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ABSTRACT

This paper examines the dynamic connectedness among the fan tokens and their corresponding stocks using the TVP-VAR approach. We use daily data from December 11, 2020, to January 31, 2022, for the Juventus FC, AS Roma, Galatasaray, and Trabzonspor tokens and stocks. Our results indicate that shocks transmitted to any token are larger than the ones to the stocks, with the tokens being the net transmitters of shocks to both the tokens and stocks. Then, our results indicate that the two asset classes are considered independent of each other, with the total connectedness decreasing over time, and indicating that less than 10% of the contributions in any token (stock) is from the stocks (remaining stocks). This implies that the idiosyncratic contributions to the variations in the utilized group of assets are considerably low when compared to the system contributions. Finally, we provide some implications for investment and portfolio management.

Keywords: Fan tokens, Football clubs, Connectedness, TVP-VAR, Spillover, Asset returns

1. Introduction

While cryptocurrencies have been in the center of attention within the broader class of crypto assets, recently different token types such as NFTs (non-fungible tokens), DeFi (decentralized finance) tokens, and Meme tokens have gained popularity. Fan token is an attractive phenomenon among crypto investors and especially fan investors. **Fig. 1** presents the weekly search results of the "Fan token" term in Google. Fan tokens are utility tokens on the Chiliz chain, a proof-of-authority sidechain built on Ethereum **(Scharnowski et al., 2021)**. Fan token holders gain access to a range of benefits and rewards, which also depend on the number of fan tokens owned. Fan tokens allow their holders to participate in a variety of fan-led decisions such as merchandise design, tour bus design, team motto, team warm-up music, and match locations. Clubs utilize tokens as a part of fan engagement strategy to build and extend their global fan bases **(https://www.chiliz.com/en/what-is-a-fan-token-and-how-do-they-work/)**. Although most of the fan tokens belong to football clubs, sports, racing, and fighting clubs also issue fan tokens. Worldwide famous football clubs (e.g., Juventus, Barcelona, Paris Saint-Germain,

Manchester City, Inter FC), national teams (such as Italy and Argentina), and relatively less-known clubs (e.g., Istanbul Basaksehir, Legia Warsaw, and Sint-Truidense Voetbalvereniging) issued fan tokens. By mid-March 2022, the market cap of the fan token market is around 426 million USD and there are 57 tradable fan tokens **(https://rocketfan.com/market)**. The leading fan token platform is Socios.com, which has partnered with UEFA to become the official fan token partner of UEFA Club Competitions. Unlike NFTs, fan tokens are fungible or in other saying interchangeable. While fan tokens provide several opportunities to token holders, tokens do not offer ownership in contrast to stocks.

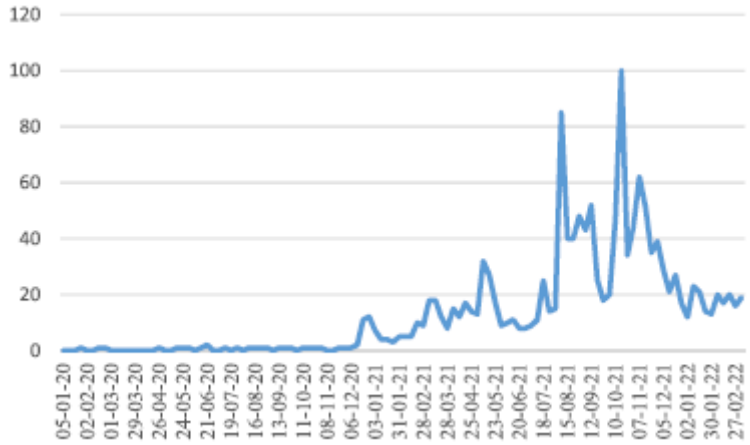

Fig. 1. "Fan token" Google Trends Search Data.

Although fan tokens are getting more popular, the literature on fan tokens is quite immature but there is a rising interest in the topic. By using data of fan tokens of 11 football clubs, **Demir et al. (2022)** explore the impact of game results on fan token returns. They find that losses (wins) in the UEFA Champions League tournament negatively (positively) affect the abnormal returns while in absolute terms, losses have a larger impact. Domestic matches and Europa League matches are not followed by similar reactions. **Mazur and Vega (2022)** examine the risk and performance of fan tokens. Football fan tokens provide a first-day return of around 150% on average. On the contrary to the outstanding one-day performance, they exhibit disappointing long-term performance. Football fan tokens underperform different crypto benchmarks such as NFTs, Defi, and Bitcoin. Moreover, **Mazur and Vega (2022)** suggest that there is no effect of game results on fan tokens. In a similar vein, **Vidal-Tomas (2022)** analyze the performance and dynamics of fan tokens and Chiliz currency. Differently from **Mazur and Vega (2022)**, they show that fan tokens are characterized by negative short-run and positive long-run performance.[1] Fan tokens do not outperform the cryptocurrency market. As expected, fan tokens are more correlated with Chiliz rather than the crypto market index. The wavelet coherence documents that there are higher co-movement between Chiliz and some of the fan tokens. **Scharnowski et al. (2021)** analyze the fan tokens in many different aspects. First, it is shown that fan token prices are highly volatile and riskier than other cryptocurrencies.

[1] Extremely large differences in the reported returns in two studies **(Mazur and Vega, 2022; and Vidal-Tomás, 2022)** are due to the selection of purchase price. While the former study assumes buying at the offering price, the latter assumes the buy at the opening price of first trading day. For example, the reported first day raw return on the Manchester City token is 767% (10%) in the former (latter) study.

Fan tokens and cryptocurrencies are positively correlated and there is a high correlation among fan tokens. For four football clubs having both stock and fan tokens, stock and token returns are almost uncorrelated which is in line with **Demir et al. (2022)**. The pairwise correlations for individual clubs' stock returns range from — 7-10%. They also find that fan token prices are mostly weak-form efficient with different levels of efficiency in sub-periods. In terms of determinants of fan token returns, Bitcoin, Ethereum, Chiliz, and Binance Coin have a positive effect. On match days, token returns are on average lower than on other days. The impact of any game result (win, draw, and loss) is negative. The effect of losses is higher in absolute terms. Investor attention regarding fan tokens, in general, is associated with substantially higher returns. Outgoing and incoming transfers do not affect fan token returns.

In this study, we explore the connectedness among fan tokens and stock returns of four football clubs namely Juventus FC (JUV) and AS Roma (ASR) from Italy and Galatasaray (GAL), and Trabzonspor (TRA) from Turkey. We use the TVP-VAR methodology proposed by **Antonakakis and Gabauer (2017)**. Those four clubs are chosen, as they are the only clubs with listed fan tokens and stock, at the same time. Fan tokens and stocks have several different features. Fan tokens are digital assets, which provide access to an encrypted ledger of voting and membership rights ownership **(Demir et al., 2022)**. On the contrary to stock ownership, fan token ownership doesn't provide any ownership in the football club. Stockholders can benefit from capital/dividend gains and have voting rights to elect directors at annual meetings. As a priori expectation, fan tokens, targeting the attention of club fans and not providing ownership rights, might be priced based on the overall demand from fans and investors. For the stocks, valuation considering the future cash flows will be more valid. The trading environments, i.e. crypto markets, and equity markets also exhibit essential differences such as efficiency and regulations. Even though fan tokens and stocks of a football club have different features by nature, they represent the same football club. Therefore, we aim to explore if two asset classes are related or distinct. Are there any spillovers from fan tokens to stocks or vice versa? Moreover, within each asset class, we inquire about the connectedness among four assets.

Based on the TVP-VAR model of **Antonakakis and Gabauer's (2017)** estimation, first, we find that each asset's contribution to its forecast error variance is larger than the contributions from other assets. Second, own contributions are relatively larger for the stocks, than those for the tokens, indicating that the returns on the stocks of football clubs are relatively more determined by the idiosyncratic factors. Third, the vast majority of the contributions to any token are either from the token itself or from the other three tokens, while the contributions from stocks to tokens are limited, and tokens are the main transmitter of shocks to stocks. The contribution from the token to the stock is larger than the one in opposite direction for all clubs. Finally, tokens (stocks) do not transmit considerably different amounts of shocks to stocks (tokens) when both assets belong to the same club.

We contribute to the literature in several ways. First, the literature on fan tokens is scarce **(e.g., Demir et al., 2022; Scharnowski et al., 2021; Vidal-Tomás, 2022)**. Moreover, the existing studies primarily focus on the effects of match results on the token prices. Because fan tokens have unique features distinguishing them from remaining asset classes, including other cryptocurrencies, examination of this relatively new asset class has the potential to enrich our understanding of current financial markets as well as to extend our views regarding the future of markets. Second, we add to the literature documenting the spillovers between various markets and assets, including equities, commodities, crude oil, and cryptocurrencies. Recent literature broadly studies the connectedness in the systems of different assets/markets. Therefore, incorporating fan tokens in such a setting sheds further light on how interrelated this new asset class is with a traditional asset class: equities. Third, as a novel approach, we examine the spillovers among assets of two classes concerning the same company, i.e. football club. **Demir et al. (2022)** and **Scharnowski et al. (2021)** make a preliminary attempt to analyze

the correlations between fan tokens and stocks of football clubs; in this paper, we go beyond this and analyze the spillovers among those assets. We demonstrate the spillovers between each club's fan token and stock, two sources of raising capital for the company. Therefore, our findings have important implications for the football clubs to raise capital as well as for the investors in token and stock markets. Finally, our findings contribute to the behavioral finance literature that documents irrational pricing and arbitrage opportunities as well as its limits in financial markets **(e.g., Shleifer and Vishny, 1997)**.[2]

The rest of the paper is organized as follows. **Section 2** explains the data and methodology. **Section 3** presents and discusses the findings. The last section concludes the paper.

2. Data and methodology

2.1. Data

We use daily prices of eight assets: the fan tokens and stocks of four clubs. The purpose of selecting the four specific clubs is solely the fact that they are the only clubs with listed fan tokens and stocks, at the same time. These clubs are Juventus FC (JUV) and AS Roma (ASR) from Italy and Galatasaray (GAL) and Trabzonspor (TRA) from Turkey. Our sample spans the period 11 November 2020-31 January 2022. We have 300 daily observations for each asset.

2.2. Methodology

We explore the connectedness and dynamic spillovers among the fan tokens and stocks of four clubs. To do so, we rely on the TVP-VAR methodology proposed by **Antonakakis and Gabauer (2017)**. The TVP-VAR method is an extension of the VAR methodology originally provided by **Diebold and Yilmaz (2009, 2012, 2014). Diebold and Yilmaz (2009, 2012, 2014)** used a rolling-window VAR to construct connectedness measures, while **Antonakakis and Gabauer (2017)** implemented a time-varying parameter vector autoregressive model (TVP-VAR) with a time-varying covariance structure proposed in **Primiceri (2005)**.

TVP-VAR is a commonly used technique for connectedness among different asset **classes (Aharon and Demir, 2022; Adekoya and Oliyide, 2021; Bouri et al., 2021; Raza et al., 2022)**. TVP-VAR method has several advantages over other alternatives. First, the TVP-VAR methodology overcomes the restrictions of the basic classical methodology of **Diebold and Yilmaz (2012)**, as it allows for fluctuations over time and therefore provides a more robust estimate. Second, it does not rely on rolling a fixed-length sample window and is suitable for small sample sizes **(Mishra and Ghate, 2022)**, therefore preserving the use of every available information. In this case, the use of the TVP-VAR model eliminates the issue of the frequently randomly selected rolling window size that might cause some quite unpredictable parameters and a lack of important observations **(Antonakakis et al., 2018, 2020)**. Third, this approach benefits from the Bayesian shrinkage for estimating high-dimensional systems without asking for computationally intensive simulation techniques **(Attarzadeh and Balcilar, 2022)**.

[2] The token and the stock of a club being highly independent from each other might be due to the fact that their returns are affected by totally different underlying factors, or at least up to certain extent irrational pricing exists in related assets.

The aforementioned methods enable us to construct a matrix of Generalized Impulse Responses, which are the transmissions of shocks one to another. The presentation of the connectedness matrix allows us to study the transmitted relationships to and from each market to others and the net transmissions. We can present TVP-VAR model as follows:

$$z_t = \beta_t z_{t-1} + u_t u_t \sim N(0, S_t), \tag{1}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + v_t v_t \sim N(0, R_t) \tag{2}$$

where z_t, z_{t-1}, and ut are $kx1$ dimensional vectors;β_t and S_t are kxk dimensional matrices; $vec(\beta_t)$ and v_t are k^2x dimensional vectors; and R_t is a k^2xk^2 dimensional matrix. After that, we calculate the H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD) and transform the TVP-VAR to its moving average (VMA) representation based on the Wold theorem as follows:

$$z_t = \sum_{i=1}^{p} B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j} \tag{3}$$

Table 1 Descriptive Statistics and the Correlation Matrix.

	JUV.T	ASR.T	GAL.T	TRA.T	JUV.S	ASR.S	GAL.S	TRA.S
Mean	-0.08	0.00	0.07	0.40	-0.24	0.08	-0.07	0.30
Stdev	9.52	12.22	11.05	11.21	2.80	3.25	2.90	3.63
Min	-55.22	-89.34	-56.60	-28.58	-28.65	-7.62	-10.45	-10.42
Max	71.92	79.03	102.85	156.90	16.43	22.38	9.53	9.53
Skewness	0.32 * *	0.22	2.81 * **	9.20 * **	-3.42 * **	2.71 * **	0.04	0.46 * **
Kurtosis	16.75 * **	20.24 * **	29.56 * **	125.51 * **	40.75 * **	13.36 * **	2.45 * **	1.09 * **
JB	3511.69 * **	5120.24 * **	11315.20 * **	201150.52 * **	21344.95 * **	2599.51 * **	75.02 * **	25.41 * **

*Notes: The table presents the descriptive statistics. Stdev is the standard deviation of the returns; skewness is from D'Agostino (1970) test; excess kurtosis (E.kurtosis) is from Anscombe and Glynn (1983) test; JB is the Jarque and Bera (1980) normality test statistic. Mean, stdev, minimum and maximum values are reported in percentages. * * and * ** represent significance at 5% and 1%, respectively.*

The (scaled) GFEVD normalizes the (unscaled) GFEVD, ϕ_{ijt}^{8}(H), so that sum of each row is one. ϕ_{ijt}^{8} (H) represents the influence variable j has on variable i in terms of its forecast error variance share that is defined as the pairwise directional connectedness from j to i. This is developed as:

$$\Phi_{ij,t}^{g}(\mathrm{H}) = \frac{S_{ii,t}^{-1} \sum_{i=1}^{H-1} \left(\iota_i' \mathrm{A}_t S_t \iota_j\right)^2}{\sum_{j=1}^{k} \sum_{i=1}^{H-1} \left(\iota_i \mathrm{A}_t \mathrm{S}_t \mathrm{A}_t' \iota_i\right)} \tag{4}$$

$$\widetilde{\Phi}_{ij,t}^{g}(\mathrm{H}) = \frac{\Phi_{ij,t}^{g}(\mathrm{H})}{\sum_{j=1}^{k} \Phi_{ij,t}^{g}(\mathrm{H})} \tag{5}$$

where $\sum_{j=1}^{k} \tilde{\phi}_{ijt}^{g}(H) = 1, \sum_{j=1}^{k} \phi_{ijt}^{g}(H) = k$, and ii is a selection of vector with unity on the ith position and zero otherwise. Next, total directional connectedness from variable j TO all other variables; total directional connectedness FROM all other variables to variable j; net (NET) total direction of connectedness associated with variable j; and the total connectedness (TCI) amongst all the variables are calculated as:

$$TO_{ji} = \sum_{i=1, i \neq j}^{k} \tilde{\Phi}_{ij,i}^{g}(\mathrm{H}) \tag{6}$$

$$FROM_{ji} = \sum_{i=1, i \neq j}^{k} \tilde{\Phi}_{ji,i}^{g}(\mathrm{H}) \tag{7}$$

$$NET_{ji} = TO_{ji} - FROM_{ji} \tag{8}$$

$$TCI_{i} = k^{-1} \sum_{j=1}^{k} TO_{ji} \equiv k^{-1} \sum_{j=1}^{k} FROM_{ji} \tag{9}$$

All the results are obtained based on the TVP-VAR modeling strategy described in detail in **Gabauer (2021), Chatziantoniou and Gabauer (2021), Bouri et al. (2021)**, and **Andre et al. (2021)**.

3. Empirical results

Table 1 reports the descriptive statistics of the returns. Tokens (stocks) of each club are differentiated with a T (S) letter. Mean daily returns on the tokens and stocks are similar and vary between — 0.24% for JUV.S and 0.4% for TRA.T. Mean annualized returns on the fan token and stock of Trabzonspor football club with recent outstanding field performance experiences are as high as around 100% and 75%. Then, the associated risk measured by the standard deviation of returns is substantially different for the tokens and stocks. While the standard deviation of stock returns is between 2.8% and 3.6%, it is much higher for the fan token of Juventus FC at 9.5% and 12.2% for the fan token of AS Roma. Moreover, the return distribution is skewed for six out of eight assets. For three of the tokens and two of the stocks, returns are positively skewed reflecting the existence of extreme positive return for most days during the sample period. Similarly, the returns on all eight assets exhibit excess kurtosis implying that the extreme values are more likely to happen in comparison to a normal distribution. The non-normality of returns is further confirmed by the Jarque-Bera test (Jarque and Bera, 1980) results.

Fig. 2 plots the time series of returns. As inferred from **Table 1**, token returns involve large spikes, especially during the last days of 2020 that are associated with substantially large absolute returns. This period, compared to the rest of the sample, exhibits mean-reversion characteristics though. For example, the fan token price of Juventus FC experienced a 72% increase on 21 December ASR, GAL and TRA stand for four clubs, namely, Juventus FC, AS Roma, Galatasaray and Trabzonspor, respectively. T and S letters next to the club names refer to the token and stock, respectively. 2021, followed by two consecutive days with a — 30% return. Similarly, AS Roma token price went up by 49% on the same day, then followed by additional increases of 79% and 67% in the next few days. The extremely high gains mostly disappeared within three days during the same week (—89%, — 47%, and — 31%). Overall, stock returns are much less volatile with the vast majority of daily observations in the — 5% and 5% range.

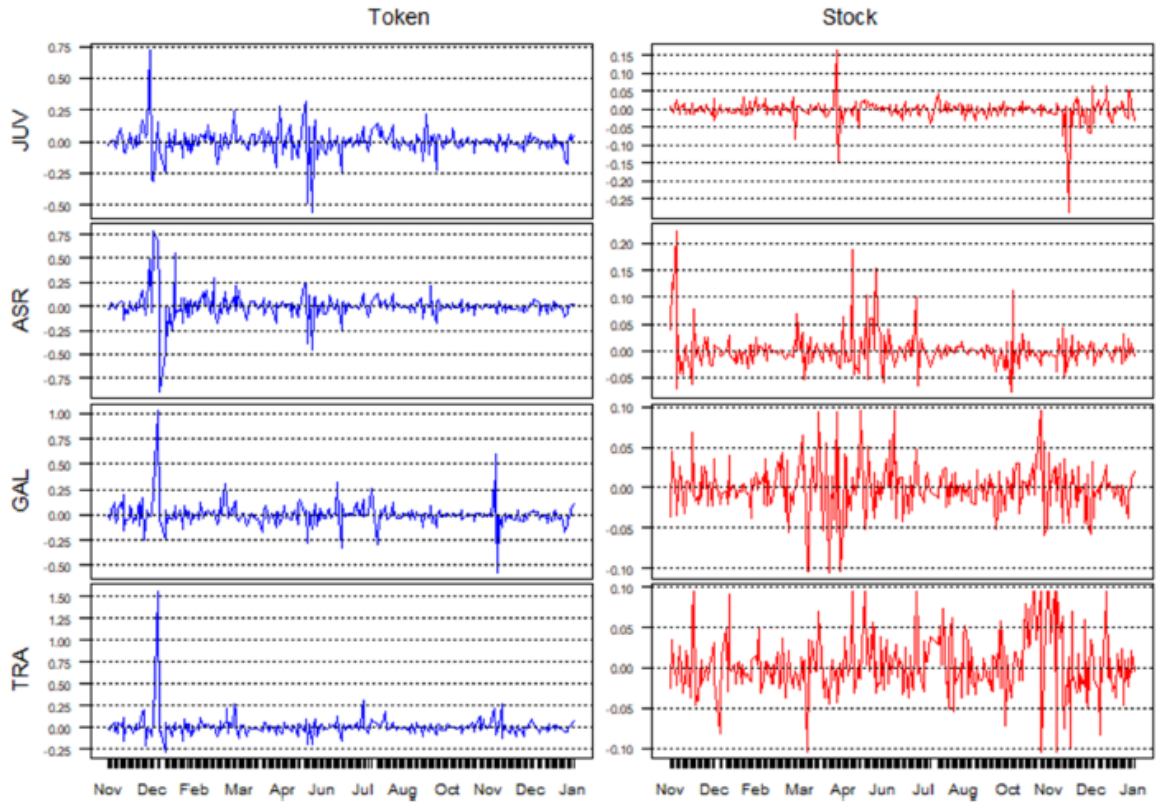

Fig.2. Time series of returns on the token and stock prices of the four clubs. The data span is 11 December 2020 – 31 January 2022, with 300 observation for each of the series. JUV, ASR, GAL and TRA stand for four clubes, namely, Juventus FC, AS Roma, Galatasaray and Trabzonspor, respectively. Plots on the left (right) hand side shows the return series for tokens (stocks) of the clubs.

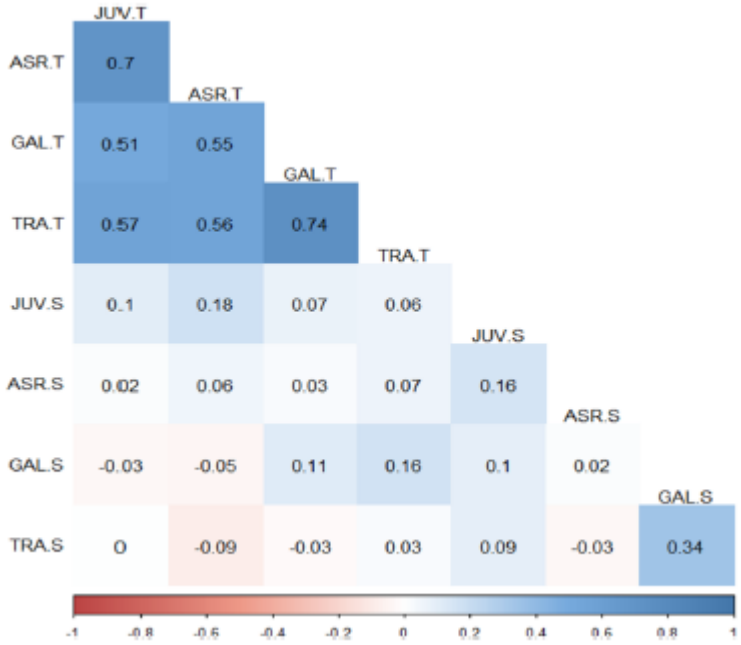

Fig. 3. Correlation matrix. Note: Spearman correlation coefficients among the returns on the examined assets are reported. The coefficients with larger than 0.1 p-value are accompanied by a crossing. JUV, ASR, GAL and TRA stand for four clubs, namely, Juventus FC, as Roma, Galatasaray and Trabzonspor, respectively. Plots on the left (right) hand side shows the return series for tokens (stocks) of the clubs.

Table 2 Averaged Results from Dynamic Connectedness TVP-VAR model.

	JUV-T	ASR-T	GAL-T	TRA-T	JUV-S	ASR-S	GAL-S	TRA-S	From Others	From Tokens	From Stocks
JUV-T	55.42	5.67	10.76	17.79	0.85	3.22	0.96	5.33	44.58	34.22	10.36
ASR-T	2.87	55.71	20.67	11.86	1.32	5.69	0.20	1.68	44.29	35.4	8.89
GAL-T	3.43	15.97	53.82	21.88	0.68	2.08	0.56	1.58	46.18	41.28	4.9
TRA-T	9.09	10.47	21.22	51.93	0.53	1.55	0.52	4.68	48.07	40.78	7.28
JUV-S	4.09	4.10	4.60	7.35	72.81	3.33	1.82	1.90	27.19	20.14	7.05
ASR-S	10.39	9.75	6.77	7.02	2.76	59.15	0.59	3.58	40.85	33.93	6.92
GAL-S	4.68	4.17	4.39	4.19	1.40	0.78	74.20	6.18	25.80	17.43	8.37
TRA-S	9.77	6.31	5.50	8.55	0.49	2.52	4.32	62.53	37.47	30.13	7.34
TCI									39.30	31.66	7.64
TO others	44.33	56.44	73.91	78.63	8.02	19.19	8.99	24.92			
TO tokens	15.39	32.11	52.65	51.53	3.38	12.54	2.24	13.27			
TO stocks	28.94	24.33	21.26	27.1	4.64	6.65	6.75	11.65			
NET	-0.25	12.15	27.73	30.56	-19.17	-21.66	-16.81	-12.54			

Notes: TVP-VAR connectedness matrix for selected fan tokens and stocks from December 11, 2020, to January 31, 2022, with 300 observations for each of the series. JUV, ASR, GAL and TRA stand for four clubs, namely, Juventus FC, AS Roma, Galatasaray and Trabzonspor, respectively. The variance decompositions are obtained based on 10-step-ahead forecasts and a lag of order 1 for the TVP-VAR model.

Fig. 3 presents the Spearman correlation coefficients, with the coefficients for the token pairs being mainly positive and substantially high (between 51% and 74%). This implies that the token prices tend to move in similar directions and might be affected by common underlying factors. Stock pairs exhibit lower and varying levels of correlations. For example, the correlation coefficient of the returns on AS Roma and Trabzonspor stocks is as low as — 3%, while the one for the GAL-TRA pair is 34%. The correlation between the two Italian stocks and the one between the two Turkish stocks are significant, while the remaining coefficients are statistically insignificant. Finally, the correlation between any stock-token pair is also relatively low, and for some pairs it is negative. The majority of the coefficients are between — 9% and 10% and are statistically insignificant. Four token-stock pairs have significantly positive correlations. The findings of relatively low correlations of stock-token pairs suggest that the two asset types do not move in similar directions. This can be explained by the different characteristics of the two asset classes and their dynamics. For example, on the contrary to stocks, fan tokens do not provide any ownership rights and are designed primarily for the fans of the clubs. Therefore, this new asset type may be affected much less by the club fundamentals and new information arrival **(Demir et al., 2022).**

Table 2 includes the results of estimating the TVP-VAR model of **Antonakakis and Gabauer (2017)** and providing the averaged dynamic connected results. The diagonal elements represent the contributions of the asset on itself while the remaining fields stand for the contributions either from or to another asset. Each row (column) reports the contributions an asset receives from (submits to) other assets. Based on **Table 2**, first, each asset's contribution to its forecast error variance is larger than the contributions from other assets, which is represented by the higher (lower) than 50% values in the diagonal (last column). For the assets involved in this specific network, the average contribution from other assets is 39.3%. Moreover, own contributions are relatively larger for the stocks. While these contributions are between 52% and 56% for the tokens, they are between 59% and 74% for the stocks of the same clubs. This by itself implies that the returns on the stocks of football clubs are relatively more determined by idiosyncratic factors.

The second line of findings concerns the comparison of the contributions based on asset types, i.e. tokens and stocks. An interesting figure extracted from **Table 2** is that the vast majority (90% or larger part) of the contributions to any token are either from the token itself or from the other three tokens. For instance, 95% of Galatasaray token contributions are from tokens. Moreover, for any token, the

contributions from the other three tokens are in considerable amounts (34-41%). On the contrary, the contributions from stocks to tokens are limited. The results regarding the shocks transmitted to stocks are similar to the tokens. Once again, rather than the stocks (other than the specific stock itself), tokens are the main transmitter of shocks to stocks. As reported in the last column of **Table 2**, for each of the four stocks, the contributions from the other three stocks are smaller than 10% and much lower when compared to the contributions from tokens. The distribution of contributions from each asset class is in line with the distribution of contributions to the asset classes. Tokens transmit shocks up to a much higher extent when compared to stocks. While the sum of contributions from Juventus FC stock to the other assets is 8.02%, this number is as high as 78.63% for the Trabzonspor token. The substantial difference between the two asset classes in transmitting shocks to other assets is valid for both the shocks transmitted to tokens and stocks. The last row in **Table 2** states whether each asset is a net transmitter or receiver of shocks. Except for the Juventus FC token with almost zero net value, the remaining three tokens are the net transmitters of shocks while all four stocks are the net receivers of shocks.

The third line of findings documented in **Table 2** includes the pairwise connectedness of the token and the stock of each club. Overall, in line with the aforementioned results, the contribution from the token to the stock is larger than the one in opposite direction for all clubs. Comparing the transmitted shocks of the four same-club token-stock pairs with the twelve different-club token-stock pairs, we do not observe a systematic pattern. In other words, tokens (stocks) seem not to transmit a considerably different amount of shocks to stocks (tokens) when both assets belong to the same club.

Fig. 4 plots the dynamic total connectedness obtained from the TVP-VAR model estimation. The total connectedness index (TCI) captures the share of the interactions among the system variables. The average TCI over the sample period is 39.3%, as reported in Table 2. Over the examined period, there is a substantial decrease in the connectedness of the system of football club tokens and stocks. TCI at the beginning of the sample period is larger than 80%.

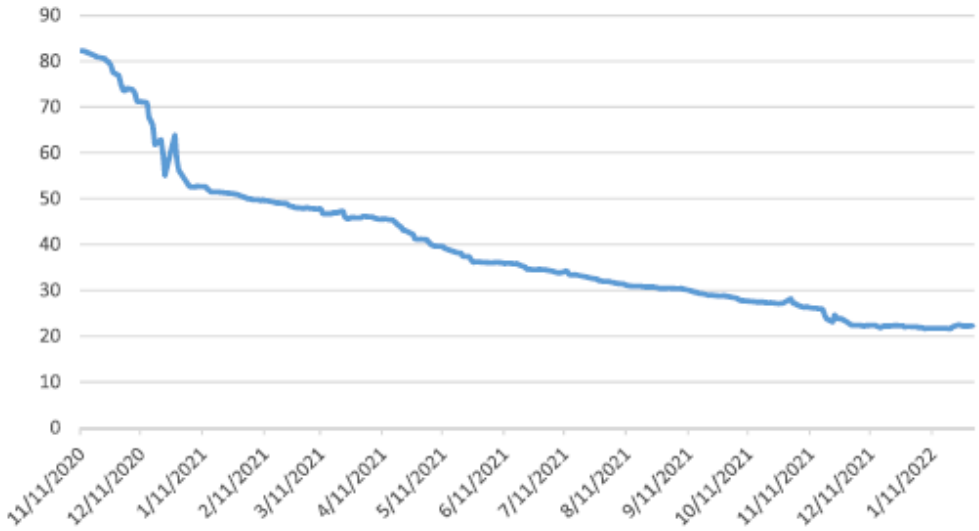

Fig. 4. Dynamic Total Connectedness Index. Note: The plot reflects the time series of TCI. Y-axis stands for the TCI in percentages. The data span is 11 December 2020 - 31 January 2022.

This indicates that the idiosyncratic contributions to the variations in the utilized group of assets are considerably small when compared to the system contributions. However, the index value decreases almost consistently and reaches 21% by the end of the period. Therefore, passing through the specific period, the initial picture has reversed. By 2022, the total connectedness among the relevant assets is very low. A large part of the loss of connectedness occurs in the first couple of months (Nov-Dec 2020), while a local positive spike exists at the end of 2020 (December 28).

To support our findings, we provide in the Appendix, Figure A1, A2, and A3 representing the behavior of TO, FROM, and NET connectedness indices. The results from the figures coincide with those reported in **Table 2** about the dynamic connectedness between the two asset classes and their behavior over the sample period.

Our main goal is to inquire about the connectedness among two specific asset classes of the same set of issuers (football clubs). One could argue that other financial assets can also be included to work with a larger system of assets. High co-movement between fan tokens and Chiliz is documented in recent studies **(Scharnowski et al., 2021; Vidal-Tomás et al., 2022)**. Therefore, we repeat our analyses with a system of nine assets, including Chiliz. Our main findings regarding the connectedness among the tokens and stocks of examined clubs are not affected by the inclusion of Chiliz. More specifically, the contributions from Chiliz to tokens (stocks) are between 5.6% and 8.8% (0.8-2.6%). These are 3-20% of the total contributions received by the remaining eight assets. In the remaining part of the contributions received by tokens and stocks, the parts of each asset class are qualitatively the same as the ones from our earlier findings. We do not report the results for the sake of brevity.

4. Conclusion

In this paper, we examine the dynamic connectedness among the fan tokens and their corresponding stocks using the TVP-VAR approach of **Antonakakis and Gabauer (2017)**. We use daily data from December 11, 2020, to January 31, 2022, for eight assets: Juventus FC, AS Roma, Galatasaray, and Trabzonspor tokens and stocks. Based on the TVP-VAR model estimation, our results indicate that each asset's own contribution to its forecast error variance is larger than the contributions from other assets. Then considering the own contributions, we find that these contributions are relatively larger for the stocks than those for the tokens, indicating that the returns on the stocks of football clubs are relatively more determined by the idiosyncratic factors. The majority of the contributions to any token are either from the token itself or from the other three tokens. Tokens are the main transmitter of shocks to both the tokens and stocks. Finally, the total connectedness index is sharply decreasing over time, implying that the spillovers among the examined assets exist up to a much lesser extent in the most recent data.

Our results have some important implications for investment and portfolio management. Football clubs' stocks are considered relatively risky stocks which might be affected by field results as well as transfer news and rumors. Similarly, fan tokens, with highly volatile returns and track of both extremely positive and negative performances, are risky investments. Therefore, low and consistently decreasing connectedness among the two asset classes might provide valuable diversification benefits over time for investors and traders. Further research may investigate the portfolio management aspects in more detail.

This study examines the connectedness between two assets of the same underlying company, and more broadly the spillovers within a system of multiple assets from two classes. We suggest tokens are the net transmitters of shocks to both the tokens and stocks. Thus, future research may inquire

about the connectedness among a large number of fan tokens to shed more light on the spillovers within the tokens. By these means, different token characteristics attributable to the transmissions can be identified. Finally, extending the analysis of two asset classes, future studies may investigate connectedness among fan tokens and other crypto-asset classes such as cryptocurrencies and NFTs; as well as traditional asset such as stocks, gold, and oil.

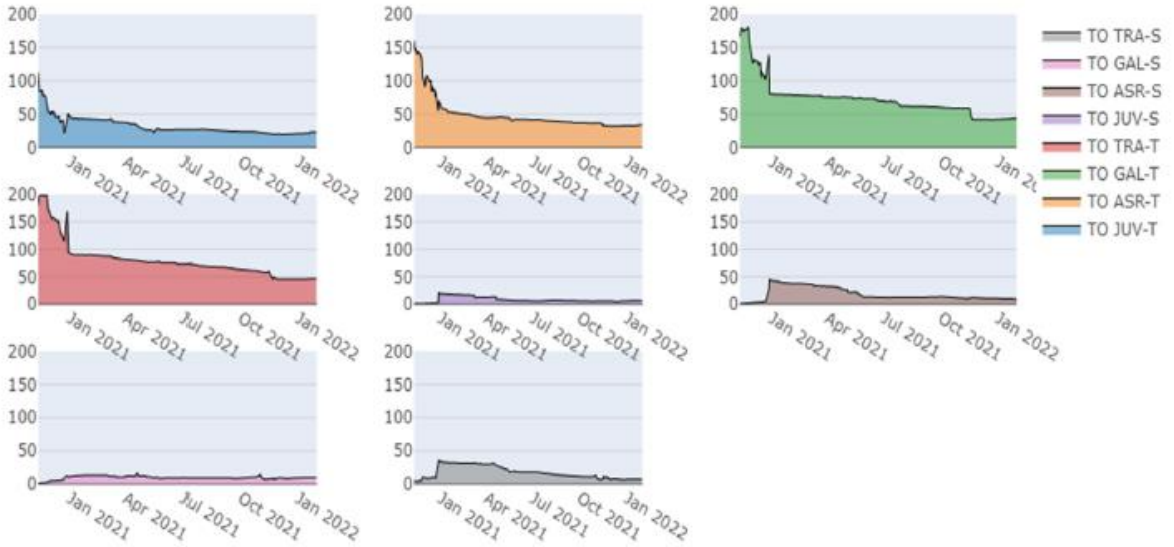

Fig. A1. TO dynamic connectedness index.

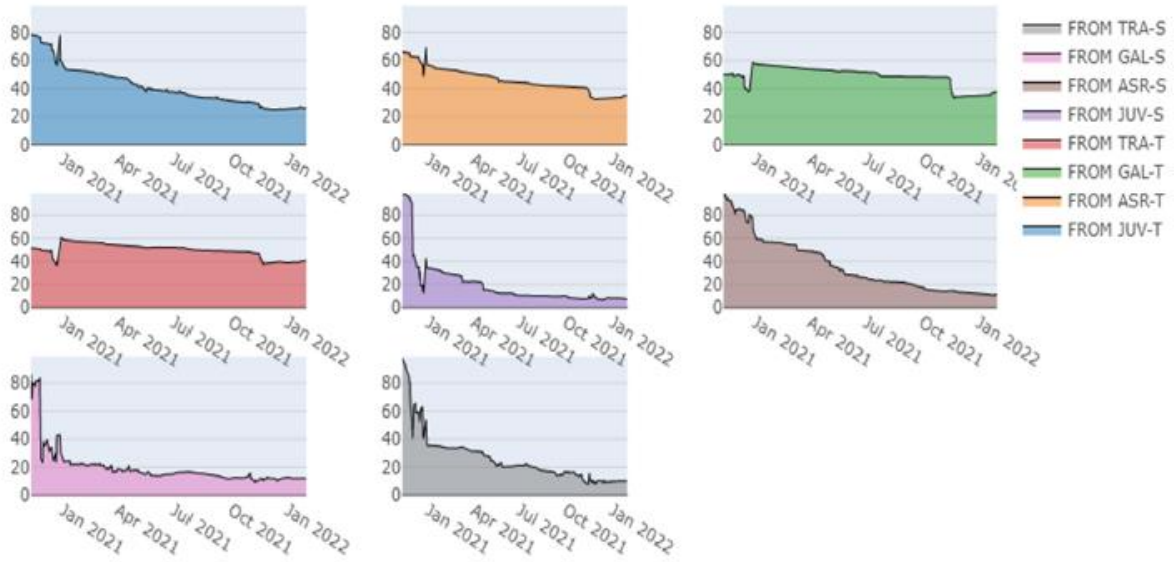

Fig. A2. FROM dynamic connectedness index.

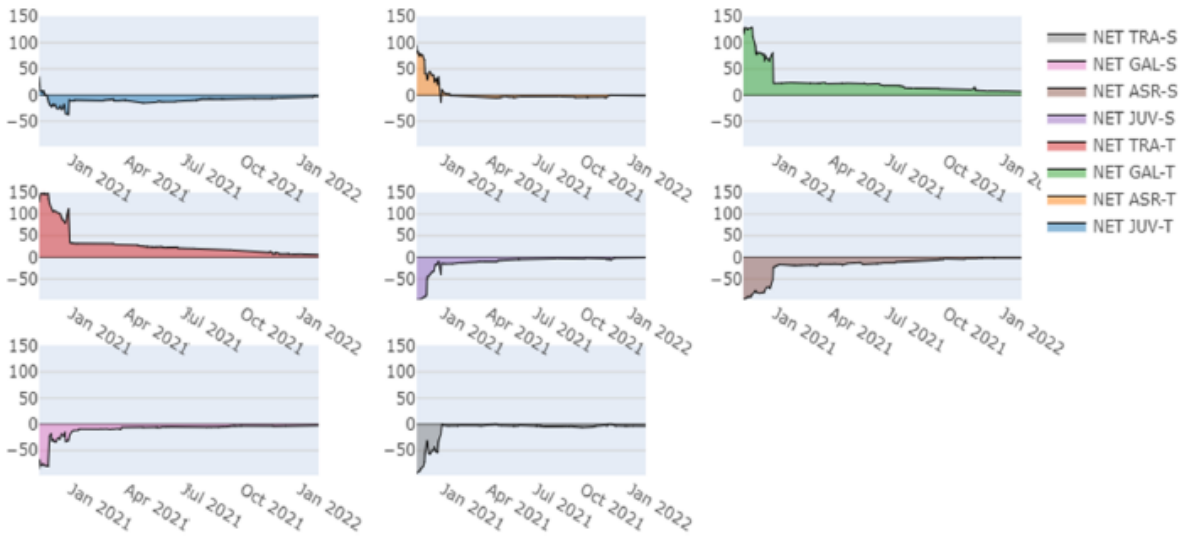

Fig. A3. NET dynamic connectedness index.

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