Enhancing Portfolio Performance with Crypto Tokens: a Correlation Network Analysis

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Abstract—**In this paper, we examine whether crypto tokens can boost portfolio performance and provide direct evidence on the claim that crypto tokens are potentially desirable alternatives for diversification. We use correlation-based networks to study the crypto token market and compare the optimal portfolio composed of tokens with that of tokens and stocks. We find that tokens with high Sharp ratios but low centrality can serve as the booster of portfolio performance. In addition, we discover that the token market resembles the stock market in terms of correlation network structure. The market is dominated by tokens from Defi, blockchain infrastructure, and GameFi sectors, and becomes more correlated during market downturns.**

Keywords—crypto tokens, cryptocurrency, blockchain, tokenomics, token returns, Fintech, complex network, portfolio selection, correlation network

I. Introduction

Crypto tokens ("tokens") are cryptographically protected digital assets on a blockchain, which can record and transmit data in an immutable manner [1]. Their flourishing secondary market and low exposure to traditional asset markets make tokens appealing to investors for diversification. However, although frequently reported by the media[1], the benefits of tokens as alternative assets have scarcely been discussed in academic literature. How can we select tokens and use them to diversify? Why the portfolio with tokens may outperform? Since there are thousands of tokens in the market, we need a strategy to select the best ones for our portfolio. We also need to understand the key features of tokens that improve portfolio performance. In recent years, there has been a growing literature on the correlation network structure in stock markets [2]–[8], but to our knowledge, no works have been done on the correlation network structure in crypto tokens market and its impact on investment decisions and market stability. In this research we aim to provide the first set of evidence on why and how including tokens can enhance portfolio performance using correlation network analysis.

According to the modern portfolio theory [9], investors need to consider both the return and inter-correlation among assets when constructing an optimal portfolio. We can lower the portfolio risk by including assets that are uncorrelated or negatively correlated with each other. To visualize the complex correlation structure among thousands of assets, we use the network theory [3]. With the correlation matrix constructed on the return of assets as the adjacency matrix, we can construct a network where each node represents an asset, and the Pearson correlation coefficients determine the intensity of links between pairs of assets. Because the centrality of an asset in the network aggregates its correlations with all other assets, assets with low centrality would be preferred to reduce portfolio risk. In practice, we prefer assets with low centrality but high Sharp ratios for diversification, as Sharp ratios measure individual assets' performance and centrality contributes to the risk of portfolio [10].

We build the optimal portfolio, or the tangency portfolio, and compare them constructed by different assets. We find that the optimal portfolio with tokens performs better than the one without tokens, and the one with only stocks is the worst. The mixed portfolio performs better over time and more resilient to interest rate hikes. Including tokens enhances the performance of the portfolio, because we can find tokens in low centrality with high Sharp ratios, but not stocks. Investors are therefore encouraged to find tokens peripheral, i.e., with low centrality, in the market for diversification, rather than those with high influence.

Besides, we also find that the correlation network constructed on tokens has similar features with that on stocks. The token market is dominated by tokens from the sectors of Defi, Blockchain Infrastructure, and GameFi, although they are not necessarily the largest sectors in terms of market capitalization. Those three sectors also show a degree of sector clustering. The intensity of correlation across the whole market, which is measured by the largest eigenvalue of the adjacency matrix, increases when the market is bearish and during the COVID-19 pandemic.

Our study contributes to the literature on crypto tokens and portfolio selection as the first one to evaluate the portfolio performance of tokens with correlation networks as an auxiliary, extending the existing research of return and risk solely on some small subsets of crypto tokens, e.g, Non-fungible Tokens (NFTs) [11], [12] and Bitcoin [13].

II. Related Works

A. Crypto Tokens

Cong *et al.* [14] proposed the first asset pricing model for crypto tokens, in which the equilibrium price is determined by aggregated heterogeneous users' demand, rather than the discounted cash flow in standard models, and the productivity of the platform that issues the underlying tokens. One of the most innovative points of their work is that it rationalizes the positive return of tokens. Only when tokens appreciate, holders are willing to forgo return from investing in other financial assets and wait for transaction value the platform could provide. Given a fixed supply of tokens, the growth of user base induced by productivity growth and network effect attracts more users and thus raises demand for tokens, driving up prices. However, the platform also faces costs of using tokens as the transaction medium, so it tries to lower the cost by increasing the velocity of tokens and reducing the number

[1] See the news report on *The Hedge Fund Journal* (https://thehedgefundjournal.com/cryptoassets-as-an-alternative-investment-class-for-cayman-islands-alternative-investment-funds/) as an example.

of tokens in use, which limits the price [15]. In addition, the enhancement of platform productivity is financed by issuing tokens, but high supply of tokens will boost inflation, urging the platform to buy back tokens to support token price [16], because future financing for improving productivity depends on the token price. To sum up, if a platform wants to develop, the baseline is a non-negative return on the corresponding token. Otherwise, holders of the token will incur loss so as to dump the tokens, triggering a price slump and making it hard for the platform to finance for future enhancement of productivity. If the productivity improvement is sluggish, the platform would lose users and thus token price would drop, creating a vicious circle.

In addition to users of the platform, another important group of participants in the token market is speculators [17]–[19]. Mayer [18] noted the relationship between users and speculators, in which speculators drive up prices of tokens, driving down users' returns and thus crowding out users. On the other hand, speculators provide liquidity even in bad times and thus act as a buffer of price, reducing the probability of the vicious circle mentioned. Moreover, the speculative premium transmits to the primary funding market, enhancing the ability of financing for the platform and thus beneficial to investment in productivity [19].

Investment from institutional investors are usually considered a signal of outperformance for tokens[1]. Institutional investors are believed to be able to pick better ventures and boost the ICO quality and post-ICO returns.. However, moral hazard in signaling could also happen, as institutional investors take advantage of dispersed investors by revealing biased signals in the early stage [20]. This moral hazard would finally backfire when dispersed investors find the fraudulence, leading to substantial price drops. Following the theoretical guidance in [14], [16], Lyandres *et al.* [21] found empirical evidence showing the positive relationship between platform adoption and post-ICO token returns. In addition, tokens price also reflect expected future network growth [22]. Momentum and investor attention also strongly help predicting future token returns. Lo and Medda [23] further addressed the impacts of token function, i.e. payment, utility, asset, or yield, on the value and market prices of tokens. The size effects emerge in the long run, in which large ICOs are more likely to be overpriced and underperform in the long run [24]. Liu and Tsyvinski [22] recorded Sharp ratios of the market portfolio of tokens at daily and weekly levels higher than those of stocks, but only comparable at the monthly level. Our work is different from [22] in that we actively allocate tokens in the portfolio rather than using the market portfolio directly, resulting in a portfolio outperforming consistently.

B. *Correlation Network in Asset markets*

As fluctuations of stock prices are not independent, the complex networks constructed using correlations among stock returns are intensively studied by previous works [2]–[8], [25]. Those works constructed asset networks using return data following the initiating work of [2], which uses the Pearson correlation coefficient of returns to weight the link between two assets and finds that companies in similar sectors are clustered in the tree spanned from the resulting network. With the graph of networks, its topological structure and properties could then be studied. Boginski *et al.* [25] found that the degree distribution of the network after filtering correlation according to large thresholds would follow a power law. [26] is the first work constructing a full network of US stocks and gives inclusive information about their correlations. The result shows that a small number of stocks are leading the volatility of stocks across the market and the financial sector is the most central sector in the market. [27] relates to our work the most but only looks at some main cryptocurrencies, like Bitcoin and Ethereum, and focuses on a filtering method using them.

Since correlation plays a crucial role in asset management according to Markowitz portfolio theory [9], a relationship between the network centrality of an asset and its weight in an optimal portfolio is proposed [10], [25], [28], based on which we draw our results.

III. Data and Approaches

A. *Data*

We use two sources of data to analyze the token market: Cryptorank (https://cryptorank.io/) and Cryptocompare (https://www.cryptocompare.com/). Cryptorank provides hourly return data from 2nd Jan. 2023 to 27th Jan. 2023 for a comprehensive profile of the current market. Cryptocompare provides daily return data from 3rd Jan. 2012 to 11th Feb 2023 for a historical correlation network analysis over time. *Cryptocompare* adopts CryptoCompare's real-time aggregate index methodology (CCCAGG) to aggregate prices of one token across different exchanges in a way that illiquid tokens are excluded[2]. Therefore, tokens included in *Cryptocompare* constitute a subset of those on *Cryptorank*. Because *Cryptocompare* excludes tokens by illiquidity and illiquid tokens are rarely traded, our results would not be impaired by this difference.

We also obtained daily return data on constituent stocks of S&P500 from 3rd Jan. 2012 to 11th Feb 2023 for comparison as the benchmark. To this end, we use the 1-Month Treasury Rate as the risk-free rate. Data on stock returns and Treasury Rates are obtained from Wind (https://www.wind.com.cn/).

B. *Correlation Network Construction*

In our model, a network $G = \{N, \omega\}$ includes a set of nodes $N = \{1,2, \dots, n\}$ and a set of links ω which connects pairs of nodes. The network information could also be contained in an $n \times n$ adjacency matrix $\mathbf{\Omega} = [\Omega_{ij}]$, where its element Ω_{ij} represents the intensity of interactions between the nodes. This intensity Ω_{ij} is regarded as the weight of the link $(i, j) \in \omega$. Readers can refer to [29] for detailed information of the network setting. In this paper, we use the correlation matrix derived using tokens' return as the adjacency matrix $\mathbf{\Omega}$ to construct the network. Therefore, weights (Ω_{ij}) on the links $((i, j) \in \omega)$ represent the Pearson correlation between token i and j (node).

We use the eigenvector centrality to measure the centrality of nodes in our correlation network according to [30]. The eigenvector centrality of node i, denoted by v_i, is calculated by:

$$v_i \equiv \lambda^{-1} \sum_j \Omega_{ij} v_j \, , \tag{1}$$

where v_i is also the i^{th} entry of the eigenvector corresponding to the largest eigenvalue, λ. Eigenvector centrality is different from the degree centrality in that it takes the centrality of neighbors into account, so node i could be highly central if it

[2] Readers can refer to the documents of CCCAGG on https://data.cryptocompare.com/reports/cryptocompare-aggregate-index-methodology-2022.

connects to some other highly central ones. In this paper, we normalize the eigenvector so that the components add to 1. As noted by [8], the largest eigenvalue, λ, measures how collective the evolution of the underlying market is, which can be regarded as an indicator of the cross-correlation of the market.

C. Tangency Portpolio Construction

To evaluate the performance of the portfolio constructed by tokens, by the constituent stocks of S&P500 (as the benchmark), and by the mixed portfolio including both tokens and stocks, we construct the tangency portfolio of the three separately according to the modern portfolio theory [9]. The tangency portfolio is the portfolio of risky assets with the highest Sharp ratio. The Sharp ratio measures the return-risk trade-off for an asset or a portfolio ($Sharp = (\mu - r_f)/\sigma$, where μ denotes the expected return, σ the standard deviation, and r_f the risk-free rate), which reflects the performance of a certain asset or portfolio. Denote the weight of risky assets by vector $\mathbf{t}$, while $\mathbf{t}$ solves the constrained maximization problem:

$$\max_{\mathbf{t}} \frac{\mathbf{t}'\boldsymbol{\mu} - r_f}{(\mathbf{t}'\boldsymbol{\Sigma}\mathbf{t})^{\frac{1}{2}}} \text{ s.t. } \mathbf{t}'\mathbf{1} = 1\,, \tag{2}$$

where $\boldsymbol{\mu}$ denotes the vector of expected return, $\boldsymbol{\Sigma}$ the covariance matrix, and r_f the return on risk-free asset. The solution is as follows:

$$\mathbf{t} = \frac{\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - r_f \cdot \mathbf{1})}{\mathbf{1}'\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - r_f \cdot \mathbf{1})}\,. \tag{3}$$

D. Software used

We use Python, with the libraries of Requests [31] for data retrieving, NumPy [32] and Pandas [33] for data handling, matplotlib [34] for plotting, Networkx [35] for network construction, Netwulf [36] for network visualization. To construct the tangency portfolio, we use MATLAB 2020b and Financial Toolbox [37].

TABLE I. NETWORK PARAMETERS

Parameters	Threshold of selection[a]		
	$\Omega_{ij} > 0$	$\Omega_{ij} > 0.5$	$\Omega_{ij} > 0.8$
Panel (a): The Token Market[b]			
Number of nodes (percentage of the full sample)	4772 (100%)	1354 (28%)	346 (7%)
Number of links	11383600	92695	4249
Average normalized centrality (adjusted)[c]	0.9544	1.9088	2.8632
Average weight	0.0656	0.5957	0.8744
Panel (b): S&P500 constituent stocks[d]			
Number of nodes (percentage of the full sample)	503 (100%)	474 (94%)	178 (35%)
Number of links	126253	31585	440
Average normalized centrality (adjusted)[c]	1.0060	1.0060	1.1066
Average weight	0.3958	0.5807	0.8444

a. Since the Pearson Correlation of every pair of tokens (nodes) is non-trivial, every node naturally has the same number of links. To represent the properties of the subnetwork in which tokens are highly correlated, we list the case when only the links with Pearson Correlation (weights) larger than a certain value being retained.

b. Parameters of the correlation network of the token market is estimated using hourly return data from 2nd Jan. 2023 to 27th Jan. 2023.

c. To make the case of token market and S&P500 comparable, we adjust the normalized centrality by multiplying it by the sample size of each case.

d. Parameters of the correlation network of the S&P500 portfolio is estimated using daily return data from 3rd Jan. 2019 to 17th Feb. 2023 to ensure balance of the data.

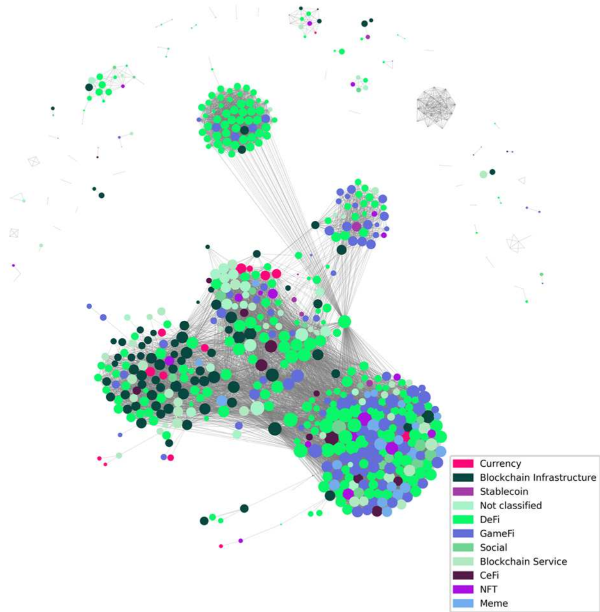


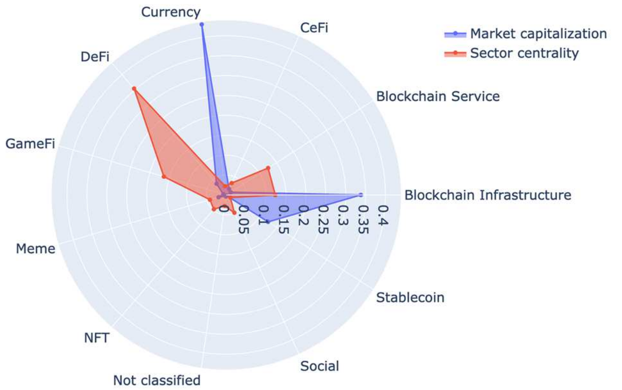
Fig. 1. Correaltion network of the token market. Only the node with the 10000 largest weights on links are shown in this figure. Nodes are colored according to their sector membership. Details of sector classification could be found in https://cryptorank.io/categories.

IV. RESULTS AND ANALYSIS

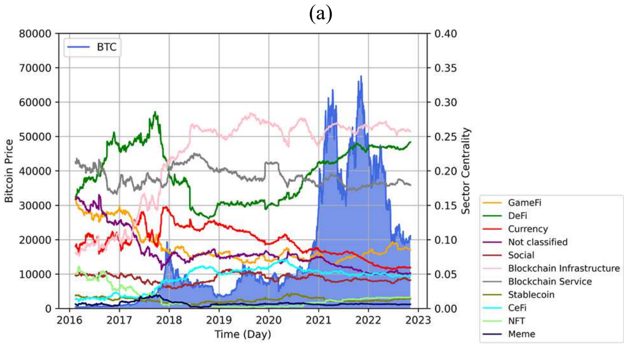
A. Correlation Network and Sector Centrality

Firstly, we construct the correlation network using data from *Cryptorank*. TABLE I. reports the key parameters of the correlation network constructed on *Cryptorank*, as well as parameters of the network constructed using constituent stocks of S&P500 for comparison. Since Pearson correlation could be in negative value while negative weights on links do not have obvious interpretation, we use the absolute value of Pearson correlation as the weights instead, following [38]. According to [26], we report the parameters of the network by screening links according to their weights, their absolute value of correlation. TABLE I. shows that for the whole network ($\Omega_{\mathrm{ij}} > 0$), the average normalized centrality adjusted by the sample size for S&P500 (1.0060) is larger than that for tokens (0.9644), while if we only consider the network with large weights on links ($\Omega_{\mathrm{ij}} > 0.5$ or $\Omega_{\mathrm{ij}} > 0.8$) the average normalized adjusted centrality for tokens is larger than that for S&P500. Moreover, the percentage of nodes with high weights ($\Omega_{\mathrm{ij}} > 0.5$ or $\Omega_{\mathrm{ij}} > 0.8$) on links is far less for tokens (28% or 7%) than that for S&P500 (94% or 35%), suggesting a higher proportion of nodes with small weights on links for tokens. This pattern also holds for centrality, as centrality measures correlation across nodes. Knowing the distribution of centrality is crucial for constructing the optimal portfolio, which would be discussed in later sections.

Fig. 1 displays the correlation network constructed based on the data of tokens from *Cryptorank*. Since the original network is too dense to be drawn, we only display the nodes with the 10000 largest weights on links. In Fig. 1, the network is dominated by nodes in the sector of Defi, Blockchain Infrastructure, and GameFi. Nodes from those three sectors also show a degree of sector clustering, similar to the case of S&P500 stocks noted by [38]. Panel (a) of Fig. 2 depicts the sector centrality as well as the market capitalization for each



(a)



(b)

Fig. 2. (a) Sector centrality and sector market capitalization for tokens. (b) Sector centrality overtime for tokens. Panel (a) is drawn using data from *Cryptorank*, while panel (b) is drawn using data from 14th Feb. 2016 to 11st Feb. 2023 on *Cryptocompare*. We divide the dataset into 2455 of 100-days long rolling windows with 1-day displacement steps. Details of sector classification could be found in https://cryptorank.io/categories.

sector. We firstly normalize the centrality for each token and then sum them by sectors to get sector centrality. It is shown that Defi is the most central sector, though its market capitalization is not the largest. There is also a lack of positive correlation between market capitalization and centrality in other sectors. This feature resembles the case of the stock market [10], [26], [39], [40], in which the financial sector is the most centralized but not the largest in terms of market capitalization. To show how sector centrality changes over time, panel (b) of Fig. 2 plots the rolling window results. Blockchain Infrastructure, Defi, and Blockchain Service are consistently the leading sectors in centrality over time[3].

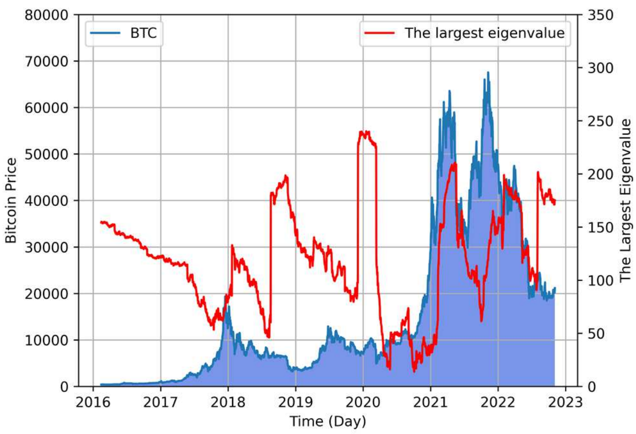


Fig. 3. The largest eigenvalue of the correlation network on tokens overtime. We divide the dataset into 2455 of 100-days long rolling windows with 1-day displacement steps.

[3] Details of sector classification could be found in https://cryptorank.io/categories. Tokens issued by one platform could be classified into different sectors if they have different functions.

TABLE II. DESCRIPTIVE STATISTICS

Parameters		Sample		
		S&P500	*Cryptorank*	*Cryptocompare*
Number of tokens (stocks)		503	4772	1441
R_m[a]	Mean	0.0006	0.0002	-0.0016
	Std	0.0115	0.0027	0.0504
	Sharp ratio	0.0426	0.0335	-0.0296
	ADF[b]	-13.7218***	-20.7417***	-10.8263***

a. R_m denotes the series of average daily market return, and we report three statistics of it.
b. *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.

We use the rolling window to plot the largest eigenvalue of the correlation matrix over time. Fig. 3 depicts the largest eigenvalue over time as well as the price of Bitcoin, which can reflect the market condition of tokens. It is shown that the largest eigenvalue increases (red line) when the bitcoin price (blue line) plunges, indicating the crash of the token market. Except during the market crash, the largest eigenvalue noticeably picks up at the beginning of 2020 when COVID-19 broke out. The change in the largest eigenvalue shows that the token market tends to be more correlated during bearish time than that during bullish time. This finding is consistent with the findings in the stock market, in which the largest eigenvalue reached its maximum during the financial crisis of 2008/2009 [38].

B. Optimal Portfolio Weights and Asset Centralities

Previous literature on optimal portfolio and asset centrality shows that assets with low centrality should be assigned higher weights or that assets at the peripheries of the network are preferred [28]. In addition to centrality, Peralta *et al.* [10] emphasized the performance of individual assets measured by their own Sharp ratios, should be considered in selecting assets. While individual assets with high Sharp ratios improve portfolio performance, large centrality raises the risk of the portfolio. Therefore, assets with high Sharp ratios and low level of centrality should be assigned with high weight in an optimal portfolio.

On average, S&P500 outperforms tokens in both market return and Sharp ratio as shown in TABLE II. However, the optimal portfolio on tokens could outperform that on S&P500. As centrality and Sharp ratio of individual assets play a crucial role in asset allocation, we can have a glance of the relationship between the Sharp ratios and centrality among individual assets using the following specification:

$$Centrality_i = \beta_0 + \beta_1 Sharp_i + \varepsilon_i, \quad (4)$$

where i denotes individual asset i. TABLE III reports the estimation results of (4), and the negative estimated β_1 (-0.0023) indicates a negative relationship between centrality and individual asset's Sharp ratio for tokens, but a positive relationship for S&P500 constituent stocks is shown

TABLE III. REGRESSION RESULTS

Dependent Variable	Estimated Coefficient[a]		
	β_0	β_1	R^2
Panel (a):The Token Market			
Centrality	0.0009*** (39.80)[b]	-0.0023*** (-4.96)	0.0230
Panel (b): S&P500			
Centrality	0.0020*** (78.23)	0.0013** (1.76)	0.0062

a. This table reports estimation results based on (4).
b. In the parentheses is the t-statistics.
c. *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.

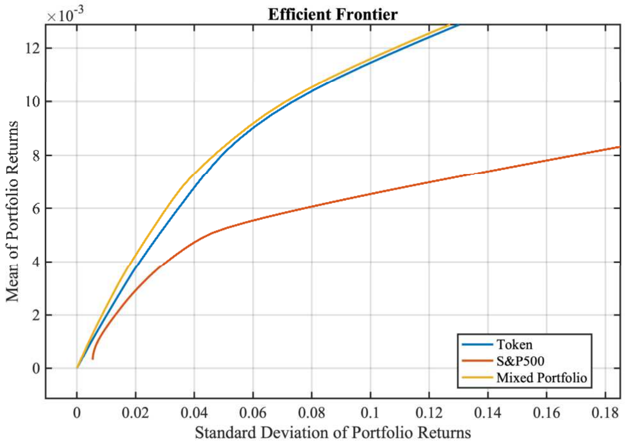


Fig. 4. Efficiet frontiers of the portfolios. The blue curve presents the effienct frontier formed by tokens, the red one presents that by S&P500 constituent stocks, and the yellow one presents that by the mixed portfolio including both tokens and S&P500 constituent stocks.

by the positive estimated β_1 (0.0013). Tokens with low centrality averagely have higher sharp ratios than those with high centrality, and thus we can find tokens with both low centrality and high Sharp ratios. In contrast, there is always a trade-off between performance and centrality for S&P500 constituent stocks. Therefore, this pattern gives us a chance to build a portfolio with tokens not only in low centrality but also with high Sharp ratios, outperforming the portfolio by S&P500 constituent stocks.

C. *Portfolio Construction and Performance Evaluation*

Following Markowitz [9], investors wish to find portfolios with the best return-risk trade-off, so they should choose their portfolio from the efficient frontier. Fig. 4 illustrates three efficient frontiers constructed by tokens, S&P500 constituent stocks, and their mixed portfolio. The efficient frontier of the portfolio on S&P500 is inside that on tokens, which in turn is included by the efficient frontier of the mixed portfolio. Therefore, the mixed portfolio gives the best return-risk ratio, followed by efficient portfolios by tokens, while portfolios by S&P500 performs the worst.

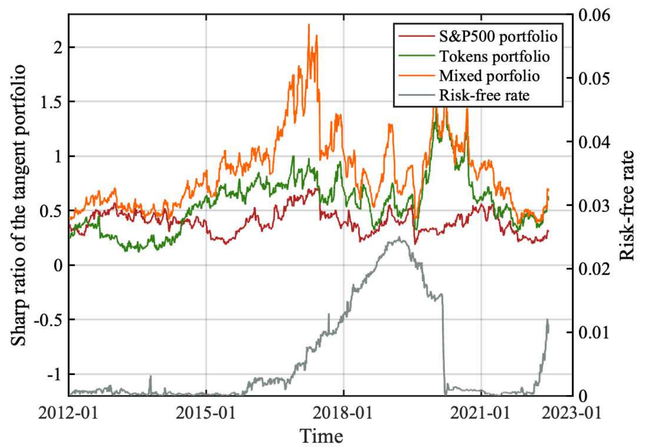


Fig. 5. Sharp ratio of the tangency portfolio overtime. To make the data consistent, we retain data of tokens only on trading days of the stock market and then there are 2626 trading days in our sample. We divide the dataset into 2496 of 150-days long rolling windows with 1-day displacement steps to draw this figure. The Federal Reserve started to raise interest rate from 2016 (https://money.cnn.com/2016/12/14/news/economy/federal-reserve-rate-hike-december/), indicated by the increasing gray line from 2016.

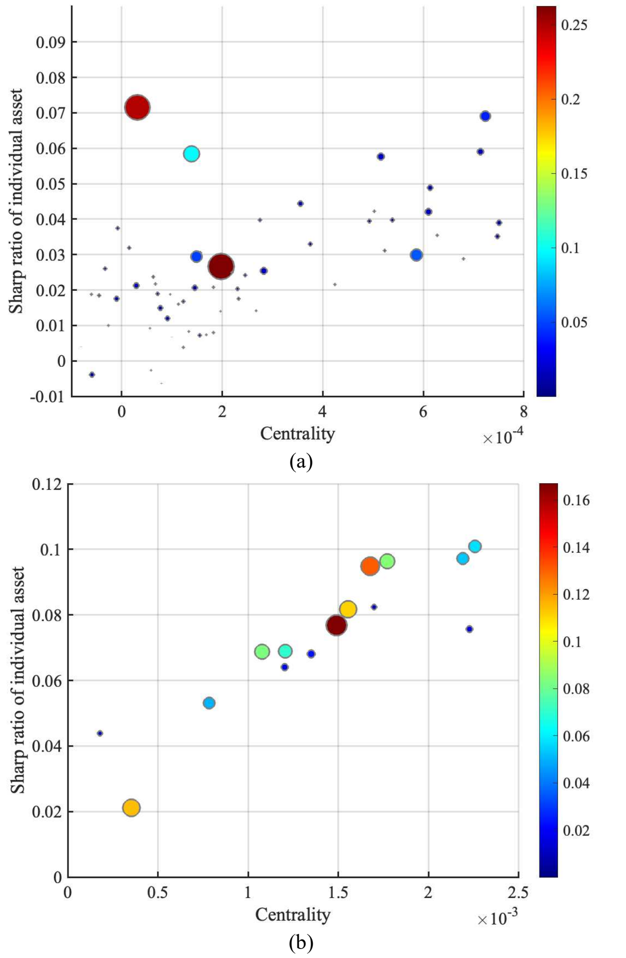


Fig. 6. Relationship among Sharp ratio, asset centrality, and weight in tangency portfolio. Panel (a) depicts the case for tokens, while Panel (b) the case for S&P500 consituent stocks. Assets in both panels correspond to bubbles whose size and colors reflect their weights in the tangency portfolio.

Since the tangency portfolio on the efficient frontier, calculated by (3), has the highest Sharp ratio, we depict the Sharp ratio of the tangency portfolios constructed by tokens, S&P500 constituent stocks, and their mixture overtime to evaluate their performance through time in Fig. 5. It is shown that after 2014, the Sharp ratio of the tangency portfolio by tokens is always higher than that by S&P500, and the Sharp ratio of the mixed portfolio is consistently larger than both of the other two portfolios in our whole sample period. The superiority of the mixed portfolio becomes even more prominent when Federal Reserve started to raise interest rates in 2016. This outperformance of the mixed portfolio comes from using tokens for diversification, benefited from the low exposure of tokens to stocks [22].

The relationship between individual assets' Sharp ratios and centrality sheds light on the superiority of the performance of the optimal portfolio by tokens. Fig. 6 presents scatter plots of Sharp ratio and centrality as well as the weight in the tangency portfolio. As shown in Panel (a) of Fig. 6, there exist tokens with both low centralities and high Sharp ratios, which are given high weights (indicated by large size and hotter color) in the tangency portfolio. However, no stocks have such features. As in Panel (b) of Fig. 6, S&P500 stocks are of high Sharp ratio only when with high centrality, substantiating our conclusion in the last section.

Our results rationalize the inclusion of tokens into portfolio formation for investors. As there are tokens at the peripheries of the correlation network (in low centrality) with high Sharp ratios, portfolios on those assets could achieve better performance than S&P500 stocks.

V. Conclusion

In this paper, we construct a correlation-based network on the crypto token market and analysis how the property of centrality relates to the superiority in optimal portfolio performance for tokens. Our study is the first to show the benefit of including tokens for diversification, evidenced by that tokens with low centrality but with high Sharp ratios boost the performance of portfolios.

One limitation of our study is that we only consider S&P500 in our analysis, future works may consider stocks in other stock markets.

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