Chiliz and the cryptocurrency market.

Computing the correlations between all fan tokens, the CCi30 index, and Chiliz, we observe that fan tokens exhibited a stronger correlation with Chiliz compared to the CCi30 index. This observation is logical as Chiliz serves as the on-platform currency for fan tokens. On average, the coefficients are equal to 0.5073 (Pearson) and 0.3616 (Kendall) for the co-movement between CCi30 and fan tokens. In contrast, they are 0.6170 (Pearson) and 0.5012 (Kendall) for the relation between Chiliz and fan tokens [see Fig. (6)].

Figure. 6: Boxplots of Pearson and Kendall correlations: fan tokens - CCi30 & fan tokens - Chiliz. Source: Author's own creation/work.



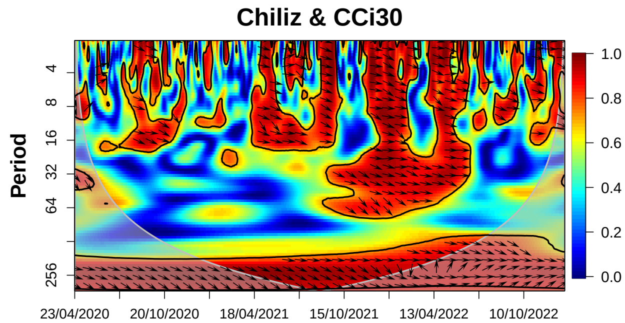
4.3.2 Wavelet coherence approach

Figs. (7) and (8) show the main results of the wavelet coherence analysis. The x-axis indicates the time domain component, while the y-axis indicates the frequency component, from lower levels of scale, which refer to high frequency variations (i.e. daily fluctuations), up to higher levels of scale, which refer to low frequency variations (i.e. weekly or monthly fluctuations). The black contours identify regions with a statistically significance coherence at the 5% level. The cone of influence, represented by the grey curve, shows the areas affected by edge effects. Finally, the degree of coherence is related to different colours: from blue (low coherence/co-movement) to red (high coherence/co-movement).

As can be observed in Fig. (7), until the end of 2021, the wavelet coherence analysis does not reveal a high dependence between Chiliz and the cryptocurrency market, as we only identify two zones in which there was a significantly high degree of positive co-movement, over 1–16-day frequency bands: (i) September 2020 and (ii) April-August 2021. However, we observe a significant high dependence since the end of 2021, which seems to be related to the collapse of the entire cryptocurrency market [see CCi30 in Fig. (3)]. Hence, we can state that Chiliz was driven by the cryptocurrency downturn at the end of 2021, which is supported by the red areas and arrows pointing to the right and downward.[8] This finding underscores the risk of investing in Chiliz, as it will also be affected by down-markets in the crypto-space.

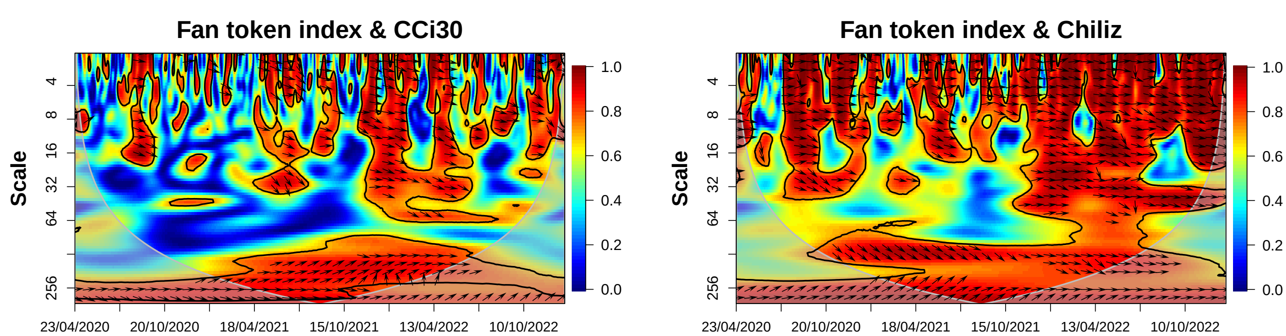
[8]Indeed, the dependence reported in May 2021, over 1–16-day frequency bands, can also be related to the down-market of the cryptocurrency market at the beginning of 2021.

Figure. 7: Wavelet coherence between Chiliz and the CCi30 index. Source: Author's own creation/work.



In Fig. (8), we report the wavelet coherence between (i) the fan token index and CCi30, and (ii) the fan token index and Chiliz. In relation to the former, we can observe consistent results that are in line with Fig. (7), since the fan token index was also driven by the cryptocurrency market during the crypto down-market at the end of 2021.[9] This finding highlights the potential financial risks that supporters may face when using these cryptocurrency assets to support their teams, given that a downturn in the cryptocurrency market will trigger a similar downturn in the fan token niche. Consequently, supporters will incur in financial losses. On the other hand, focusing on the connectedness between the fan token index and Chiliz, we observe that the fan token index was driven by Chiliz, which is expected given the role of Chiliz as the exclusive on-platform currency. Thus, a decrease/increase in demand for Chiliz will also result in a decrease/increase in demand for fan tokens. This connectedness was stronger during the crypto down-market, at the end of 2021. Last but not least, and in line with Pearson/Kendall correlations in Fig. (6), we note that Chiliz was more correlated to the fan token index than CCi30. Additional figures in the supplementary material support the previous statement since most of the wavelets between the fan tokens and CCi30 generally show low co-movements, represented by the dominance of the blue color. In contrast, we observe a higher co-movement between Chiliz and most of the fan tokens, such as ALL, APL, DAVIS, EFC, LEV, ROUSH, or STV.

Figure. 8: Wavelet coherence between the fan token index and CCi30 index/Chiliz. Source: Author's own creation/work.



[9]Fan tokens index seems to drive CCi30 at very low frequencies, given the generalised down-market of the fan token index since the beginning of 2021.

5 Conclusion

In this paper, we examined a blockchain application in the sport industry through the analysis of Socios.com. To the best of our knowledge, this is the first paper to analyse the performance, bubble phenomenon, and dynamics of the fan token market segment and the exclusive on-platform currency, Chiliz. Our study provides three significant contributions to the existing literature. First, we demonstrate that supporters will incur financial losses by investing in fan tokens to support their favorite sports teams, while traders can potentially outperform the market by investing in Chiliz. Second, we state that fan tokens were a transient trend, as evidenced by their declining value following the burst of a bubble in 2021. Finally, we observe that the fan token niche was driven by the cryptocurrency market and Chiliz during the down-market, which highlights the risks of supporting sports teams through crypto assets.

These results contribute to a new strand of the literature in which blockchain companies are offering digital products with new technical and financial characteristics. Therefore, scholars and policy-makers must analyse the properties of these digital assets to avoid financial disinformation in society.

Appendix

Table 4: List of fan tokens. Source: Author's own creation/work.

Nº	Name	Symbol	Nº	Name	Symbol
1	AC Milan Fan Token	ACM	27	Legia Warsaw Fan Token	LEG
2	Arsenal Fan Token	AFC	28	Levante U.D. Fan Token	LEV
3	Alanyaspor Fan Token	ALA	29	Leeds United Fan Token	LUFC
4	Alliance Fan Token	ALL	30	Flamengo Fan Token	MENGO
5	Aston Martin Cognizant Fan Token	AM	31	Millonarios FC Fan Token	MFC
6	Apollon Limassol	APL	32	MIBR Fan Token	MIBR
7	Argentine Football Association Fan Token	ARG	33	Napoli Fan Token	NAP
8	AS Roma Fan Token	ASR	34	Natus Vincere Fan Token	NAVI
9	Atletico De Madrid Fan Token	ATM	35	Novara Calcio Fan Token	NOV
10	Aston Villa Fan Token	AVL	36	OG Fan Token	OG
11	FC Barcelona Fan Token	BAR	37	Portugal National Team Fan Token	POR
12	Brazil National Football Team Fan Token	BFT	38	Paris Saint-Germain Fan Token	PSG
13	Club Atletico Independiente	CAI	39	Roush Fenway Racing Fan Token	ROUSH
14	Manchester City Fan Token	CITY	40	Samsunspor Fan Token	SAM
15	Davis Cup Fan Token	DAVIS	41	Alfa Romeo Racing ORLEN Fan Token	SAUBER
16	Dinamo Zagreb Fan Token	DZG	42	S.C. Corinthians Fan Token	SCCP
17	Everton Fan Token	EFC	43	Spain National Fan Token	SNFT
18	FenerbahÃ§e Token	FB	44	Sao Paulo FC Fan Token	SPFC
19	Fortuna Sittard Fan Token	FOR	45	Sint-Truidense Voetbalvereniging Fan Token	STV
20	Peruvian National Football Team Fan Token	FPFT	46	Team Heretics Fan Token	TH
21	Galatasaray Fan Token	GAL	47	Trabzonspor Fan Token	TRA
22	Clube Atlético Mineiro Fan Token	GALO	48	Universidad de Chile Fan Token	UCH
23	Göztepe S.K. Fan Token	GOZ	49	UFC Fan Token	UFC
24	İstanbul Başakşehir Fan Token	IBFK	50	Valencia CF Fan Token	VCF
25	Inter Milan Fan Token	INTER	51	Team Vitality Fan Token	VIT
26	Juventus Fan Token	JUV	52	Young Boys Fan Token	YBO

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