EGE AKADEMİK BAKIŞ / *EGE ACADEMIC REVIEW*

Cilt 24 • Sayı 2 • Nisan 2024
SS. 221/232
Doi: 10.21121/eab.1309596
Başvuru Tarihi: 04.06.2023 • Kabul Tarihi: 08.03.2024

Article Type: *Research Article*

The Determinants of Prices of Fan Tokens as a New Sports Finance Tool

Emrah ÖGET[1], Ersin KANAT[2], Ferudun KAYA[3]

ABSTRACT

In the Covid-19 era, the income sources of sports clubs decreased, but the importance of fan tokens as new communication, management, and income source for sports clubs increased with Blockchain technology. For this reason, we examined the relationships between fan token prices and club success, transaction volume, and attractiveness factors and tried to be revealed the important determinants of fan token prices. First of all, cross-section dependence, homogeneity, and unit root tests carried out to determine the most suitable methods for panel data model. Then the durbin test was performed and it was concluded that the variables were cointegrated. Finally, the PMG/ARDL test and it was observed that the most important determinants of fan token prices were club success and transaction volume, respectively. While these factors affect fan token prices positively, the effect of the attractiveness factor is seen as less important and negative compared to other factors. In addition, in the error correction model established, the existence of a long-term equilibrium relationship between the variables was confirmed. It was concluded that the short-term deviations returned to the equilibrium after approximately 21 days.

Keywords: Fan Token, Sports Finance, Club Success, Google Trends, Euro Club Index.

JEL Classification Codes: G12, G15, G4, Z23

Referencing Style: APA 7

INTRODUCTION

Due to the Covid-19 epidemic worldwide, sports clubs have experienced great income losses. The postponement of the 2020 European Football Championship caused the clubs to postpone their gains from such organizations. In addition, the clubs were deprived of another important source of income because the matches were held without spectators so that the virus does not spread. Football clubs faced a very difficult process financially with the decrease in stadiums, sponsorships, and broadcaster revenues. In the face of all these developments, the importance of social distance all over the world has made the digitalization of all kinds of communication compulsory. Tremendous growth has occurred in the cryptocurrency sector with the effect of increasing digitalization during the epidemic period, and Blockchain technology has become a new communication, governance, and income source for sports clubs. First launched as a blockchain-based app in late 2019, Socios.com has provided the ability to connect with sports organizations through fan tokens minted as exchangeable digital assets on the Chiliz blockchain (Chiliz, n.d.). Chiliz, a blockchain fintech company, has collaborated with more than 60 sports organizations as well as World giants such as Juventus, Paris-Saint Germain, AS Roma, and FC Barcelona. Fan token holders enjoy privileges such as VIP rewards as well as participating in club decision-making processes. For example, Juventus FC fans were able to choose the congratulatory song and the first official car of the team. AS Roma fans had the opportunity to ask questions to during a live briefing. Paris Saint-Germain fans were able to vote for the club's annual awards (GSIC, 2021).

While fan token holders have the right to participate in the decision-making processes of clubs, sports clubs can also raise funds from fan token sales. For example, the AC Milan club generated more than US $6 million in digital revenue from the first sale of fan tokens (IWF, 2021). In the news of Reuters (2021), it was stated that a part of the fee of the world-famous star Lionel Messi, who was transferred to France's largest football club Paris-Saint Germain, will be paid as PSG fan tokens. In the news of Marca (2022), it was mentioned that fan tokens will be the second-largest source of income for the sports industry. The total value of the fan token market is around US $300 Million as of February 2022, and Socios' presence is growing rapidly with the participation of formula one giants, leading e-sports teams, UFC and NBA teams (Chliz, n.d.).

[1] Zonguldak Bülent Ecevit University, Zonguldak, Turkey, emrahoget@hotmail.com

[2] Zonguldak Bülent Ecevit University, Zonguldak, Turkey, ersinkanat44@hotmail.com

[3] Bolu Abant İzzet Baysal University, Bolu, Turkeys, kayaferudun@gmail.com

Most of the studies in the literature are related to major cryptocurrencies other than fan tokens. In research on Bitcoin and other major cryptocurrencies, in general, factors such as supply and demand, trading volume, exchange rate, gold price, oil price, attractiveness measured via Twitter, Wikipedia, and Google Trends, hash rate, and Dow Jones industrial average are associated with cryptocurrency prices (Kaminski, 2014; Yelowitz and Wilson, 2015; Georgoula et al., 2015; Kristoufek, 2015; Ciaian, Rajcaniova and Kanc, 2016; Wang, Xue and Liu, 2016; Zhu, Dickinson and Li, 2017; Sukamulja and Sikora, 2018; Panagiotidis, Stengos and Vravosinos, 2018; Sovbetov, 2018; Guizani and Nafti, 2019). In addition to these studies, Kwon (2021) revealed that the consumer sentiment index, US economic policy uncertainty index, exchange rate, and corporate bond index returns have significant effects on Bitcoin price.

Since fan tokens are quite new, there are limited studies on fan tokens in the literature (Demir et al., 2022; Scharnowski et al., 2023; Vidal-Tomás, 2022). When these studies were examined; Demir et al. (2022) found that the UEFA Champions League match results led to abnormal returns on fan token prices, but investors did not act similarly against domestic matches and European matches. Scharnowski et al. (2023) found no correlation between stocks of publicly listed sports clubs and fan token returns. They revealed that fan token prices determinants are football match results and investor interest as measured by Google Trends. On the other hand, Vidal-Tomás (2022) revealed that investors can reduce their risks through diversification with fan tokens. In this study, besides club success, the effect of transaction volume and attractiveness factors on fan token prices was analyzed by following the relevant cryptocurrency literature. Hash rate and supply-demand data for fan tokens could not be included in the study as it is not available. Unlike similar studies in the literature, this study focuses on the effects of a sustainable club success, not the effect of a single football match on fan token prices. This is because it is thought that the one-match success of a favorite team or a team that has guaranteed to leave or not to leave the group will have a limited effect on fan token prices.

Fan tokens have not yet received the necessary attention in the scientific world in terms of sports finance, despite being accepted around the world, being adopted by important sports clubs, being the subject of world-renowned magazines and news organizations, and an ever-growing ecosystem. Fan tokens have increasingly become a tool of sports management due to their potential to interact with fans, involve fans in management processes, and raise funds. For these reasons, the study aims to trying to determine the factors associated with fan tokens, which we believe to be a new management tool in terms of sports finance and to make inferences about the future of fan tokens. Thus, it is aimed to benefit the fund management of sports clubs, the support of fans to support their teams more appropriately, the investment decisions of investors and researchers. The findings will be able to reveal which factor is more important for fan token predictions. Due to all these explanations, in the next parts of the study, the relationships between fan token prices and club success, transaction volume, and attractiveness factors were tried to be revealed and important determinants of fan token prices were tried to be determined.

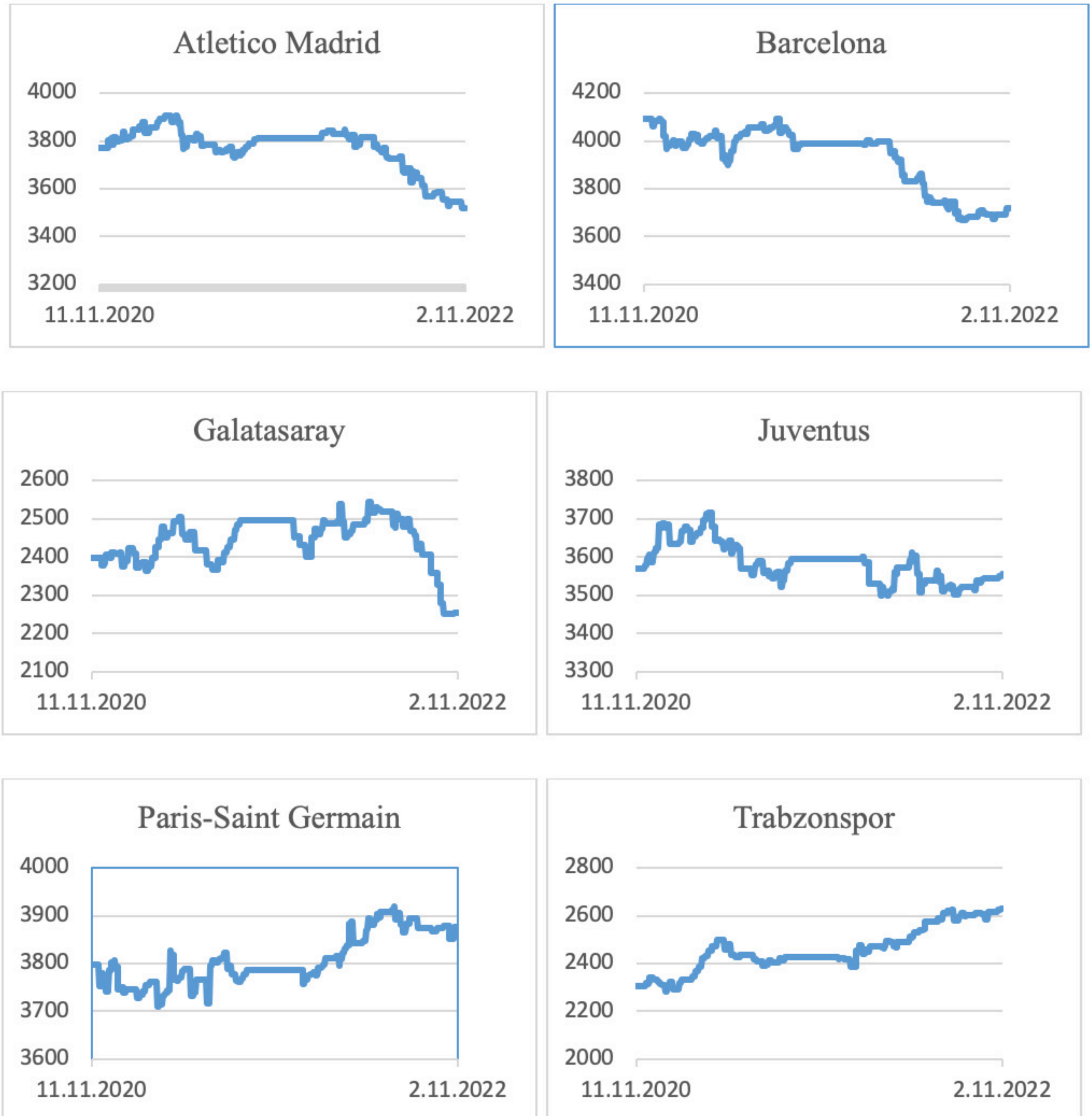
DATASET AND RESEARCH MODEL

In the study, a balanced panel data model was created using 458-day data for the period 11.11.2020-11.02.2022 to investigate the determinants of fan token prices. The fact that many of the fan tokens have just entered circulation and the insufficiency of historical data has caused the selection of the relevant period. For fan tokens, which are fairly new and have specific characteristics that differ from Bitcoin, the impact of a limited number of factors can be analyzed. This is because the historically available supply-demand data for Bitcoin in the current literature is not yet available for fan tokens. In addition, the lack of mining feature of fan tokens means that there is no hash rate for fan tokens. On the other hand, to investigate the effects of global factors on fan tokens, the data on Bitcoin closing prices, CCi30 index, and Dow Jones sector averages are neither stationary at the level of I(0) nor at the first difference I(I) for the period examined. For these reasons, this study is an early research report for relatively new fan tokens and includes the aforementioned limitations. In line with the existing literature, the applicable factors for fan token prices are transaction volumes and attractiveness factors. For this reason, transaction volumes of fan tokens as a factor of use in trade and Google Trends data of sports clubs as an attractiveness factor were used in the model. In addition, due to the relevance of fan tokens to the sports sector, Euro Club Index (ECI) data are included in the model as an indicator of club success.

$$FAN_{it} = ATT_{it} + SUCCESS_{it} + VOL_{it} + \varepsilon_{it} \tag{1}$$

Closing prices (FAN_{it}) and transaction volumes (VOL_{it}) of fan tokens, Google Trends data (ATT_{it}) and ECI data ($SUCCESS_{it}$) were obtained from https://coinmarketcap.com/, https://trends.google.com/ and Hybercube Business Innovation, respectively.[1] The natural logarithms

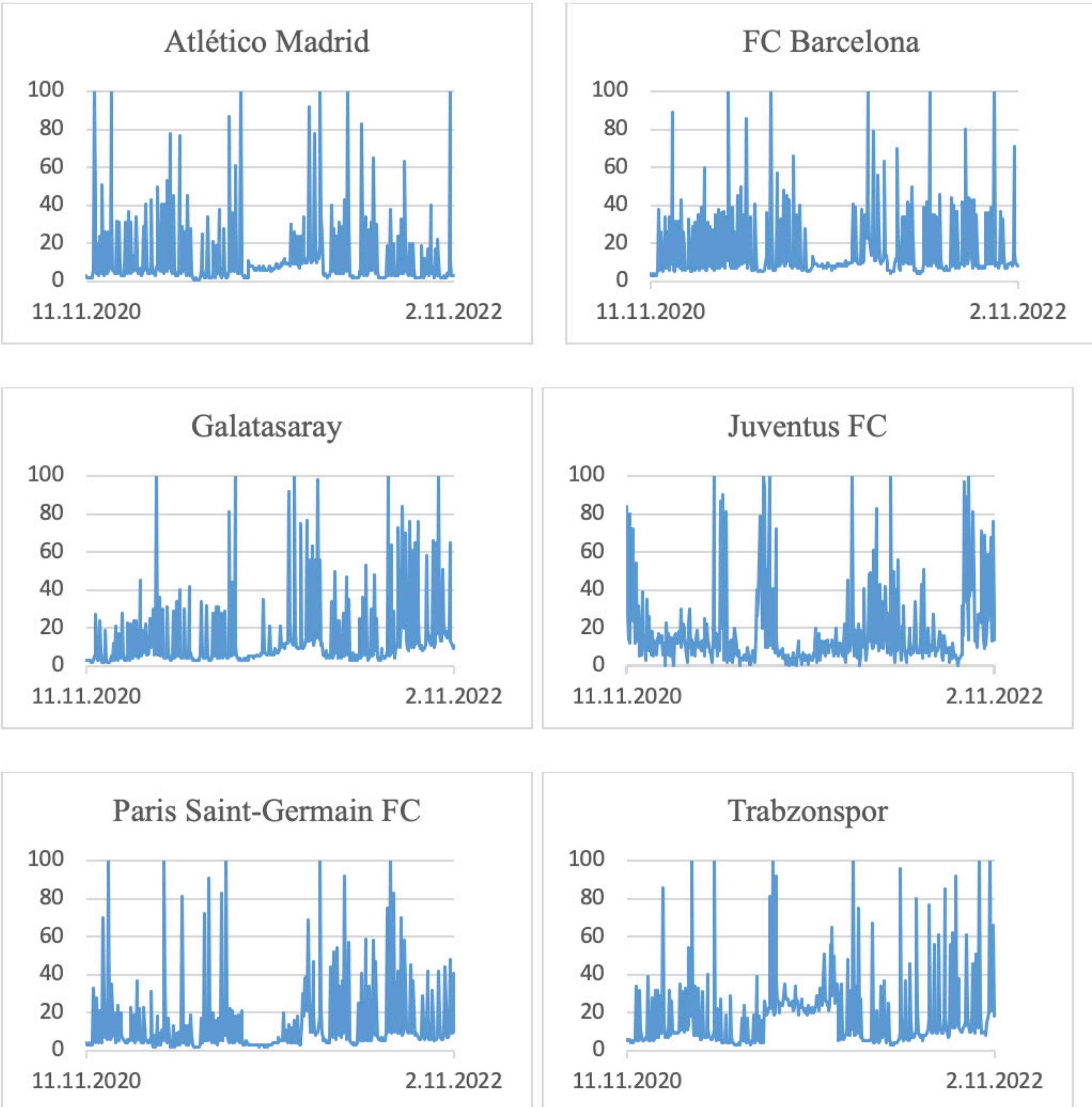
[1] We thank Mr. John Kleppe, consultant at Hybercube Business Innovation, for his assistance in providing the ECI data.



Graph 1. Historical ECI values for the review period

of all data were used within the scope of the study. To limit this analysis to the market capitalized rates of fan tokens, we collected the daily close price of Paris Saint-Germain (PSG), FC Barcelona (BAR), Juventus (JUV), Trabzonspor (TRA), Atletico Madrid (ATM), Galatasaray (GAL) from CoinMarketCap. This selection criterion is a common method for studies on cryptocurrencies (see: Wang, Andreeva and Martin-Barragan, 2023; Bouri and Jalkh, 2023; Bhambhwani, Delikouras and Korniotis, 2023). The fan tokens examined include fan tokens related to sports clubs in Spain, Italy, Turkey and France. Fan tokens are global and each fan token can be purchased by investors in different countries. Therefore, the results have a general implication, not a national one.

Euro Club Index (ECI): It is anticipated that there will be a positive relationship between fan token prices and club success, and the most important determinant of fan token prices will be club success. This is because the clubs that achieve successful results in sports competitions have more fans and therefore more investor potential. Also, while success may encourage investors to invest, fans resentful of the club as a result of failure are likely to dispose of their assets. ECI was chosen as an indicator of the club's success. ECI scores, which measure the success of clubs according to the results of national and international competitions, calculate a cumulative score by adding the new competition result to the previous competition results. ECI was developed by Hypercube

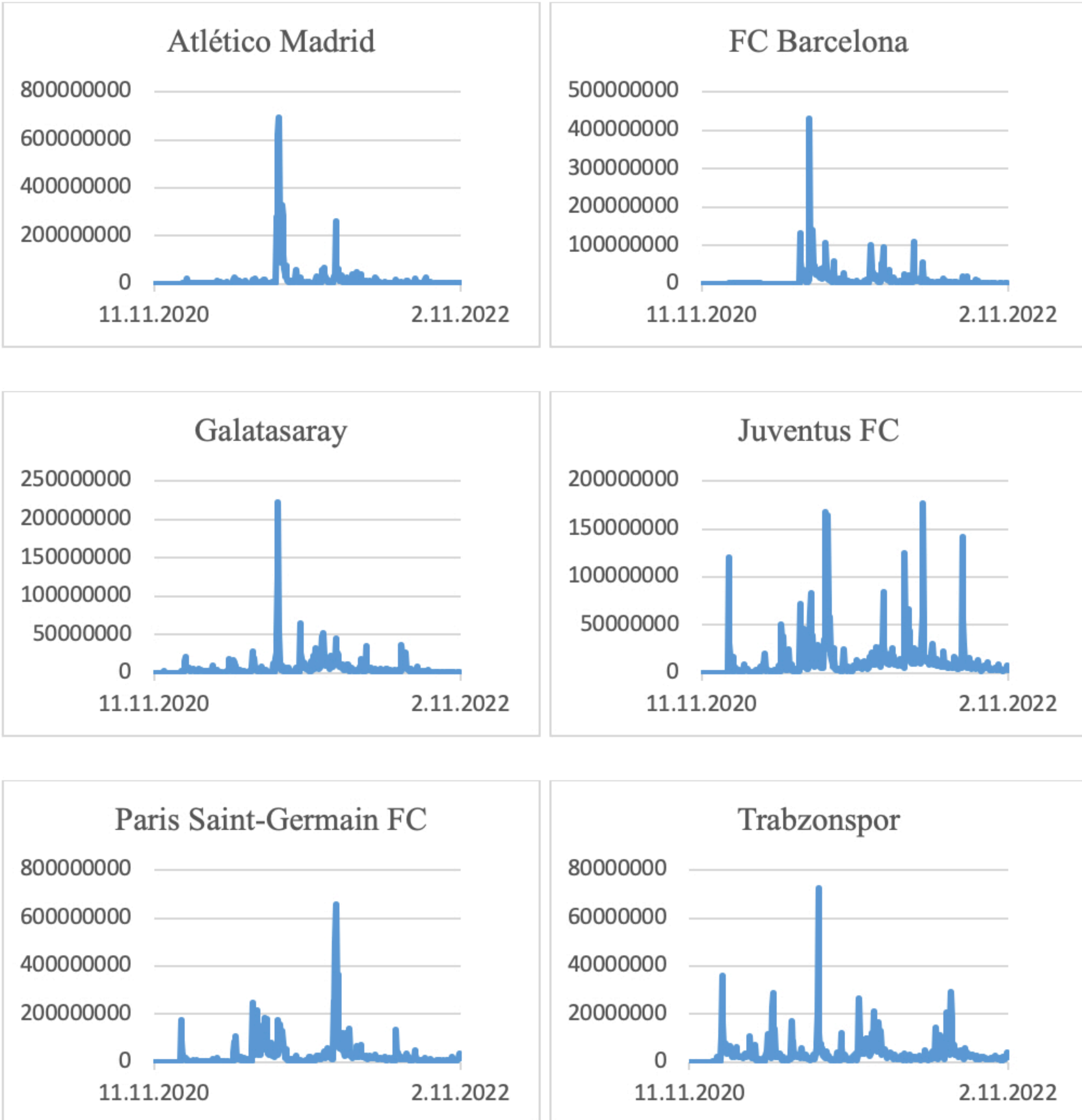


Graph 2. Historical Google Trends data for the review period

which is in close collaboration with Infostrada Sports. Information about ECI is given in Hybercube, which states that ECI is a solid indicator of a club's sporting power, which is the key to their brand value, transfers, and sponsorships.

Updated ECI values reflect changes in clubs' playing strength. A better-performing club rises in ECI, while a worse-performing club declines in ECI. The important advantage of ECI is that a strong club does not place a high ECI value on a victory against a weak team. Therefore, when favorite teams win, their ECI goes up a few points, while a weak club gets a higher ECI when they beat a strong club. The historical ECI values of the clubs included in the research for the research period are shown in Graph 1.

In Graph 1, it is seen that the clubs with the highest ECI values for the review period are Barcelona, Paris Saint-Germain, Atletico Madrid, Juventus, Trabzonspor, and Galatasaray, respectively. The period of May-August, where the ECI values do not change, shows the periods when the matches were not played. There are big differences between the ECI values of the clubs. However, these differences are not significant for the study. It is the changes in the ECI values that are important for the study. It is noteworthy that the ECI values of Atletico Madrid, Barcelona, and Galatasaray clubs decreased gradually in the 2021-2022 season, the ECI values of Paris Saint-Germain and Trabzonspor gradually increased, and the ECI value of Juventus remained almost flat. ECI



Graph 3. Historical trading volume data for the review period

does not designate clubs as successful or unsuccessful based on the result of a single match but is an indicator of sustainable success. It is expected that the increase/decrease in fan token prices of clubs rose/fell in ECI after a good/bad season.

Attractiveness: Google, Twitter, and Wikipedia sources have been used in many studies to measure the investment attractiveness of cryptocurrencies. To measure Bitcoin's investment attractiveness: Ciaian, Rajcaniova, and Kancs (2016) used Wikipedia; Sovbetov (2018) and Yelowitz and Wilson (2015) used Google Trends; Kristoufek (2015) used Google Trends and Wikipedia; Kaminski (2014) used Twitter; Georgoula et al. (2015) used Twitter and Wikipedia. Although the search engines used for the attractiveness factor have changed, generally positive relationships have been found between the Bitcoin price and the attractiveness factor in the studies. In this study, inquiries about sports club names were examined, not inquiries at a certain cryptocurrency level unlike the studies in the literature. The reason for this is to catch the level of following of the sports club that the fans are passionate about and the popularity of the club. Therefore, the relationship between the popularity of sports clubs in searches and the fan token prices of sports clubs is tried to be determined. Google Trends data was used to measure the popularity of sports clubs in searches. Google Trends search terms and daily search volumes for the research period are shown in Chart 3.

Google Trends scores search words from 0-100 based on their search volume. In Graph 2, it is seen that Google Trends data is highly changeable daily. A club, which is very popular by reaching 100 points from time to time, may lose its popularity completely after a day. On the graph, it is seen that the Google search volumes for all clubs decreased in the May-August 2021 period. This is because the clubs go on vacation after the leagues are over. There may be an increase in the search volume of the clubs on match days. Therefore, it is highly probable that the football club with a negative result on the match day will also achieve high scores in search volumes. In this way, a team that falls in ECI can rise in Google Trends.

Volume: Trading volumes are often used as a measure of the use of cryptocurrencies in trade (Kaminski, 2014; Kristoufek, 2015; Wang, Xue and Liu, 2016; Kwon, 2021). The studies examined, it is understood that while there were positive and significant relationships between the trading volume and Bitcoin price in the early stages of Bitcoin, these relationships decreased with the maturation of the market. However, since fan tokens are relatively new cryptocurrencies compared to Bitcoin, it is expected that there will be strong positive relationships between trade volume and fan token prices, as in the early stages of Bitcoin. Historical transaction volume data of fan tokens for the research period are shown in Graph 3.

In Graph 3, it is seen that the transaction volumes of fan tokens related to sports clubs other than Paris-Saint Germain FC reached the maximum level between April and May 2021. However, the high transaction volumes realized in the April-May 2021 period generally did not recur during the review period and gradually decreased. PSG fan token transaction volume reached its maximum level in August 2021 and gradually moved away from this level in the following periods. Another noteworthy situation is the transaction volume data of the Juventus Fan token. Among the examined clubs, only the trading volume of Juventus fan tokens repeated the high trading volume values in May 2021 in September, October, and December 2021 periods.

METHODOLOGY

The study first used Pesaran and Yamagata (2008) Delta test for the homogeneity of slope coefficients of fan token prices, transaction volumes, attractiveness and club success variables. In this test, it is assumed that the error terms are distributed independently, and heterogeneous variance is allowed (Bersvendsen and Ditzen, 2021, p. 53).

Based on Pesaran and Yamagata (2008), the hetorogeneous panel data model with $k = k_1 + k_2$ regressors can be expressed as follows;

$$y_{i,t} = \mu_i + \beta'_{i1}x_{i1,t} + \beta'_{i2}x_{i2,t} + \varepsilon_{i,t} \tag{2}$$

The cross-sectional dimension in the model is represented by $i=1,...,N$, and the time dimension by $t=1,...,T$. μ_i is the unit-specific constant. β_{i1} and β_{i2} are vectors of unknown slope coefficients $k_1 x\ 1$ and $k_2 x$, respectively. $x_{i1,t}$ and $x_{i2,t}$ are vectors containing extrinsic regressors $k_1 x\ 1$ and $k_2 x\ 1$ respectively. In this case, the slope homogeneity hypotheses;

$$H_0: \beta_{i2} = \beta_2 \ for\ all\ i\ values$$

$$H_1: \beta_{i2} \neq \beta_2 \ for\ some\ values\ of\ i$$

The delta and adjusted delta test are as follows (Pesaran and Yamagata, 2008, p. 57);

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S}_2 - k}{\sqrt{2k}}\right) \tag{3}$$

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S}_2 - E(\tilde{z}_{iT})}{\sqrt{Var(\tilde{z}_{iT})}}\right) \tag{4}$$

$$Var(\tilde{z}_{iT}) = \frac{2k_2(T-k-1)}{T-k_1+1} \tag{5}$$

The weighted difference between the pooled estimate and the cross-section specific estimate is known as $\tilde{S}_2$.

The CD test recommended by Pesaran (2004) was used to test the cross-sectional dependence. CD test is a powerful test for panel data models with or without heterogeneous and structural breaks (Pesaran, 2004, p. 18). The degree of bidirectional cross-section dependence in the panel is measured by factor loads Y_i and Y_j. The test hypotheses are as follows (Pesaran, 2004: 13);

$$H_0: \gamma_i = 0,$$

and the opposite hypothesis is shown as;

$$H_0: \gamma_i \neq 0\ (for\ some\ i\ values) \quad i = 1, \dots \dots N$$

CD test statistics are shown by Pesaran (2004, p. 17) as follows;

$$CD = \sqrt{\frac{2}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\sqrt{T_{ij}}\,\hat{p}_{ij}\right) \tag{6}$$

where T_{ij} is the number of observations for which the correlation coefficient is calculated, p_{ij} is the binary correlation coefficients. Under the null hypothesis that there is no cross-sectional dependence when $T_i > k+1$, $T_{ij} > 3$, and N are large enough, the distribution conforms to the $CD \sim N(0,1)$ distribution.

CIPS test, which was suggested by Pesaran (2007) and created by taking the arithmetic average of the CADF test statistics, and allowing cross-sectional dependence, was used.

CIPS test statistics shown in equation (9) are obtained by taking the arithmetic average of the results obtained from the CADF test statistics (Pesaran, 2007: 276);

$$CIPS(N,T) = N^{-1} \sum_{i=1}^{N} t_i(N,T) \tag{7}$$

After these tests, the Durbin-Hausman test, which allows cross-sectional dependence and was developed by Westerlund (2008), was used and the cointegration relationship between the variables was revealed. The dependent variable was found to be stationary at the first difference I(I) and the independent variables at the level I(0) or the first difference I(I). The Durbin test can be used under these conditions.

Finally, in our study, the pooled mean group (PMG) test recommended for heterogeneous panel models by Pesaran, Shin, and Smith (1999) was applied to determine the coefficients of the variables. In this method, regardless of whether the variables are I(0) or I(1), the variables must not be I(2). The estimation of an ARDL(p,q,,q) model with time dimension $t = 1, \dots, T$ and group dimension $i = 1, \dots, N$ can be expressed as follows (Pesaran, Shin, & Smith, 1999: 623) ;

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} x_{i,t-j} + \mu_i + \varepsilon_{it} \tag{8}$$

Here x_{it} $(kx1)$ is the vector of explanatory variables for group μ_i and represents the fixed effect. λ_{ij} is the lagged coefficients of the dependent variables, δ'_{ij} and $kx1$ are the coefficient vectors. The error correction form (ECM) of the equation can be derived as:

$$\Delta y_{it} = \theta_{it} y_{i,t-1} + \beta'_i x_{i,t} + \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta^{*\prime}_{ij} \Delta x_{i,t-j} + \mu_i + \varepsilon_{it} \tag{9}$$

Here, the error correction rate of the tuning term is calculated as $\theta_i = -(1 - \sum_{j=1}^{p} \lambda_{ij})$, $\beta_i = \sum_{j=0}^{q} \delta_{ij}$. When $\theta_i = 0$, there is no long-term relationship. If the variables revert to a long-run equilibrium, this parameter is predicted to be strongly negative. β'_i shows the coefficient of the long-term relationships between the variables. $y_{i,t-j}$ and $x_{i,t-j}$ represent the j-term lagged values of the variables and Δ represent the first differences of the variables. λ^*_{ij} and δ^*_{ij} are obtained with the help of the following equations;

$$\lambda^*_{ij} = -\sum_{m=j+1}^{p} \lambda_{im} \qquad j = 1,2,\dots\dots,p-1 \tag{10}$$

$$\delta^*_{ij} = -\sum_{m=j+1}^{q} \delta_{im} \qquad j = 1,2,\dots\dots,q-1 \tag{11}$$

These equations provide the short-run dynamics corresponding to the long-run dynamics defined in the cointegration equation. In order to talk about the existence of a long-term equilibrium, the ECM parameter must be found to be negative and significant.

FINDINGS

The slope coefficients were heterogeneous vis-à-vis Delta test, a cross-section dependency in all our variables vis-à-vis Pesaran (2004) CD-test and the variables were stationary in their first differences vis-à-vis Pesaran (2007) CIPS-test results in the established model. These results on the preconditions of our analysis are presented in Tables 1a-1b and 1c in the Appendix 1.

According to the Durbin-Hausman test results shown in Table 1, it is seen that the $H_0: \emptyset_i = 1$ hypothesis is rejected for both group statistics and panel statistics. Therefore, it is possible to say that the panel data model created is cointegrated and there is at least one cointegration relationship between the groups in the panel.

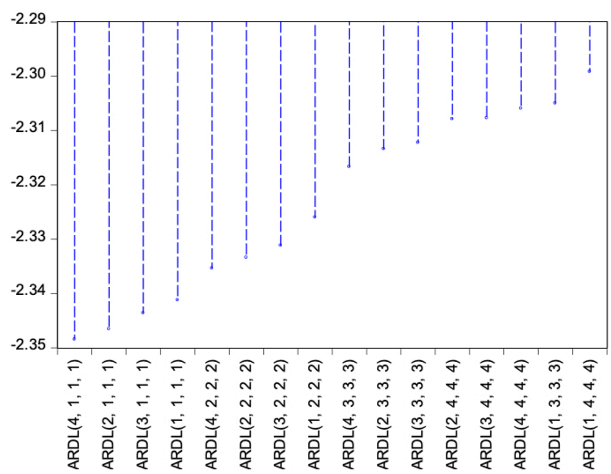
Hannan-Quinn Criterion (HQC) was used to determine the appropriate lag length before the ARDL limit test is applied. The lag length information of the 16 most suitable selected models is shown in Graph 4.

As can be seen in Graph 4, the most suitable model according to the HQC is the ARDL (4,1,1,1) model. Therefore, this model was taken as the basis for the analyzes carried out. Information on the PMG/ARDL test results performed for our model is shown in Table 2.

Table 1. Durbin-Hausman Cointegration Results

	Statistic	p-value
DH_g	-0.101	0.000
DH_p	3.322	0.000

Note: DH_g shows the group statistics for the Durbin Hausman test, and DH_p shows the panel statistics.



Graph 4. The 16 Most Suitable Models

When the long-term relationships of the ARDL (4,1,1,1) model in Table 2 are examined, it is seen that the SUCCESS, ATT and VOL variables are significant at the 1% level. Looking at the signs of the coefficients obtained from the test result, it is seen that club success and transaction volume affect fan token prices positively, while the attractiveness factor based on Google Trends negatively affects fan token prices. As can be seen from the results, the most influential factor on fan token prices is club success. Increasing of 1% in club success leads to an increase in fan token prices of approximately 3.5%. A 1% increase in Google search volumes causes a 0.14% decrease in fan token prices, while a 1% increase in transaction volumes causes an approximately 0.28% increase in fan token prices.

When the short-term relationships for the ARDL (4.1,1,1) model in Table 6 are examined, it is seen that the ECM (-1) error correction term coefficient is -0.048340 and significant. According to these results, the existence of a long-term equilibrium relationship is confirmed. This result indicates that if a shock occurs in the variables, the short-term deviations will be corrected by approximately 4.8% the next day. Therefore, short-term deviations come to equilibrium after about 21 days.

When the coefficients related to the short-term relationships in Table 8 are examined, it is seen that the D(ATT) and D(VOL) variables are significant at the 1% level. Therefore, a 1% increase in Google search volumes causes a decrease of approximately 0.0056% in fan token prices in the short term, while a 1% increase in transaction volumes causes an increase of approximately 0.045% in fan token prices in the short term. The coefficients of club success and fan token price first, second and third differences were found to be statistically insignificant.

Tablo 2. PMG/ARDL Test Results

Variable	**Coef.**	**Std. Er.**	**t-stat.**	**p value**
	Long Run Eq.			
SUCCESS	3.507878	0.703043	4.989561	0.0000
ATT	-0.136023	0.031675	-4.294316	0.0000
VOL	0.282356	0.019731	14.30996	0.0000
	Short Run Eq.			
ECM (-1)	-0.048340	0.013955	-3.464051	0.0005
D(FAN(-1))	-0.006187	0.047134	-0.131266	0.8956
D(FAN(-2))	-0.027593	0.025545	-1.080202	0.2801
D(FAN(-3))	0.065513	0.037675	1.738874	0.0822
D(SUCCESS)	0.591008	0.473255	1.248815	0.2118
D(ATT)	-0.005666	0.001374	-4.123708	0.0000
D(VOL)	0.045168	0.004910	9.199954	0.0000
C	-1.451921	0.416545	-3.485630	0.0005

Note: The maximum lag length was taken as 4. ECM (-1) represents the error correction term coefficient. Fan tokens are denoted as FAN, Euro Club Index as SUCCESS, trading volume as VOL and attractiveness factor as ATT.

ROBUSTNESS CHECK

There are studies showing that the price of Fan tokens can be affected by the price of other cryptocurrencies or the main cryptocurrencies used to purchase them (Demir and Aktaş, 2022; Scharnowsk, Scharnowski and Zimmermann, 2023). For this reason, we included the prices of Chiliz, a token used to purchase fan tokens, and Bitcoin, the largest cryptocurrency, in the PMG/ARDL model to test the robustness of the results. The results we obtained in Table 2 can be compared to Appendix 1, Table 1d. The results are in line with our previous findings. It was found that the results obtained are not driven by the prices of Chiliz and Bitcoin and are therefore robust to changes in the prices of other cryptocurrencies.

CONCLUSION AND DISCUSSION

In this study, long and short-term relationships between fan token prices, club success, transaction volume and attractiveness factors were tried to be revealed. As a result of the analysis, it has been determined that fan token prices are in a long-term equilibrium relationship with club success, transaction volume and attractiveness factors.

The most important determinant of the fan token price in the long-term equation was the club success. This situation shows the importance of sustainable success for the sports clubs. Continued long-term success or failure is significantly reflected in fan token prices. For this reason, it is recommended that sports clubs that have not yet issued fan tokens or have not released their entire supply to the market should wait for a season in which the club is progressing successfully. Entering the market at the right time will contribute to raising more funds for the sport club. The second most important determinant of fan token prices is transaction volumes. Transaction volumes are positively reflected in fan token prices in both the long and short term. For this reason, it is important for clubs to research the market where the fan tokens will be listed and try to list fan tokens on exchanges with high number of users and transaction volume. In addition, in order to increase the use of fan tokens in commerce, it is recommended that clubs provide more privileges for fan token holders and organize events frequently. The attractiveness factor negatively effects fan token prices both in the long and short term. This situation makes us think that the bad news about the clubs is on the agenda more than the good news. Therefore, it can be deduced that every negativity related to the clubs, which had a particularly turbulent and bad season, is closely followed by the fans and that these negativities are reflected in the fan token prices. For this reason, it is recommended that club managers focus on policies and measures to ensure unity of purpose from the lowest business unit to the highest business unit in order not to share in-club conflicts and disagreements with the media.

The fact that Google search volumes and club success effect fan token prices suggests that fan tokens can be considered as an emotional investment tool for investors. In addition, fan tokens come to the fore as a new source of funding for sports clubs after the loss of income during the Covid-19 epidemic. The market value of fan tokens is expected to increase exponentially in the future due to the growing ecosystem of fan tokens, the financial need of sports clubs, and the emotional attachment of fans. Therefore, finally, our advice for fan token investors is to invest in fan tokens of sports clubs that they believe will have a successful season, are listed on major exchanges in terms of trading volume, and where intra-club conflicts are minimal. In future studies on fan tokens, it is recommended to investigate whether fan tokens can be seen as an alternative investment tool to sports stocks and to investigate the effectiveness of fan tokens in participating in the management decisions of the fans.

Additionally, the study has some limitations. ECI values do not change during off-season periods. Therefore, the findings regarding ECI are valid for in-season periods. In addition, the attractiveness factors captured by Google Trends may vary greatly on clubs' match days and on dates when there is important good and bad news about the clubs. Therefore, the results of this study indicate that bad news is searched more in search engines. However, the maximum value for Google Trends data is 100, which means that all clubs with a value of 100 are at the same search level. However, this may not actually be the case. This is one of the important limitations of the study. Therefore, different attractiveness factors can be used in future studies. For example, X or Wikipedia.

REFERENCES

Bhambhwani, S. M., Delikouras, S. and Korniotis, G. M. (2023). Blockchain characteristics and cryptocurrency returns. Journal of International Financial Markets, Institutions and Money, 86, 1-18. Doi: 10.1016/j.intfin.2023.101788

Bersvendsen, T. and Ditzen, J. (2021). Testing for slope heterogeneity in Stata. The Stata Journal, 21(1), 51-80. Doi: 10.1177/1536867X211000004

Bouri, E. and Jalkh, N. (2023). Spillovers of joint volatility-skewness-kurtosis of major cryptocurrencies and their determinants. International Review of Financial Analysis, 90, 1-17. Doi: 10.1016/j.irfa.2023.102915

Chiliz (n.d.). Chiliz $CHZ - Driving Socios.com forward. Avaliable at: https://www.chiliz.com/en/our-story/

Ciaian, P., Rajcaniova, M. and Kancs D. (2016). The economics of Bitcoin price formation. Applied Economics, 48(19), 1799–1815. Doi: 10.1080/00036846.2015.1109038

CoinMarketCap (n.d.). Historical data [Data], Avaliable at: https://coinmarketcap.com/

Demir, E., Ersan, O. and Popesko, B., (2022). Are Fan Tokens Fan Tokens? Finance Research Letters, 102736. Doi: 10.1016/j.frl.2022.102736

Demir, M. A. and Aktaş, R. (2022). The relationship between fan tokens and cryptocurrencies: An empirical evıdence. International Journal of Economic and Administrative Studies, 37, 55-70. Doi: 10.18092/ulikidince.1112054

Georgoula, I., Pournarakis, D., Bilanakos, C., Sotiropoulos, D. and Giaglis, G.M. (2015). Using Time-Series and Sentiment Analysis to Detect the Determinants of Bitcoin Prices, MCIS 2015 Proceedings. 20, Avaliable at: https://aisel.aisnet.org/mcis2015/20

GoogleTrends (n.d.). Discover what topics are searched all over the World [Data], Avaliable at: https://trends.google.com/

GSIC (2021). The sports industry and the digital transformation: 5 years ahead [Report]. Avaliable at: https://sport-gsic.com/

Guizani, S. and Nafti, I. K. (2019). The determinants of Bitcoin price volatility: An investigation with ARDL model. Procedia Computer Science, 164, 233-238. Doi: 10.1016/j.procs.2019.12.177

Hypercube (n.d.). Euro Club Index (ECI) [Data], Avaliable at: https://www.euroclubindex.com/

IWF (2021). AC Milan crypto launch raises $6m as early trading volumes top $50m [Newsletter], Avaliable at: https://www.insideworldfootball.com/

Kaminski, J. C. (2014). Nowcasting the Bitcoin market with Twitter signals. Working Paper, Doi: 10.48550/arXiv.1406.7577

Kristoufek, L (2015) What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. PLoS ONE, 10(4), 1-15. Doi: 10.1371/journal.pone.0123923

Kwon, J. H. (2021). On the factors of Bitcoin's value at risk, Financial Innovation, 7, 1-31. Doi: 10.1186/s40854-021-00297-3

Marca (2022). Fan Tokens to become second largest source of revenue for sports industry [Newsletter]. Avaliable at: https://www.marca.com/

Panagiotidis, T., Stengos, T. and Vravosinos, O. (2018) On the determinants of bitcoin returns: A LASSO approach. Finance Research Letters, 27, 235-240. Doi: 10.1016/j.frl.2018.03.016

Pesaran, M.H. (2004). General diagnostic tests for cross-sectional dependence in panels. Cesifo Working Paper No. 1229, 1-39. Avaliable at: https://www.cesifo.org/

Pesaran, M.H. (2007). A simple panel unit root test in the presence of cross-section dependence, Journal of Applied Econometrics, 22, 265-312. Doi: 10.1002/jae.951

Pesaran, M.H. and Yamagata, T. (2008). Testing slope homogeneity in large panels, Journal of Econometrics, 142(1), 50-93. Doi: 10.1016/j.jeconom.2007.05.010

Pesaran, M.H., Shin, Y. and Smith, R.P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. Journal of the American Statistical Association, 94(446), 621-634. Doi: 10.2307/2670182

Reuters (2021). Messi joins crypto craze as gets part of PSG fee in fan tokens [Newsletter]. Avaliable at: https://www.reuters.com/

Scharnowski, M., Scharnowski, S. and Zimmermann, L., (2023). Fan Tokens: Sports and Speculation on the Blockchain, Journal of International Financial Markets, Institutions & Money, 89, 1-27. Doi: 10.1016/j.intfin.2023.101880

Sovbetov, Y. (2018). Factors influencing cryptocurrency prices: Evidence from Bitcoin, Ethereum, Dash, Litcoin, and Monero. Journal of Economics and Financial Analysis, 2(2), 1-27. Doi: 10.1991/jefa.v2i2.a16

Sukamulja, S. and Sikora, C. O. (2018). The new era of financial innovation: The determinants of Bitcoın's price. Journal of Indonesian Economy and Business, 33(1), 46-64. Doi: 10.22146/jieb.30646

Vidal-Tomás, D., (2022). Blockchain, sport and fan tokens. Munich Personal RePEc Archive. MPRA Paper No. 111350. https://mpra.ub.uni-muenchen.de/111350/

Wang, J., Xue, Y., and Liu, M. (2016). An analysis of bitcoin price based on VEC model. International Conference on Economics and Management Innovations.

Wang, Y., Andreeva, G. and Martin-Barragan, B. (2023). Machine learning approaches to forecasting cryptocurrency volatility: Considering internal and external determinants. International Review of Financial Analysis, 90, 1-21. Doi: 10.1016/j.irfa.2023.102914

Westerlund, J. (2008). Panel cointegration tests of the fisher effect. Journal of Applied Econometrics, 23, 193-233. Doi: 10.1002/jae.967

Yelowitz, A. and Wilson. M. (2015). Characteristics of Bitcoin users: an analysis of Google search data. Applied Economics Letters, 22(13), 1030-1036. Doi: 10.1080/13504851.2014.995359

Zhu, Y., Dickinson, D. and Li, J. (2017). Analysis on the influence factors of bitcoin's price based on VEC model. Financial Innovation, 3(1), 1-13. Doi: 10.1186/s40854-017-0054-0.

Appendix 1. Preliminary model checks

Table 1a. Delta Test Results

	Statistic	p-value
$\tilde{\Delta}$	33.813	0.000
$\tilde{\Delta}_{adj}$	33.999	0.000v

Table 1b. Cross-section Dependency Test Results

Variables	CD-test	p-value
FAN	51.14	0.000
SUCCESS	-6.25	0.000
ATT	17.98	0.000
VOL	59.57	0.000

Table 1c. Unit Root Test Results

	I(0)			I(I)	
	Specification without trend			Specification without trend	
Variable	Zt-bar	p-value	Variable	Zt-bar	p-value
FAN	-1.175	0.120	DFAN	-11.975***	0.000
SUCCESS	1.959	0.975	DSUCCESS	-11.975***	0.000
ATT	-11.975***	0.000	DATT	-11.975***	0.000
VOL	-11.975***	0.000	DVOL	-11.975***	0.000
	Specification with trend			Specification with trend	
Variable	**Zt-bar**	**p-value**	**Variable**	**Zt-bar**	**p-value**
FAN	-1.029	0.152	DFAN	-11.982***	0.000
SUCCESS	-0.177	0.430	DSUCCESS	-11.982***	0.000
ATT	-11.982***	0.000	DATT	-11.982***	0.000
LNVOL	-11.982***	0.000	DVOL	-11.982***	0.000

Note: "***" indicate 1% significance levels.

Table 1d. Robustness check

Variable	Coef.	Std. Er.	t-stat.	p value
	Long Run Eq.			
SUCCESS	3.267837	0.804681	4.061032	0.0001
ATT	-0.140124	0.035944	-3.898377	0.0001
VOL	0.279872	0.026909	10.40052	0.0000
CHZ	0.024048	0.026292	0.914649	0.3605
BTC	-0.002734	0.083405	-0.032777	0.9739
	Short Run Eq.			
ECM (-1)	-0.044425	0.012302	-3.611249	0.0003
D(FAN(-1))	-0.023918	0.044848	-0.533319	0.5939
D(FAN(-2))	-0.035863	0.029138	-1.230809	0.2185
D(FAN(-3))	0.060606	0.033223	1.824238	0.0682
D(SUCCESS)	0.438466	0.455764	0.962046	0.3361
D(ATT)	-0.004277	0.001092	-3.914510	0.0001
D(VOL)	0.045595	0.005471	8.334323	0.0000
D(CHZ)	0.329566	0.030207	10.91010	0.0000
D(BTC)	0.007778	0.007960	0.977133	0.3286
C	-1.243957	0.340278	-3.655704	0.0003

Note: The maximum lag length was taken as 4. ECM (-1) represents the error correction term coefficient. The most suitable model according to the HQC is the ARDL (4,1,1,1,1,1) model.