Blockchain, sport and fan tokens

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Abstract

We examine a blockchain application in the sport industry through an analysis of Socios.com. In particular, we study the performance and dynamics of fan tokens and the exclusive on-platform currency, Chiliz. Our contribution to the literature is two-fold. First, we show that supporters do not lose money by supporting their sports teams through fan tokens and Chiliz, on average, and traders can outperform the market with Chiliz. Second, given the absence of a correlation with the cryptocurrency market, traders can use these assets to diversify their cryptocurrency portfolios, and supporters own tokens that are not driven by the cryptocurrency market.
JEL codes: 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), education (Chen et al., 2018), 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 exchange 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, which is attractive in a (post-)pandemic context characterised by a drastic decrease in sports teams' sales due to government restrictions.[2]

Interestingly, the popularity of this blockchain company is increasing over time, 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, in the near future, we can expect that (i) more supporters will engage with their sports team through fan tokens, and (ii) more traders will regard fan tokens and Chiliz as an alternative kind of digital asset in which to invest.[4] However, given the novelty of these new assets and the lack of related literature, there are important unresolved questions for potential supporters and investors: Can sport fans lose money by supporting their teams? Are fan tokens and Chiliz driven by the behaviour of the cryptocurrency market? Is it possible to diversify a cryptocurrency portfolio with fan tokens and Chiliz?

Within this context, the main aim of this paper is to answer these questions by analysing the performance and

[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).

dynamics of these new digital assets. To do so, on the one hand, we analyse their short- and long-term performance by computing (abnormal) first-day and (abnormal) buy-and-hold returns. On the other hand, 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.

2. Data

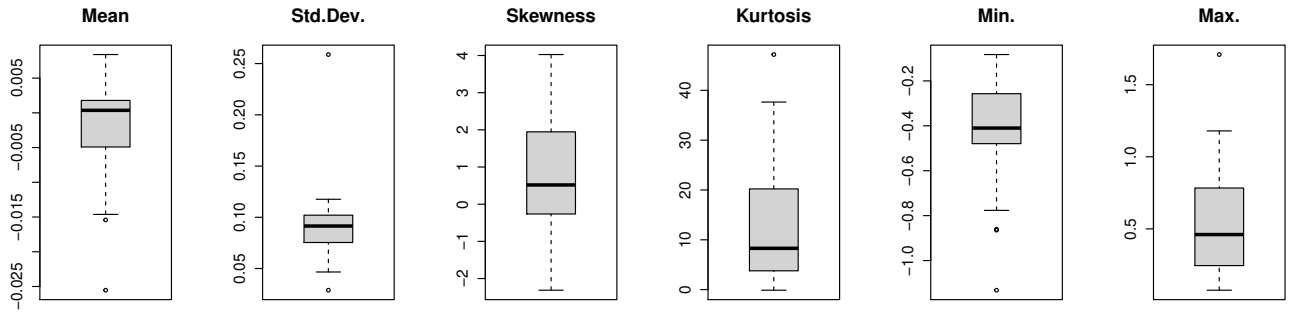
For the purpose of this paper, we use cryptocurrency prices from the CoinGecko database (CG, 2021) in daily frequency. More specifically, we analyse Chiliz and 39 fan tokens between 17 April 2020 and 31 October 2021, given that the first trading day of the first fan token (Juventus FC) occurred on 17 April 2020.[5] Moreover, we also use the CCi30 index as the cryptocurrency market capitalization-weighted benchmark (see, e.g., Manahov, 2020 and Vidal-Tomás, 2021). Thus, we can also analyse the performance and dynamics of fan tokens and Chiliz in relation to the behaviour of the market.

For all the price time series, we compute daily log-returns, whose descriptive statistics are shown in Table 1 and Fig. (1). Interestingly, we can observe that Chiliz is characterised by a higher mean than the CCi30 index, which supports its increasing interest by sports teams, supporters and investors. However, focusing on fan tokens, Fig. (1) shows heterogeneous results, as 20 (19) fan tokens show a positive (negative) mean, which leads to an average performance close to 0 (see Table (1)).[6,7]

Table 1: Descriptive statistics of daily log-returns for the CCi30 index, Chiliz and fan tokens (median).

	N	Mean	Std.Dev.	Skewness	Kurtosis	Min.	Max.
CCi30	562	0.0039	0.0452	-1.2920	8.2350	-0.3474	0.1957
Chiliz	562	0.0073	0.0844	1.7393	15.5054	-0.4457	0.7263
Fan tokens (Median)	170	0.0004	0.0915	0.5180	8.2884	-0.4100	0.4607

Figure. 1: Descriptive statistics of daily log-returns for the entire sample of fan tokens.



[5]The list of fan tokens used in this paper, with names and symbols, is available in the supplementary material.
[6]The higher volatility of Chiliz and fan tokens can be related to its higher illiquidity and shorter life compared to the CCi30 index.
[7]For the sake of space, the table of descriptive statistics including fan tokens is reported in the supplementary material.

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), 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 17 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 $P_{i/Chiliz,0}$.

3.2. Dynamics

3.2.1. Pearson and Kendall correlations

To obtain an initial picture of the dependences 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. 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).[8]

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. Specifically, in this section we only focus on fan tokens with more than 90 observations to obtain reliable results. 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:

$$W_n^{x,y}(u,s) = W_n^x(u,s) * W_n^y(u,s), \tag{6}$$

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

$$R^2(u,s) = \frac{|S(s^{-1}W^{xy}(u,s))|^2}{S(s^{-1}|W^x(u,s)|^2)S(s^{-1}|W^y(u,s)|^2)}, \tag{7}$$

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:

[8]The correlation coefficient ranges from -1 ro 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.

$$\psi_{x,y}(u,s) = tan^{-1}\left(\frac{\Im\{S(s^{-1}W^{xy}(u,s))\}}{\Re\{S(s^{-1}W^{xy}(u,s))\}}\right), \tag{8}$$

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 can observe that, despite the negative performance during the first week, after the release of the Juventus fan token, Chiliz has increased its value by about 4723%, indicating the interest of traders and supporters in this new platform and currency. We could 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 were offered, supporters bought new Chiliz tokens, giving rise to an increase in demand and price. This positive performance could be also connected with the up-market of the cryptocurrency market since January 2021. However, BHAR reports an increase in value by about 3898%, even when deleting the effect of the market represented by the CCi30 index. Therefore, we can conjecture that supporters will not suffer from a decrease in value when buying Chiliz tokens with the purpose of purchasing any fan token, and traders could even outperform the cryptocurrency market, as long as we assume that new fan tokens will be created in the future, with a corresponding increase in Chiliz's demand. Nevertheless, following Carlsson-Wall and Newland (2020), supporters and traders must 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.

Chiliz	1 week	1 month	3 months	6 months	9 months	1 year	Entire sample
BHR	-0.0111	0.4389	0.8065	0.6042	1.6000	69.5898	47.2332
BHAR	-0.0586	0.2686	0.4550	-0.0341	-0.6603	61.7629	38.9834

Focusing on the performance of fan tokens, we can observe in Table 2 that these assets are characterised by negative short-run and positive long-run performance. Hence, even though supporters suffered from a decrease in fan token value during the first week, they observed positive performance after the first month. Thus, on average, supporters do not lose money by supporting their favourite sports team. However, for future decisions, they should

consider that this possibility exists, as we report in Fig. (2). Indeed, considering the entire sample period, 20 fan tokens suffered from a decrease in value, while 19 tokens increased in price. Moreover, supporters should also consider the high uncertainty of this market, as can be observed with the fluctuations of $\overline{BHR}$ and $\overline{BHAR}$ for different holding periods (τ).

Finally, from a financial perspective, we show that traders cannot use fan tokens to outperform the cryptocurrency market, on average, given the negative results reported by $\overline{AR}$ and $\overline{BHAR}$, which is in line with Momtaz (2019), given the extreme positive performance of cryptocurrencies like Bitcoin or Ethereum. Despite this fact, investors could find "golden eggs", such as SAUBER and STV, which outperformed the market with 337.87% and 56.87% growth, respectively.[9]

Table 3: Short and long-run performance of fan tokens.

$\overline{R}$	1 day	$\overline{BHR}$	1 week	1 month	3 months	6 months	9 months	1 year	Entire sample
Mean	-0.0358	Mean	-0.0719	0.1421	1.0390	1.6911	2.1848	1.5683	0.3697
Median	-0.0290	Median	-0.0714	-0.0593	0.1112	0.3348	2.0918	1.2737	0.0294
$\overline{AR}$	1 day	$\overline{BHAR}$	1 week	1 month	3 months	6 months	9 months	1 year	Entire sample
Mean	-0.0422	Mean	-0.1113	-0.1011	0.2314	0.0273	-0.7135	-3.2498	-1.6826
Median	-0.0136	Median	-0.1229	-0.2429	-0.3968	-0.3080	-1.4754	-3.2104	-1.2436
Fan tokens	39	Fan tokens	39	37	28	19	15	7	39

4.2. Dynamics

4.2.1. Pearson and Kendall correlations

We start the dynamics analysis by computing Pearson and Kendall correlations for the CCi30–Chiliz pair, whose coefficients are 0.5166 and 0.4316, respectively. Consequently, we cannot state that a strong dependence exists between Chiliz and the cryptocurrency market.

Computing the correlations between all the fan tokens and the CCi30 index and Chiliz, we observe that fan tokens are more correlated to Chiliz than the CCi30 index, which is expected given that Chiliz is the on-platform currency for fan tokens. On average, the coefficients are equal to 0.3714 (Pearson) and 0.2806 (Kendall) for the dependences between CCi30 and fan tokens, while they are 0.5291 (Pearson) and 0.4349 (Kendall) for the relation between Chiliz and fan tokens. At any rate, fan tokens do not seem to be highly correlated with Chiliz, since most of the correlations are around 0.5, as can be observed in Fig. (3), in which we report all the correlations by means of boxplots.[10]

[9] The list of first-day (abnormal) returns and buy-and-hold (abnormal) returns for each fan token individually is provided in the supplementary material.

[10] We provide the correlations for each fan token individually in the supplementary material.

Figure. 2: Histogram of first-day (abnormal) returns (R & AR), and buy-and-hold (abnormal) returns (BHR & BHAR) for the entire sample of fan tokens.

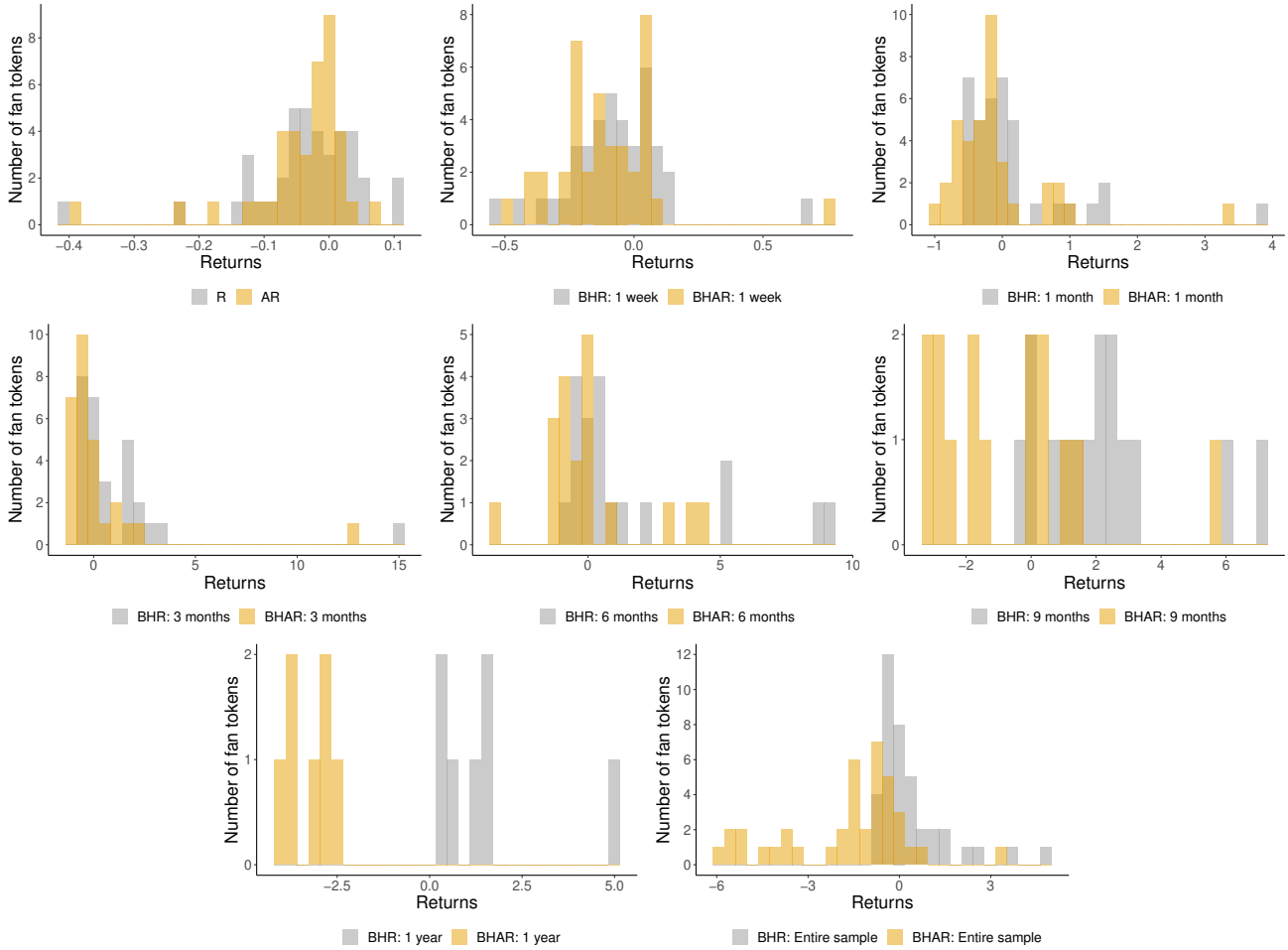
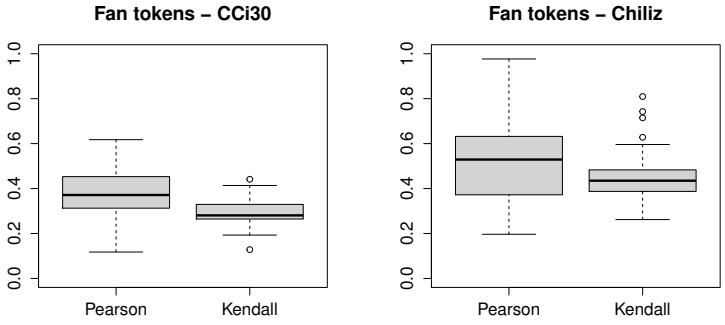


Figure. 3: Boxplots of Pearson and Kendall correlations: fan tokens - CCi30 & fan tokens - Chiliz.

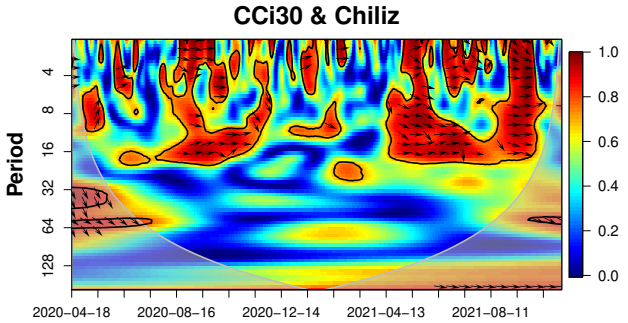


4.2.2. Wavelet coherence approach

Figs. (4), (5) and (6) 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).[11]

Figure. 4: Wavelet coherence between the CCi30 index and Chiliz.



As can be observed in Fig. (4), 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 is a significantly high degree of positive co-movement, over 1–16-day frequency bands, given the red areas and the arrows pointing to the right: (i) September 2020 and (ii) since April 2021. Moreover, we do not observe dependences for low frequencies (over 16–128-day frequency bans). Thus, we observe (weak) co-movement for high frequencies and absence of co-movement for low frequencies, which is supported by the Pearson/Kendall correlations, with coefficients that are only around 0.5. Therefore, Chiliz seems to be a good diversifier for the cryptocurrency market in the long run.[12]

Focusing on Fig. (5), in which we report the wavelet coherence between fan tokens and the CCi30 index, we can generally observe low co-movement for most of the pairs, represented by the dominance of the blue color. These results are supported by Pearson/Kendall correlations, whose coefficients are around 0.4.[13] Thus, we can conclude that (i) investors can use fan tokens to diversify cryptocurrency portfolios, and (ii) supporters own fan tokens that are not driven by the cryptocurrency market, although they must consider their higher volatility (see Table 1).

Finally, in Fig. (6), we observe a higher co-movement between Chiliz and some of the fan tokens compared to CCi30 outcomes, such as APL, BAR, IBFK, NAVI, NOV, PFL, TH, and specially, SAUBER. However, we do not observe a generalised result, given that other fan tokens, such as ACM, ARG, CITY, FOR, LEG and UCH show low co-movement with Chiliz. Therefore, Chiliz cannot be considered a key driver of fan tokens, despite the fact

[11] Figs. (5) and (6) are presented in the supplementary material with a higher resolution and size.

[12] For comparative and illustrative purposes, we show in the Appendix, Sec. (6), the wavelet coherence between Bitcoin and the CCi30 index. With this figure, the reader can observe the wavelet coherence for two time series that are highly correlated, and compare it to the low co-movement observed for most of the pairs in this section.

[13] Some exceptions are, for instance, the fan tokens AM, NAVI, NOV, PFL, SAUBER, STV and VIT, characterised by higher co-movement with more red areas.

that it is the exclusive on-platform currency.

Figure. 5: Wavelet coherence between fan tokens and the CCi30 index.

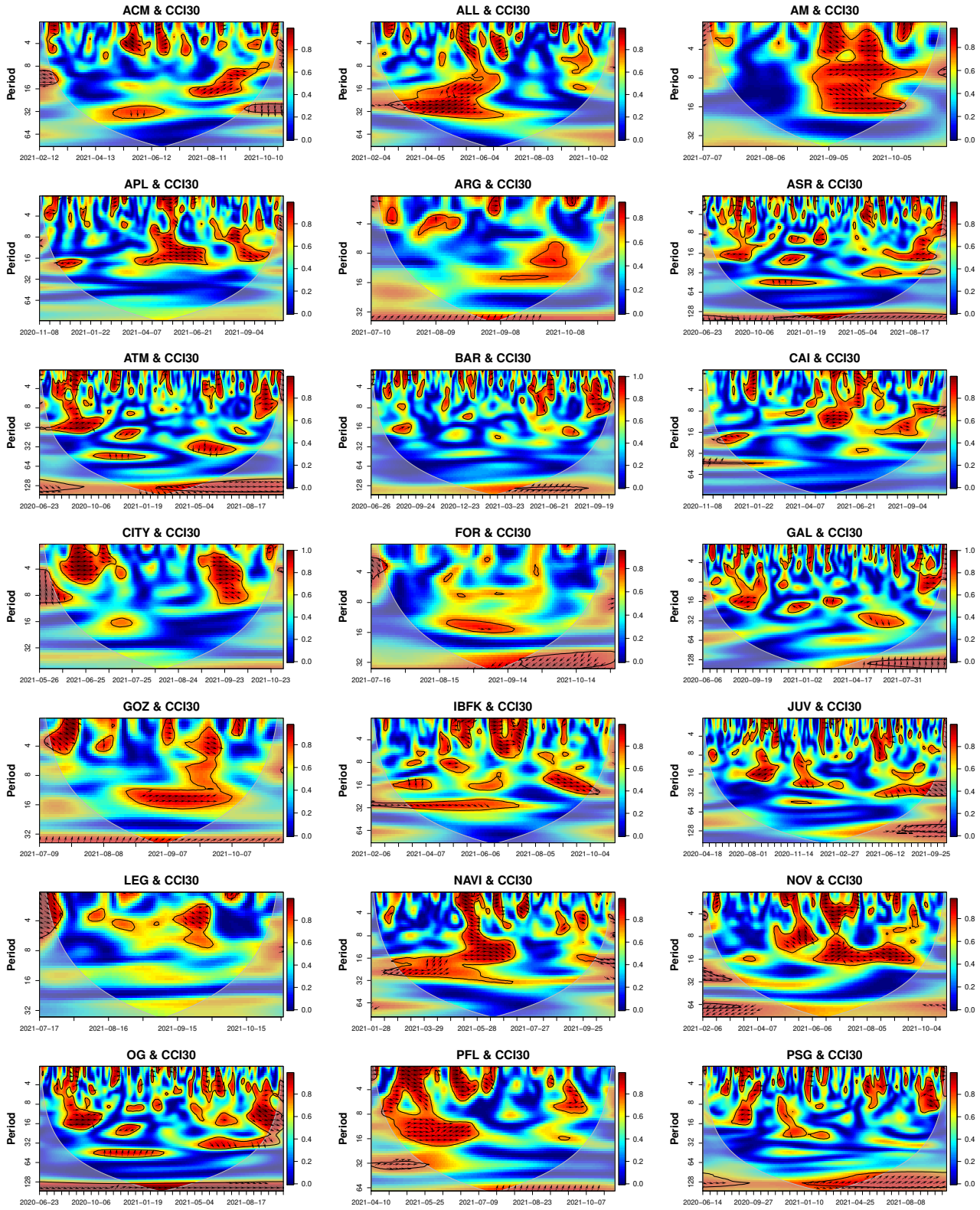


Figure. 5: Wavelet coherence between fan tokens and the CCi30 index.

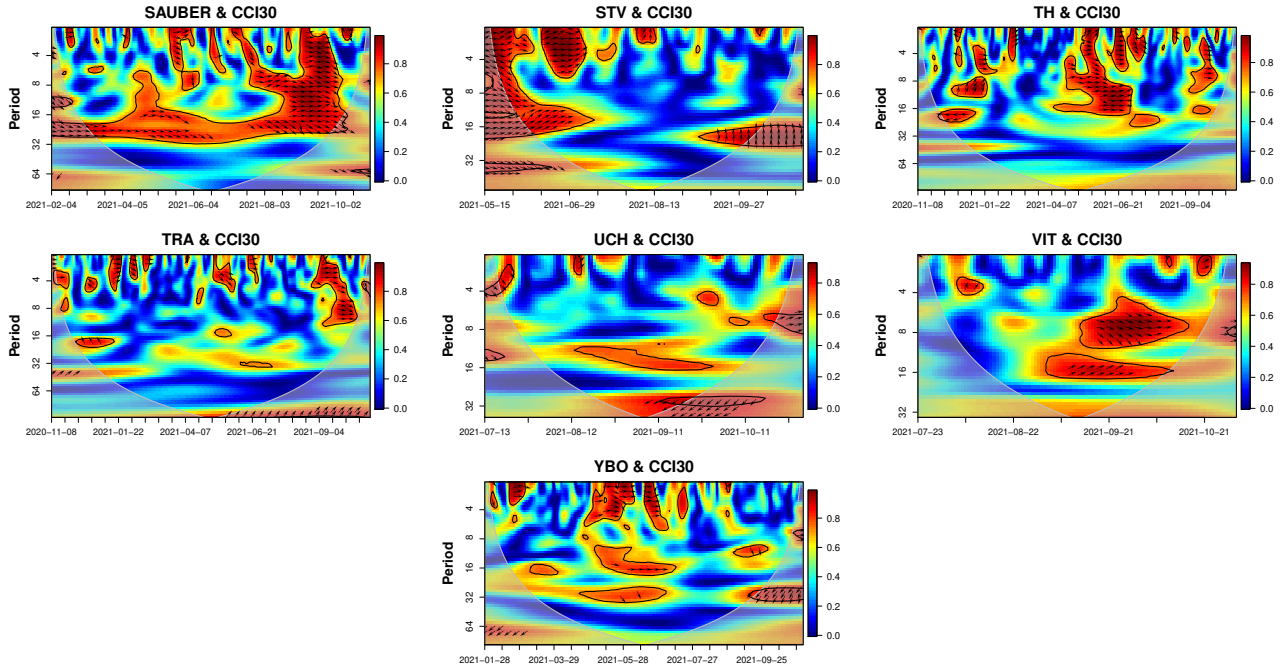


Figure. 6: Wavelet coherence between fan tokens and Chiliz.

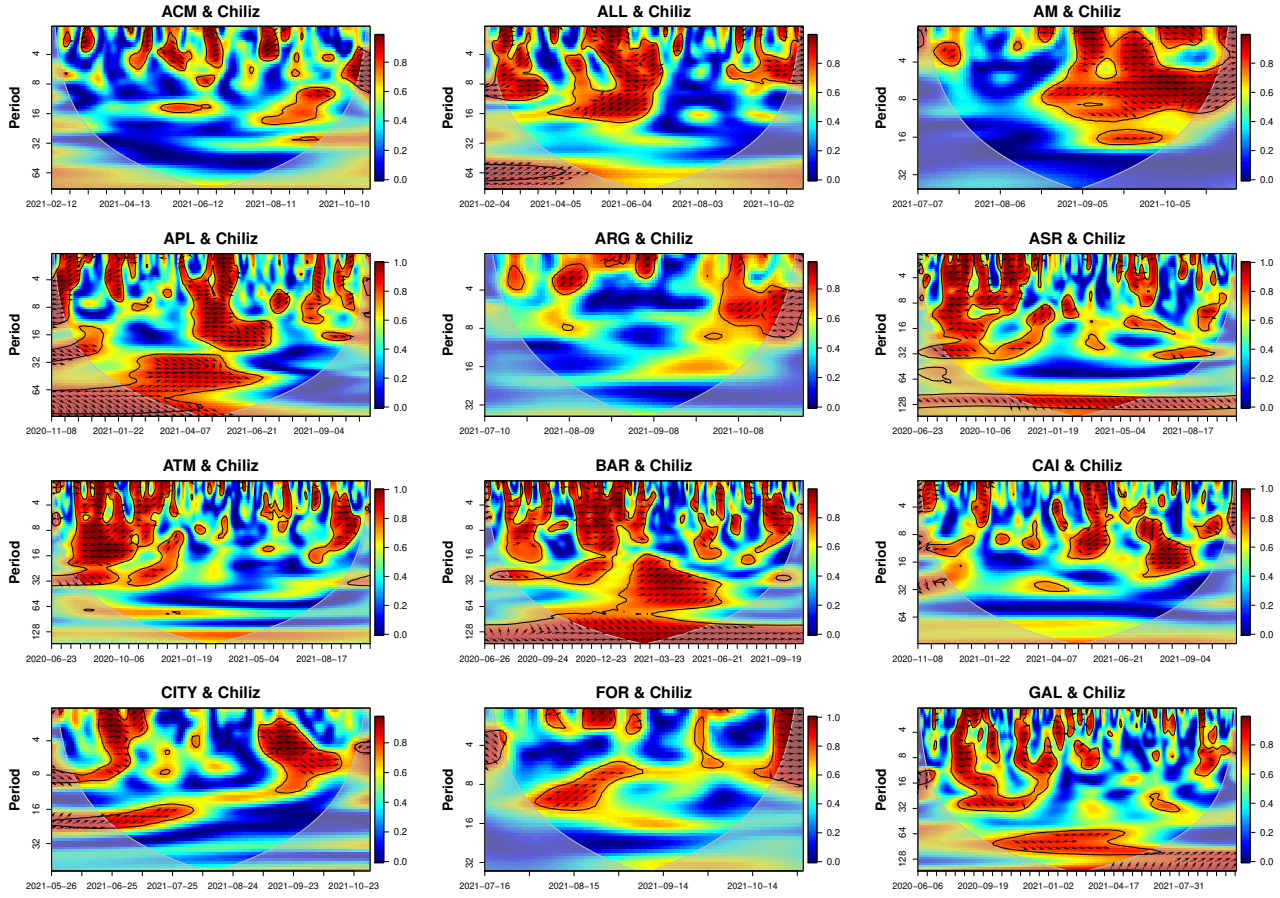
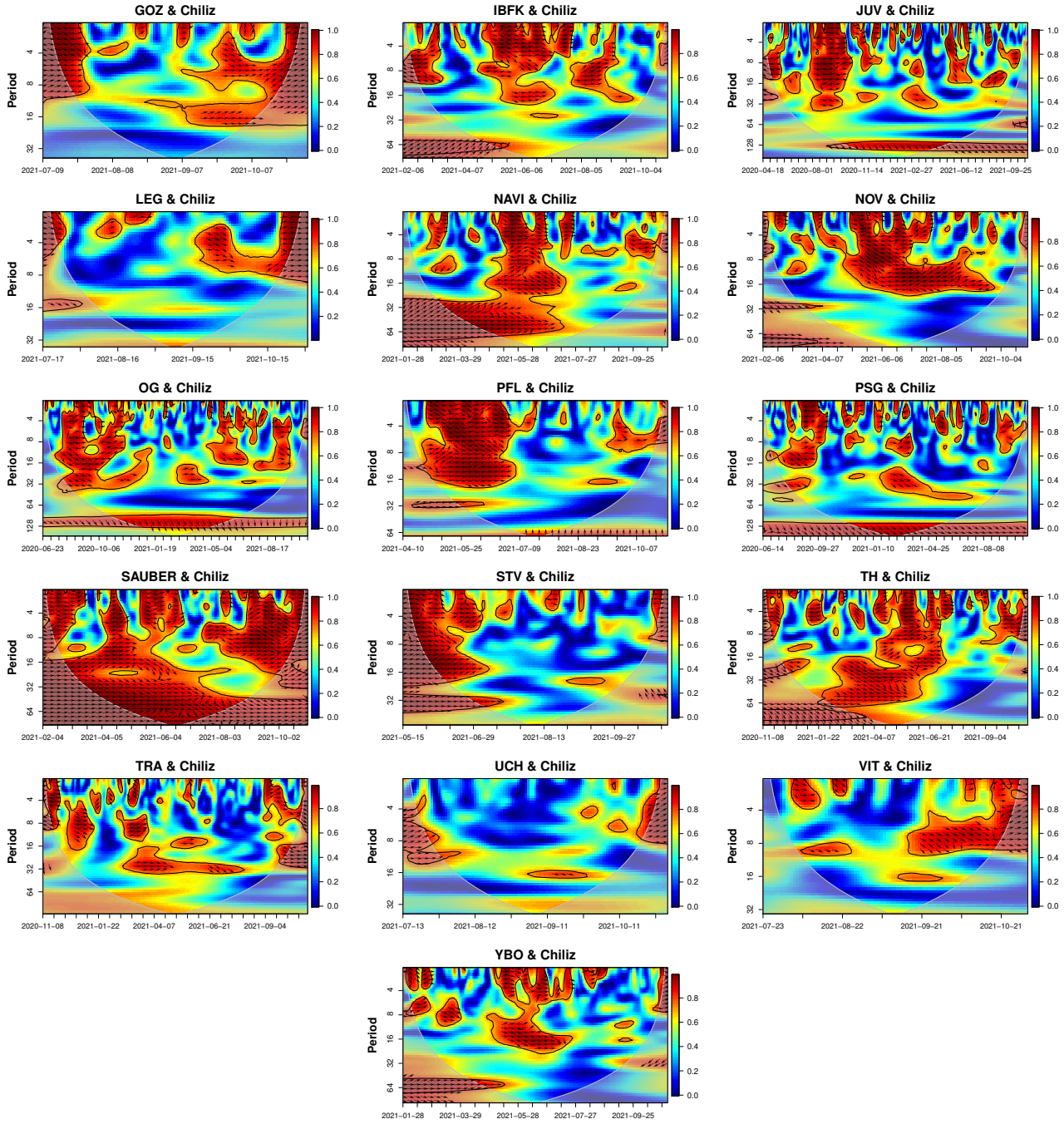


Figure. 6: Wavelet coherence between fan tokens and Chiliz.



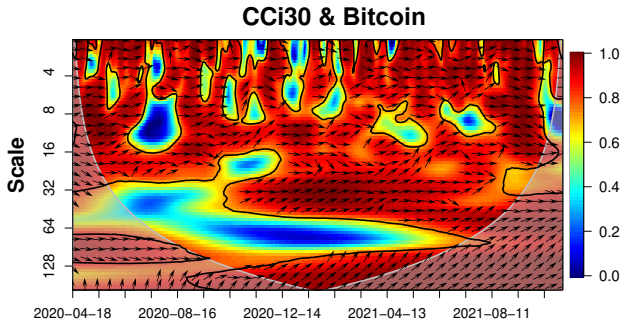
5. Conclusion

To the best of our knowledge, this is the first paper to analyse the performance and dynamics of fan tokens and the exclusive on-platform currency, Chiliz. On the one hand, our results indicate that supporters and investors can trust in the value of Chiliz tokens due to their positive performance, which could be related to the continuous creation of fan tokens and the popularity of Socios.com. However, supporters should be cautious of fan tokens given the negative performance of some of them, even though we report positive performance in the long run, on average. On the other hand, we find that Chiliz and fan tokens are weakly correlated to the cryptocurrency market. Hence, (i) investors can used them for diversification purposes, and (ii) supporters do not need to be concerned about the behaviour of the cryptocurrency market, although they must consider the high volatility of fan tokens and Chiliz.

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.

6. Appendix

Figure. 7: Wavelet coherence between the CCi30 index and Bitcoin.



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Supplement to: "Blockchain, sport and fan tokens"

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1 List of fan tokens

Table 1: List of fan tokens.

Symbol	Fan token	Symbol	Fan token
ACM	AC Milan Fan Token	LEG	Legia Warsaw Fan Token
ALA	Alanyaspor Fan Token	LEV	Levante U.D. Fan Token
ALL	Alliance Fan Token	NAVI	Natus Vincere Fan Token
AM	Aston Martin Cognizant Fan Token	NOV	Novara Calcio Fan Token
APL	Apollon Limassol Fan Token	OG	OG Fan Token
ARG	Argentine Football Association Fan Token	PFL	Professional Fighters League Fan Token
ASR	AS Roma Fan Token	POR	Portugal National Team Fan Token
ATM	Atletico Madrid Fan Token	PSG	Paris Saint-Germain Fan Token
BAR	FC Barcelona Fan Token	ROUSH	Roush Fenway Racing Fan Token
CAI	Club Atletico Independiente Fan Token	SAUBER	Sint-Truidense Voetbalvereniging Fan Token
CITY	Manchester City Fan Token	SCCP	S.C. Corinthians Fan Token
DZG	Dinamo Zagreb Fan Token	STV	Göztepe S.K. Fan Token
FB	Fenerbahçe Token	TH	Team Heretics Fan Token
FOR	Fortuna Sittard Fan Token	TRA	Trabzonspor Fan Token
GAL	Galatasaray Fan Token	UCH	Universidad de Chile Fan Token
GALO	Clube Atlético Mineiro Fan Token	UFC	UFC Fan Token
GOZ	Alfa Romeo Racing ORLEN	VCF	Valencia CF Fan Token
IBFK	İstanbul Başakşehir Fan Token	VIT	Team Vitality Fan Token
INTER	Inter Milan Fan Token	YBO	Young Boys Fan Token
JUV	Juventus Fan Token		

2 Descriptive statistics

Table 2: Descriptive statistics of daily log-returns for the CCi30 index, Chiliz and fan tokens.

	N	Mean	Std.Dev.	Skewness	Kurtosis	Min.	Max.
CCi30	562	0.0039	0.0452	-1.2920	8.2350	-0.3474	0.1957
Chiliz	562	0.0073	0.0844	1.7393	15.5054	-0.4457	0.7263
Fan token	N	Mean	Std.Dev.	Skewness	Kurtosis	Min.	Max.
ACM	262	0.0010	0.1016	3.8865	47.1845	-0.4615	1.0642
ALA	19	0.0084	0.1176	0.9856	3.4050	-0.2534	0.3761
ALL	270	-0.0010	0.1070	3.1120	31.0442	-0.4486	1.0226
AM	117	-0.0141	0.0790	-0.8110	4.0378	-0.3228	0.2611
APL	358	0.0010	0.1078	1.5752	10.7983	-0.4001	0.8222
ARG	114	-0.0110	0.0935	-1.4273	10.8386	-0.5196	0.3599
ASR	496	0.0008	0.0975	-0.1578	25.1436	-0.8609	0.7971
ATM	496	0.0018	0.0990	-0.6809	23.6918	-0.8646	0.6277
BAR	493	0.0017	0.0742	0.5649	6.4809	-0.3916	0.4607
CAI	358	0.0019	0.1029	2.8155	21.9128	-0.4100	0.9088
CITY	159	-0.0028	0.0669	-2.3135	14.7139	-0.4502	0.1702
DZG	25	-0.0255	0.0635	-0.4619	0.8510	-0.1999	0.1061
FB	76	-0.0081	0.0288	0.3885	2.3406	-0.0826	0.0997
FOR	108	0.0007	0.1004	2.3110	10.1663	-0.2849	0.4997
GAL	513	0.0011	0.0803	0.5150	15.0061	-0.6152	0.5417
GALO	34	-0.0036	0.0757	2.7329	10.4724	-0.0944	0.3446
GOZ	115	-0.0091	0.0646	-0.1236	4.5874	-0.2612	0.2612
IBFK	268	-0.0011	0.0837	-0.3598	4.0161	-0.4490	0.3169
INTER	47	-0.0041	0.0609	0.8124	1.9606	-0.1516	0.1812
JUV	562	0.0029	0.0789	0.0205	11.7051	-0.5631	0.5095
LEG	107	0.0004	0.0884	0.9766	5.4495	-0.2755	0.4120
LEV	37	0.0015	0.0751	-0.7638	3.6410	-0.2716	0.1930
NAVI	277	-0.0008	0.0915	0.0242	3.9104	-0.4425	0.4028
NOV	268	-0.0012	0.1094	-0.1961	8.2884	-0.6397	0.4895
OG	496	0.0015	0.1074	2.2043	37.6473	-0.7766	1.1795
PFL	205	-0.0083	0.0994	2.2674	20.3899	-0.4280	0.7701
POR	39	-0.0146	0.0466	-0.4494	0.4309	-0.1501	0.0748
PSG	505	0.0026	0.0950	0.6750	20.0402	-0.6806	0.8405
ROUSH	33	0.0009	0.0607	-0.3306	0.7455	-0.1623	0.1472
SAUBER	270	0.0065	0.1163	0.7705	5.5760	-0.4648	0.6181
SCCP	52	-0.0154	0.0832	-1.3981	6.8689	-0.3970	0.2013
STV	170	0.0021	0.0979	0.7058	6.7560	-0.4264	0.5010
TH	358	-0.0001	0.1123	1.8159	15.1993	-0.4940	0.9196
TRA	358	0.0033	0.0791	4.0257	32.5355	-0.2231	0.7206
UCH	111	0.0058	0.2588	2.9477	23.2992	-1.1321	1.7091
UFC	38	0.0052	0.0930	0.5180	-0.1194	-0.1680	0.2410
VCF	47	-0.0057	0.0667	0.0775	1.5974	-0.1896	0.1841
VIT	101	-0.0057	0.0787	0.3773	1.5930	-0.2603	0.2499
YBO	277	-0.0024	0.1025	2.0758	22.2175	-0.4242	0.8979
Median	170	0.0004	0.0915	0.5180	8.2884	-0.4100	0.4607

Table 3: R, AR, BHR and $BHAR$ for each fan token.

	R				BHR				AR				BHAR			
Fan token	1d	1w	1m	3m	6m	9m	1y	E.S.	1d	1w	1m	3m	6m	9m	1y	E.S.
ACM	-0.0290	0.0335	0.9619	0.4192	0.5183	-	-	0.3034	-0.0794	-0.1461	0.7031	-0.8505	0.1663	-	-	-0.4748
ALA	-0.0301	-0.0752	-	-	-	-	-	0.1729	-0.0624	-0.1229	-	-	-	-	-	0.0616
ALL	-0.1192	-0.0795	1.4305	1.4305	-0.3713	-0.0993	-	-0.2450	-0.1018	-0.3900	0.8933	-0.3549	-0.9242	-1.4754	-	-1.6301
AM	-0.2312	-0.5493	-0.5493	-0.7593	-	-	-	-0.8081	-0.2257	-0.5086	-0.6421	-1.2010	-	-	-	-1.4490
APL	0.0374	0.0841	0.1682	0.5981	9.3411	2.4252	-	0.4299	-0.0028	0.0565	-0.1353	-0.6723	3.8550	0.1163	-	-3.7696
ARG	-0.4052	-0.4314	-0.4888	-0.6646	-	-	-	-0.7132	-0.3890	-0.3572	-0.7659	-1.2085	-	-	-	-1.4072
ASR	0.0118	-0.2346	-0.2512	-0.1137	-0.2109	1.6185	0.4336	0.5213	0.0043	-0.2136	-0.3569	-0.4387	-1.2784	-2.9362	-4.0504	-5.9987
ATM	-0.0021	-0.2037	-0.1564	-0.0247	0.0823	1.5247	1.2737	1.4959	-0.0096	-0.1827	-0.2621	-0.3496	-0.9852	-3.0300	-3.2104	-5.0242
BAR	-0.0735	-0.2652	-0.3514	-0.4058	0.6070	6.0831	1.6166	1.3498	-0.0632	-0.2513	-0.4710	-0.6093	-0.3415	1.5191	-2.4093	-5.0787
CAI	0.0616	0.0849	0.1610	2.0252	5.3227	2.6273	-	0.9642	0.0214	0.0573	-0.1425	0.7548	-0.1634	0.3184	-	-3.2353
CITY	0.0997	-0.3217	-0.5089	-0.0152	-	-	-	-0.3544	0.0213	-0.3360	-0.2576	-0.1603	-	-	-	-0.6178
DZG	-0.0260	-0.1775	-	-	-	-	-	-0.4719	-0.0236	-0.1652	-	-	-	-	-	-0.5821
FB	-0.0500	-0.1174	-0.2675	-	-	-	-	-0.4586	-0.0010	-0.1546	-0.2988	-	-	-	-	-0.6030
FOR	-0.0478	-0.1394	-0.1833	-0.1355	-	-	-	0.0757	-0.0136	-0.0820	-0.6736	-0.7008	-	-	-	-0.6839
GAL	-0.0987	-0.1052	-0.5343	-0.5107	-0.4528	0.7682	0.3605	0.5708	-0.0914	-0.0388	-0.4615	-0.8795	-1.1588	-2.7506	-3.7429	-5.3972
GALO	-0.0847	-0.1271	-0.0593	-	-	-	-	-0.1144	-0.0528	-0.2548	-0.3413	-	-	-	-	-0.3979
GOZ	-0.0105	-0.0667	-0.1193	-0.5825	-	-	-	-0.6474	-0.0344	0.0266	-0.2429	-1.0203	-	-	-	-1.2436
IBFK	0.0057	0.1494	1.2874	1.6149	0.1494	-	-	-0.2644	-0.0014	-0.2044	0.8023	-0.2419	-0.3080	-	-	-1.5545
INTER	0.1093	-0.0575	0.0794	-	-	-	-	-0.1749	0.0782	0.0546	0.0241	-	-	-	-	-0.3239
JUV	-0.0383	-0.1954	0.8774	1.4291	1.4866	2.6628	4.9923	3.7893	-0.0380	-0.2429	0.7071	1.0777	0.8483	0.4025	-2.8346	-4.4023
LEG	0.0072	-0.0143	-0.1792	-0.1505	-	-	-	0.0394	0.0013	-0.0141	-0.7390	-0.8282	-	-	-	-0.7872
LEV	0.0256	-0.0256	0.1378	-	-	-	-	0.0577	0.0321	0.0228	-0.0549	-	-	-	-	-0.1411
NAVI	0.0312	0.0446	0.0402	3.3661	0.3348	-0.1250	-	-0.2009	-0.0106	-0.0459	-0.5560	1.7152	-0.1916	-1.7123	-	-1.8014
NOV	-0.0720	0.1160	1.4520	1.4040	0.2400	-	-	-0.2760	-0.0792	-0.2379	0.9669	-0.4529	-0.2175	-	-	-1.5662
OG	-0.0459	-0.0361	-0.0393	-0.0262	-0.4000	2.0918	0.7508	1.0590	-0.0534	-0.0151	-0.1451	-0.3511	-1.4675	-2.4629	-3.7333	-5.4611
PFL	-0.1200	-0.1677	-0.4385	-0.8000	-0.7831	-	-	-0.8169	-0.1722	-0.4079	-0.8676	-0.4996	-0.7902	-	-	-0.9350
POR	-0.0154	-0.2231	-0.3962	-	-	-	-	-0.4346	-0.0381	-0.2230	-0.7292	-	-	-	-	-0.8018
PSG	-0.1499	-0.1261	-0.1335	0.2377	0.8556	1.0512	1.5503	2.7276	-0.1310	-0.0928	-0.2040	-0.0238	0.1170	-3.2539	-2.7679	-3.5680
ROUSH	-0.0343	0.0637	0.0196	-	-	-	-	0.0294	-0.0597	-0.0914	-0.2065	-	-	-	-	-0.2942
SAUBER	-0.0295	0.0959	3.8598	14.7306	5.0332	7.0406	-	4.7638	-0.0121	-0.2145	3.3226	12.9453	4.4804	5.6645	-	3.3788
SCCP	-0.0548	-0.0171	-0.4829	-	-	-	-	-0.5514	-0.0071	-0.0598	-0.4957	-	-	-	-	-0.6730
STV	-0.0586	-0.3468	-0.4775	-0.4775	-	-	-	0.4369	0.0014	-0.1178	-0.0875	-0.1695	-	-	-	0.5687
TH	0.0427	0.0610	0.1768	2.2256	8.5427	2.1524	-	-0.0244	0.0025	0.0333	-0.1267	0.9552	3.0566	-0.1565	-	-4.2239
TRA	0.0450	0.0541	0.0541	1.4324	2.2072	3.2793	-	2.2162	0.0049	0.0264	-0.2494	0.1620	-3.2789	0.9703	-	-1.9833
UCH	-0.0159	-0.0714	0.1270	3.0000	-	-	-	0.9127	0.0125	0.0452	-0.1453	2.4771	-	-	-	0.2590
UFC	-0.1180	0.6667	0.4218	-	-	-	-	0.2183	-0.0524	0.7464	0.2277	-	-	-	-	-0.0076
VCF	0.0436	-0.0073	0.0036	-	-	-	-	-0.2364	0.0125	0.1049	-0.0516	-	-	-	-	-0.3853
VIT	0.0222	0.0356	-0.2933	-0.4400	-	-	-	-0.4400	-0.0136	-0.1418	-0.9903	-1.2290	-	-	-	-1.3037
YBO	0.0221	-0.1107	-0.0923	0.2841	-0.3727	-0.3284	-	-0.4834	-0.0197	-0.2012	-0.6885	-1.3667	-0.8991	-1.9157	-	-2.0839

4 Pearson and Kendall correlations for each fan token

Table 4: Pearson and Kendall correlations for each fan token.

	CCi30			Chiliz	
Fan token	Pearson	Kendall	Fan token	Pearson	Kendall
ACM	0.4067	0.3311	ACM	0.3089	0.3251
ALA	0.1175	0.1930	ALA	0.9767	0.7427
ALL	0.4000	0.2928	ALL	0.5291	0.4669
AM	0.4481	0.2892	AM	0.6412	0.4619
APL	0.3589	0.2611	APL	0.4041	0.4429
ARG	0.3671	0.2286	ARG	0.4015	0.3810
ASR	0.3392	0.3569	ASR	0.4153	0.4564
ATM	0.2686	0.3138	ATM	0.3639	0.4296
BAR	0.3714	0.2642	BAR	0.5435	0.4579
CAI	0.3102	0.2720	CAI	0.4219	0.4058
CITY	0.2673	0.2645	CITY	0.3400	0.3196
DZG	0.2817	0.2333	DZG	0.7725	0.5200
FB	0.6175	0.4138	FB	0.3551	0.3394
FOR	0.2862	0.3567	FOR	0.6067	0.4769
GAL	0.3477	0.2673	GAL	0.3804	0.3721
GALO	0.1941	0.2513	GALO	0.2312	0.3405
GOZ	0.3887	0.2658	GOZ	0.7541	0.4893
IBFK	0.5399	0.3142	IBFK	0.6292	0.4705
INTER	0.5224	0.2840	INTER	0.3880	0.4061
JUV	0.4061	0.3015	JUV	0.3976	0.3936
LEG	0.3153	0.2806	LEG	0.6878	0.4349
LEV	0.3291	0.2763	LEV	0.9025	0.7147
NAVI	0.4590	0.2656	NAVI	0.6349	0.4083
NOV	0.3931	0.2515	NOV	0.6044	0.4561
OG	0.3377	0.3374	OG	0.4238	0.4138
PFL	0.4815	0.3517	PFL	0.5415	0.4901
POR	0.5388	0.2119	POR	0.5754	0.5223
PSG	0.3406	0.2709	PSG	0.3463	0.3398
ROUSH	0.5226	0.3280	ROUSH	0.7039	0.8095
SAUBER	0.4427	0.3641	SAUBER	0.8209	0.6282
SCCP	0.4747	0.4413	SCCP	0.3132	0.4308
STV	0.4693	0.3673	STV	0.6435	0.4985
TH	0.3472	0.2696	TH	0.5684	0.4723
TRA	0.2619	0.2600	TRA	0.3372	0.3563
UCH	0.1753	0.2702	UCH	0.2003	0.3607
UFC	0.2653	0.1281	UFC	0.1965	0.2619
VCF	0.4580	0.3350	VCF	0.5800	0.5960
VIT	0.4098	0.2829	VIT	0.5813	0.4284
YBO	0.4438	0.2980	YBO	0.4740	0.4260

5 Wavelet coherence analysis: fan tokens and CCi30

Figure. 1: Wavelet coherence between fan tokens and the CCi30 index.

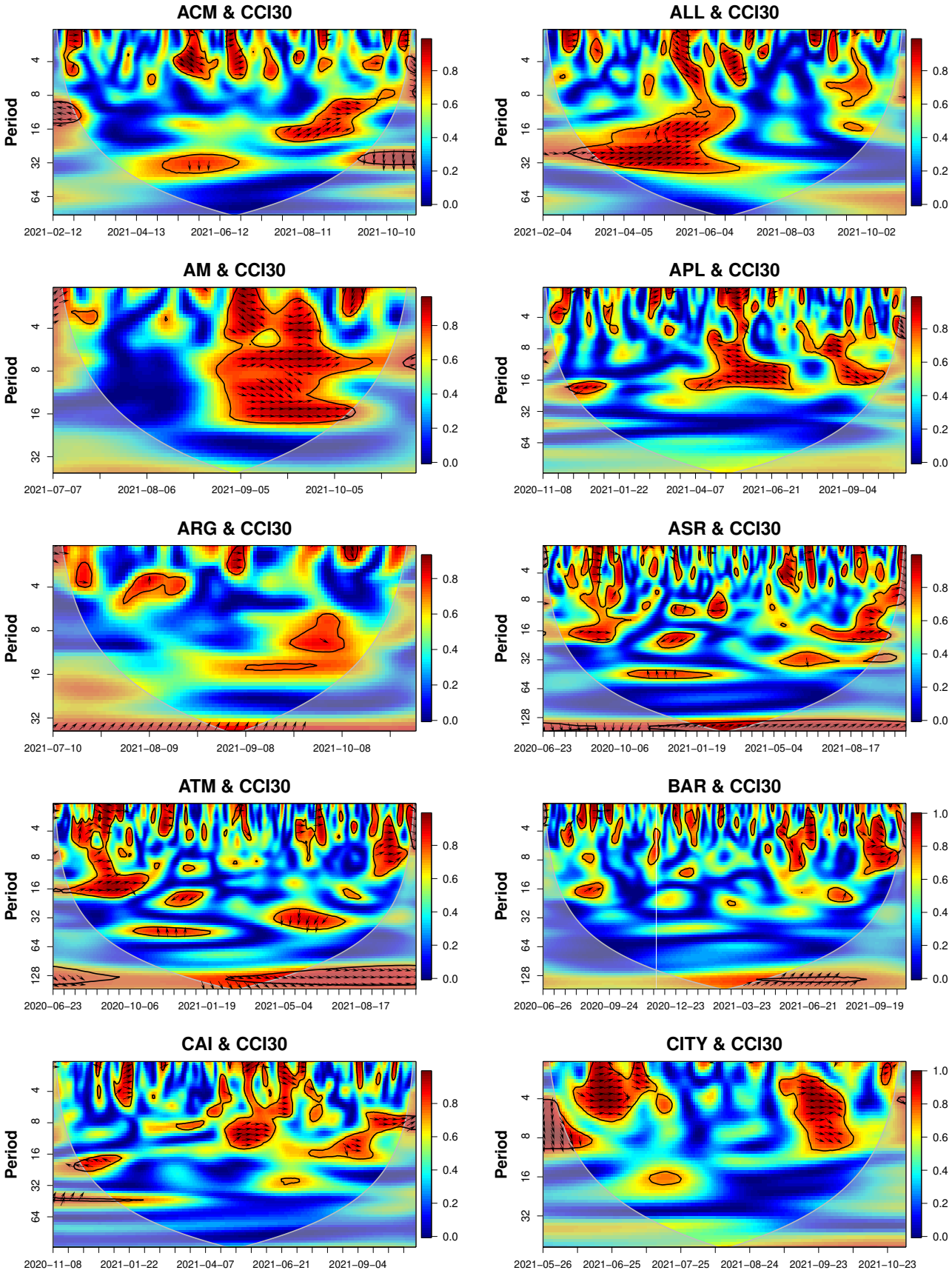


Figure. 1: Wavelet coherence between fan tokens and the CCi30 index.

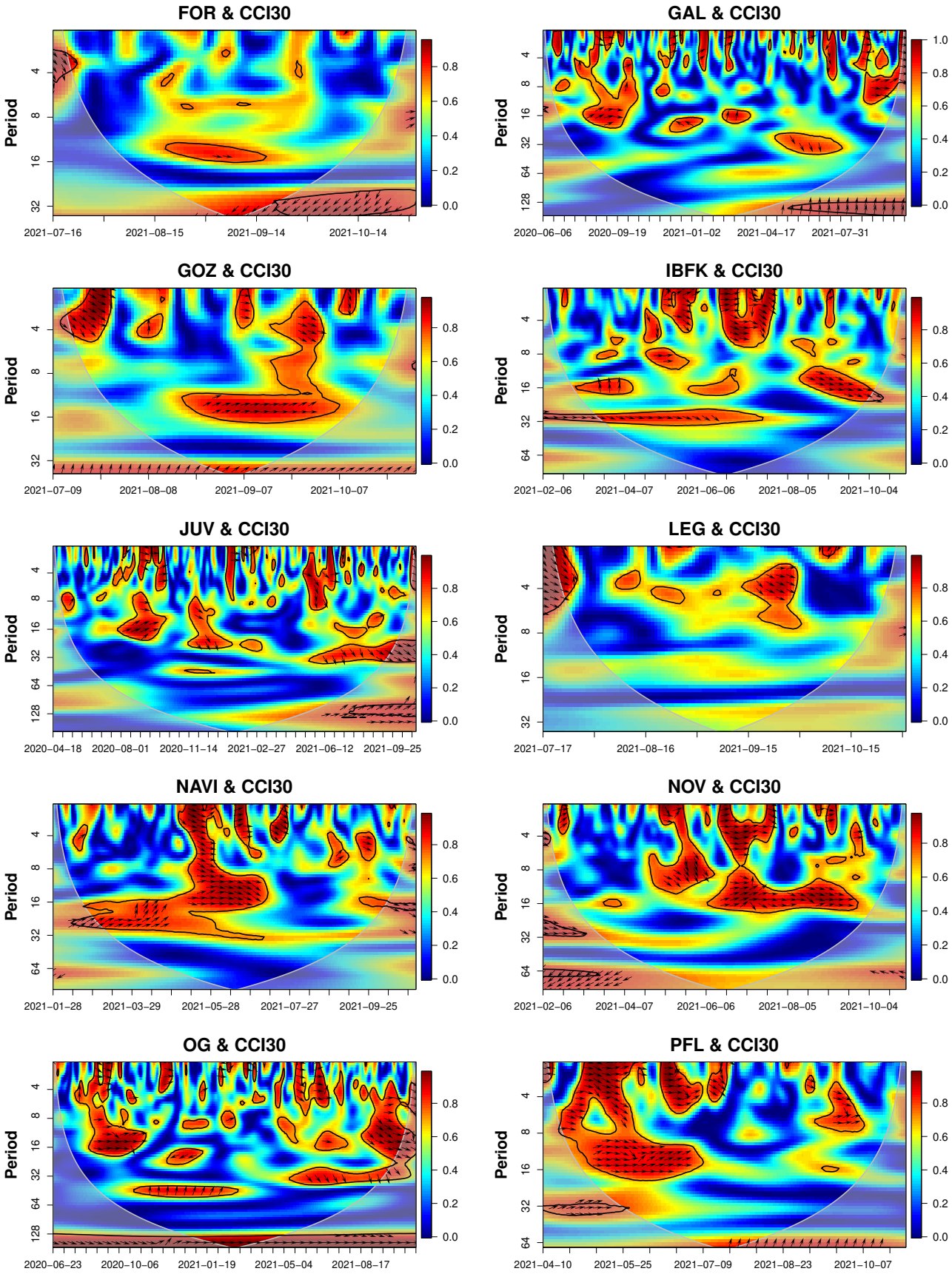
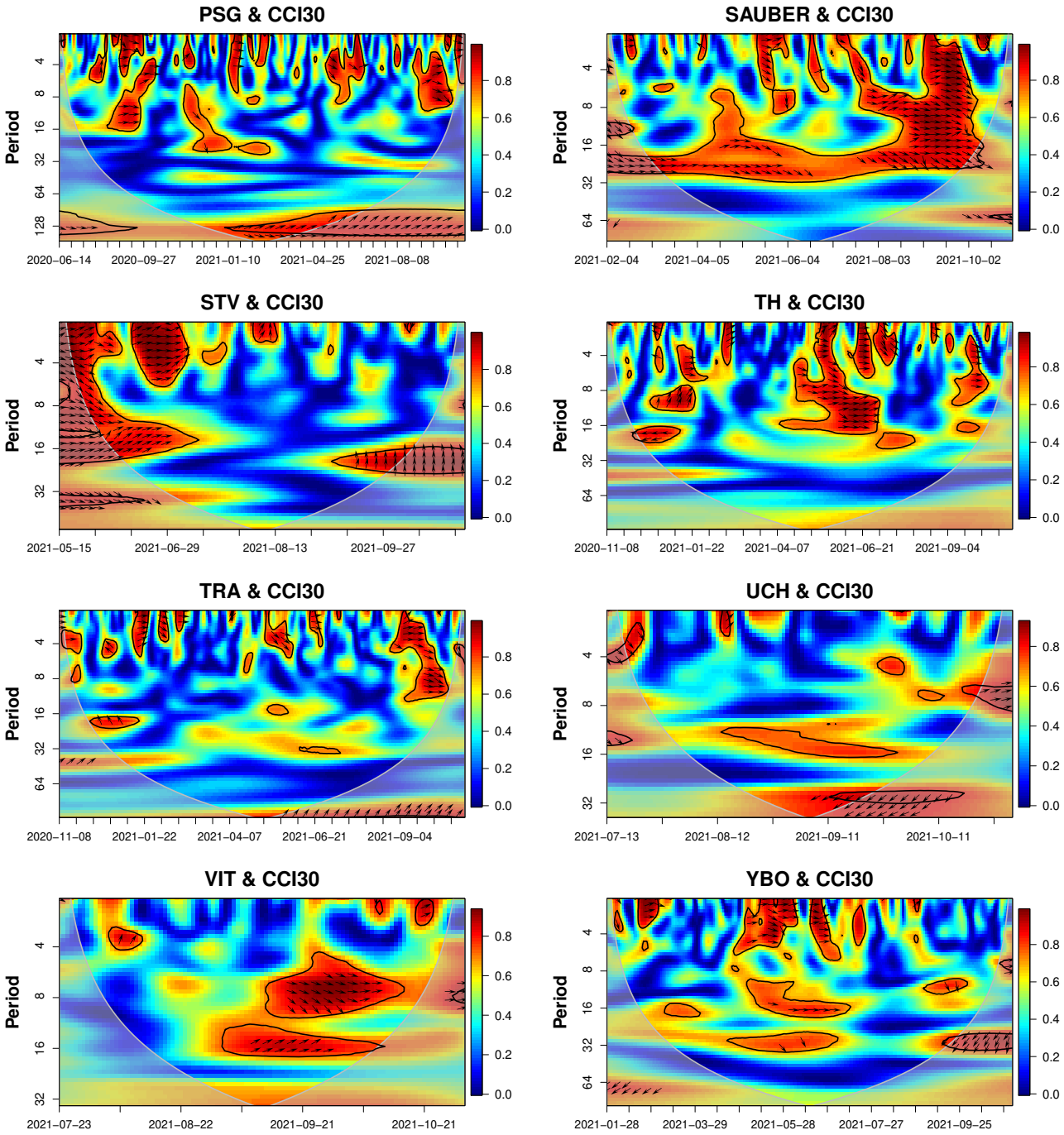


Figure. 1: Wavelet coherence between fan tokens and the CCi30 index.



6 Wavelet coherence analysis: fan tokens and Chiliz

Figure. 2: Wavelet coherence between fan tokens and Chiliz.

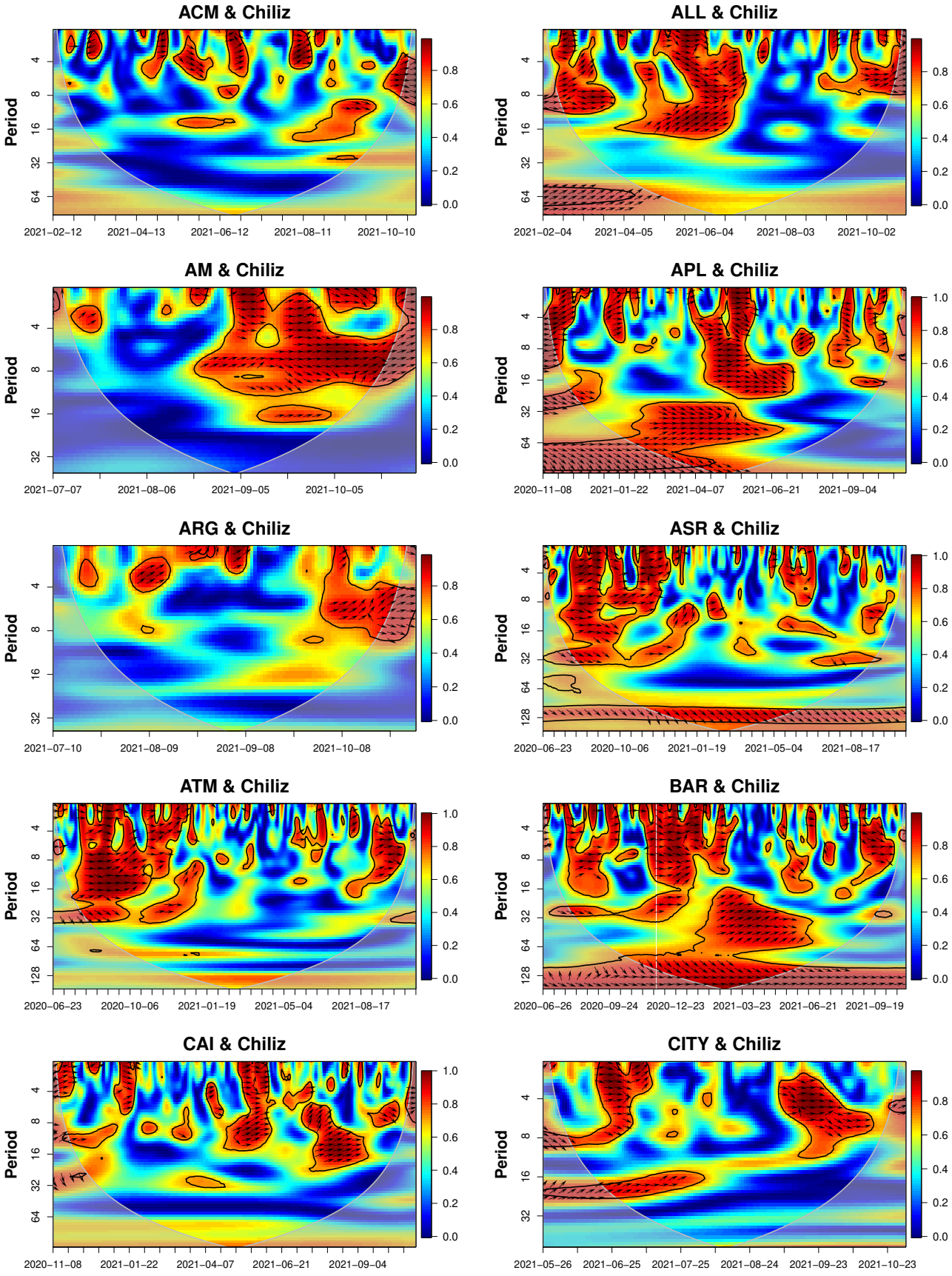


Figure. 2: Wavelet coherence between fan tokens and Chiliz.

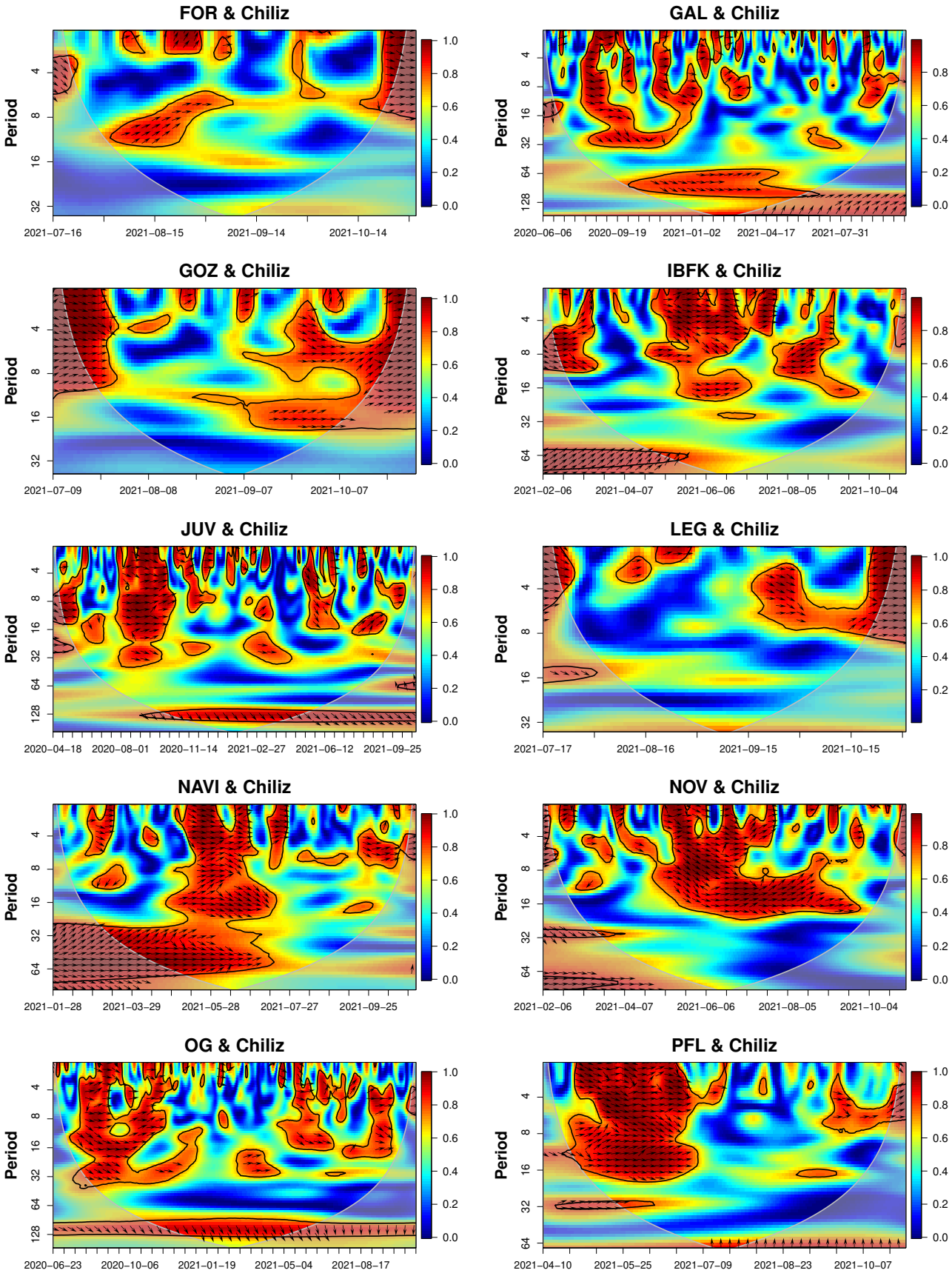


Figure. 2: Wavelet coherence between fan tokens and Chiliz.