Dependence Structure between NFTs and Cryptocurrency; Evidence from Copula Approach

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Abstract

This paper investigates the dependence structure between the crypto coins and the NFTs. We have taken data of 5 years from 2017 to 2022 and used crypto currency (Bitcoin, Ethereum & BNB). Through an analysis of price formation from the prices of various cryptocurrencies, the study offers fascinating insights into the possibility of NFT price prediction. The paper identifies the nature and strength of the dependence structure between NFTs and cryptocurrencies, revealing they exhibit positive dependence. Our findings reveal a positive dependence between NFTs and major cryptocurrencies (Bitcoin, Ethereum, and BNB), though with weak correlations. This suggests that while there is some level of interconnection, the dynamics of NFT markets may not directly mirror the movements of cryptocurrencies. However, the weak dependence still opens avenues for diversification in portfolios that contain both assets. Investors who are heavily exposed to the volatility of cryptocurrencies may consider NFTs as an alternative or complementary asset, especially given the potential for price prediction models based on cryptocurrency price movements.

Key Words: Cryptocurrency, NFT, Copula

Introduction

The market has transformed into a intricate network of various interconnected instruments, including cryptocurrencies, fungible tokens, and non-fungible tokens (NFTs). With daily volumes surpassing 60 billion USD, their significance in the investment strategies of many individuals is undeniable (Fakhfekh et al., 2024). Furthermore, Non-fungible tokens (NFTs) have become very popular with investors, legislators, and the general public after a Christie's auction house in 2021 sold one for $69.3 million, these tokens are basically a blockchain-enabled pure digital asset (Urom et al., 2022). NFT is distinct from traditional cryptocurrencies like Bitcoin due to its inherent characteristics. Bitcoin is a standard coin, meaning that each coin is identical to every other one. On the other hand, NFT is non-fungible (i.e., unique and cannot be traded like for like), which makes it appropriate for uniquely identifying an object or someone (Wang et al, 2021).

NFTs have attracted a great deal of interest from the scientific and industrial worlds in recent years. According to reports, the NFT market has an average 24-hour trading volume of 4, 592,146,914 USD, whereas the total cryptocurrency market has an average 24-hour trading volume of 341,017,001,809 USD. In such a short time, the liquidity of NFT-related solutions has accounted for 1.3% of the total cryptocurrency market. Early investors sell exclusive digital items and make a thousand times their investment back. In addition to the information above, people have shown interest in a variety of NFT kinds. This includes Gaming NFTs, Art NFTs, Music NFTs, Collectibles, Virtual Land, Memes etc. All of this information shows huge potential in NFTs for future business opportunities. It has emerged as a separate class where the investors may get the opportunity to diversity within the crypto market, which was earlier limited to the diversification is the Bitcoin and Alt coins (Alt Coins refer to the coins with small volume, other than the major coins). When the argument of diversification in the same market is established, the empirical testing opportunities for the researchers emerge. Therefore, the objective of the underlying study is to check the dependence structure between the crypto coins and the NFTs.

Ante (2022) studied the relationship between the NFTs and the Bitcoin. For this purpose, the researchers obtain the daily data and tested the hypothesis. The findings of the study reveal that a spike in NFT sales is caused by a shock to the price of bitcoin. Additionally, ether price shocks decrease the quantity of NFT wallets in use. The findings also demonstrate that there is no negative correlation between the expansion and development of the (smaller) NFT sector and the size of cryptocurrency marketplaces. According to Katsiampa (2019), there are a lot of interdependencies among the various cryptocurrencies.

The impact of spillover between Bitcoin and other asset classes (bonds, stocks, commodities, and currency) was examined by Bouri et al. (2018). They found that Bitcoin is typically a receiver rather than a transmitter of volatility spillover. According to Wang et al. (2019), there is no correlation between Bitcoin and the unpredictability of economic policy. Moreover, Corbet et al. (2018) and Aslanidis et al. (2019) found that cryptocurrencies are generally separate from traditional assets like stocks, bonds, or gold, although they show similar average correlations with each other. Koutmos (2018) discovered a two-way relationship between Bitcoin returns and transaction activity, while Giudici and Abu-Hashish (2019) observed a strong correlation in Bitcoin prices across different exchanges. More recently, Aslanidis et al. (2022) showed that cryptocurrency returns and volatilities are not connected to broad uncertainty measures (like those from Google Trends), but instead to more market-specific uncertainty indicators. Overall, the literature agrees that cryptocurrencies are correlated with each other but do not move in sync with other financial assets.

The role of cryptocurrencies as a safe haven is also debated. Bouri et al. (2017) found that Bitcoin is not an effective hedge, but rather works better for diversification. On the other hand, Urquhart and Zhang (2020) suggested that Bitcoin could serve as an intraday hedge against certain fiat currencies, while acting as a diversifier for others.

This study broadens the scope of the substantial research on crypto-market linkages, which contributes to the body of literature. By examining how tokens and cryptocurrencies with new digital currencies (NFTs) are combined in a portfolio and determining whether or not such a dependent structure could provide extra benefits for diversification. In times of economic turbulence, it advances the research of safe-haven characteristics and diversification between established and emerging cryptocurrencies. That offers a detailed examination of the possible effects of geopolitical risk (and the associated economic unpredictability) on the connection of cryptocurrencies, both new and old. The article provides intriguing insights into the potential for NFT price prediction by examining price formation from the prices of other cryptocurrencies.

Data and Methodology

We have taken data of 5 years from 2017 to 2022. The period chosen for the purpose of the underlying study represents critical phase in cryptocurrency market evolution and also takes into account significant market developments such as covid-19 pandemic. The data availability for NFT indices is also a major reason behind the selection of this period. We used crypto currency (Bitcoin, Ethereum & BNB) the data is provided by Yahoo Finance (Details mentioned in Appendix A). Copula technique has used for dependence structure of variables. The underlying study is quantitative and secondary data has used in it.

In order to find out the dependence structure of the NFT and Cryptocurrency following indices (Mentioned in Appendix A) and time-period is used. The data on NFT index was obtained from investing.com. The data was sorted in excel before importing in the R software for the purpose of analysis. Returns were calculated using the following formula.

Returns = ln (current price/previous price)

Copula method is used to check the dependence structure in R software. The bivariate copula technique uses five copula families which are as follows to identify the dependence structure. According to Hsu et al (2012) it is the most effective method of handling the corrections between the markets, copula models due to the parameters used in this model allow handling of the market correlation at greater flexibility. The underlying study also intends to examine the correlations between the series therefore Copula method is used for the purpose of this study.

Currencies name	Market capitalization
Bitcoin	$329.98B
Ethereum	$156.99B
BNB	$5.53B

Table 1 Currencies and Market Capitalization

Variable Name	Data Source	Reference
NFT	Coin market cap	By Emanuel Scicluna (2022)
Cryptocurrencies (Bitcoin,Ethereum , BNB)	Coinmarketcap Finance yahoo	Ante,2021

Table 2 Variable and Data Source

S. No.	Indices	Time Span
1.	NFT	30 June 2017 to 3 June 2022
2.	BNB	30 June 2017 to 3 June 2022
3.	ETH	30 June 2017 to 3 June 2022
4.	BTC	30 June 2017 to 3 June 2022

Table 3 Time Period of the Study

(i) Gaussian Copula

Nominal marginal disseminations are linked with Gaussian copula to create a multivariate nominal distribution, which conveys the dependence pattern of the multivariate nominal distribution (Shafique et al., 2021). The likelihood fundamental change from a typical multivariate appropriation is used to compute the Gaussian copula, which is a unit cube distribution (Raza et al., 2021). The following is how it can be expressed mathematically:

$$C^{Gauss}(w) = \sigma R \sigma^{-1}(w_1) \dots \dots \dots \dots . \sigma^{-1}(w_b)$$

(ii) Student-t Copula

The opportunity level is less than 30, and the student-t copula discusses the straight coefficient of association. The student-t copula has more tails than the Gumbel copula. The reliance between arbitrary variables on the two tails is depicted in the student-t copula work (Raza et al., 2021). Moreover, in the event where the student-t copula fits the data more accurately than the Gaussian copula and the former does not, the latter accurately represents the reliance inside the tails (Shafique et al., 2021). Student-t copula can be represented mathematically as follows:

$$C_{(w,x)} = \int_{-\infty}^{\sigma-1(w)} \int_{-\infty}^{\sigma-1(w)} \frac{1}{2\pi . \sqrt{1-\gamma^2}} \frac{a^2 - 2\gamma ab + b^2}{\{-2(1-\gamma^2)\}\, da. db}$$

(iii) **Gumbel copulas**

Clayton's produced Gumbel copula. An unbalanced Archimedean copula, the Gumbel copula exhibits a greater reliance on the negative tail than the positive tail. (Raza and others, 2021). Gumbel copula in mathematics can be represented as,

$$C_b(w, x, \gamma) = exp\{-(-1\ k\ w)^2 + [(-1\ k\ x)\gamma\ ]\}, \gamma \varepsilon (1, \infty)$$

The Gumbel copula indicates that two irregular components have a high likelihood of having simultaneous increases in their distributions (Shafique et al. 2021).

(iv) **Clayton Copulas**

The Clayton copula, suggested by Clayton, is shown as an asymmetric Archimedean copula. In general, the tail reliance of the clayton copula is on the positive tail instead of the negative tail (Raza et al., (2021). Clayton copula can be represented mathematically as,

$$C_b(w,x,\gamma) = \left\{[(w^{-\gamma} + x^{-\gamma} - 1)\frac{-1}{\gamma}, 0]\right\}, \gamma\ \varepsilon\ \{-1, \infty\}\ (0)$$

(v) Frank Copulas

The interchangeable copula, or transparent copula, is a copula that illustrates the codependency of arbitrary elements. The following is the numerical structure of a frank copula:

$$C_{\varphi}^{Qs}(w_1 \ldots \ldots \ldots w_n) = \frac{1}{-\varphi}\frac{\Pi_l(exp\ exp\ (-\varphi w_1)\ -1)}{log\ log\ (1 + exp\ exp\ (-\varphi)\ -1)}$$

If we proceed with the = 0 then the cutoff is applied for copula association. The reliance structure spanning from low to higher dependence, which can be on lower or upper tail or positive or negative tail dependence, is captured by all of the aforementioned copula capacities.

Spearman's correlation and Kendell tau's

A correlation analysis is a type of analysis that measures the strength and direction of the relationship between variables. The power can be in the range of +1 and -1. When the value is near +1, there is a perfect positive relationship between the variables; on the other hand, when the value is near -1, there is a perfect negative relationship. In this study, the relationship between the variables is measured using the Kendal tau correlation test, which is considered a non-parametric test that is used to determine the degree of the relationship among the variables, while the spearman rank correlation test is used to determine the strength of the relationship between the variables.

	BTC	ETH	BNB	NFT
Min	-0.169947	-0.3269	-0.41654	-132.911
1st quartile	-0.018583	-0.02519	-0.02	-1.21352
Median	-0.001366	-0.00084	-0.0002091	-0.06706
Mean	-0.001754	-0.000971	-0.0008491	-2.85709

3rd Quartile	0.01701	0.0271078	0.0218869	0.04256
Max	0.136196	0.230077	0.2769005	35.83293
SD	0.036943	0.05019	0.0489287	16.59126
Skewness	-0.434	-0.507719	-5.258606	-5.258

Table 4 Descriptive Statistics

Table 4 presents the full descriptive statistics for the NFT, BNB, ETH and BTC. Descriptive statistics include two indicators: central tendency and variability. A measure of central tendency includes the mean and median. A measure of variability includes minimum, maximum, standard deviation and skewness. The variability of returns is shown by the maximum and minimum values that per day, how many minimum and maximum returns these instruments can offer. Standard deviation measures the risk of the NFT, BNB, ETH and BTC stock markets. The PSX is riskier than the other series as it has the highest standard deviation of 2.818%. The standard deviation of the Shanghai composite is 1.101%, indicating the lowest risk.

	BTC	**ETH**	**BNB**	**NFT**
BTC	1	nil	nil	-0.00479
ETH	nil	1	nil	-0.02421
BNB	nil	nil	1	-0.03162
NFT	-0.00479	-0.02421	-0.03162	1

Table 5 Kendall Tau

Table 5 presents the result of Kendell's tau correlation which shows that the correlation between these variables (NFT, BNB, ETH and BTC) is extremely weak, which also supports our conclusion by the copula method. Through the above discussion, this study can conclude that the relationship between the NFT, BNB, ETH and BTC is weak and there is a dependence structure between them.

	Initial Parameter	**Final Parameter**	**Logliklihood**	**AIC**	**BIC**	**lower**	**upper**
						Tail Dependence	
Gaussian	0.032013	-0.01696	0.0855946	1.82881	6.25368	0	0
T-student	NA	-0.0181	-0.254877	4.50975	13.3595	0	1.10E-29
Gumbel	0.9763602	NA	NA	NA	NA	NA	NA

Clayton	-0.04727957	-0.04728	0.795054	0.40989	4.83476	0	0
Frank	NA	-0.2243	0.455027	1.08995	5.51482	0	0

Table 6 BTC and NFT

Table 6 estimates the initial and final copula parameters, log-likelihood, Alike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the tail dependence between the BTC and NFT. The copula with the lowest AIC is chosen in order to quantify the dependence structure between the clean energy sector and the Chinese stock market. According to Table 5, the T-Student copula has the lowest AIC value of 1.934039, making it the best-fitting copula. The long tail of the dependent pattern is measured by the T-Student copula. The t-Student copula's 0.08212 degrees of freedom reveal the fat tail dependence between the two return series.

	Initial Parameter	Final Parameter	Logliklihood	AIC	BIC
Gaussian	0.02896723	0.002905	0.00251	1.99498	6.4198
T-student	0.02896723	0.08191454	-0.3885074	4.77015	13.627
Gumbel	0.9952289	NA	NA	NA	NA
Clayton	-0.00954229	-0.0095423	0.2610868	1.477826	5.9027
Frank	NA	-0.06005	0.03298055	1.934039	6.3589

Table 7 ETH and NFT

Table 7 gives estimates of the initial and final copula parameters, log-likelihood, Bayesian information, Alike Information Criterion (AIC), and other parameters. Criteria (BIC), in addition to the tail reliance of the NFT and ETH. Given that t-student has a minimum AIC value of 4.50975, the table indicates that it is the best fitting copula to quantify reliance on ETH and NFT. The findings show that the dependence's upper and lower tails are equal, indicating that NFT and ETH returns occur at the same frequency. The t-Student correlation's degree of freedom value of 0 indicates a substantial association between NFT and ETH.

	Initial Parameter	Final Parameter	Logliklihood	AIC	BIC	lower	upper
						Tail Dependence	
Gaussian	0.004274991	-0.04004	0.4773899	1.04522	5.47009	0	0
T-student	Na	0.004274991	0.06820112	3.863598	12.7133	8.20E-29	8.25E-29
Gumbel	0.9693477	Na	Na	Na	Na	Na	Na
Clayton	-0.0613046	-0.0613	2.128049	-2.256098	2.16877	0	0
Frank	Na	-0.2764	0.7038761	0.5922477	5.01712	0	0

Table 8 BNB and NFT

Table 8 gives estimates of the tail dependence between the NFT and BNB, as well as the initial and final copula parameters, log-likelihood, Alike Information Criterion (AIC), and Bayesian Information Criterion (BIC). With a minimum AIC value of 3.863598, it demonstrates that the t-student copula is the best fitted copula to measure reliance on BNB and NFT. The results show that the dependence's upper and lower tails are similar, indicating that the NFT and BNB returns have the same frequency. The t-Student correlation's degree of freedom value of 0.00 indicates a strong association between NFT and BNB.

Conclusion

NFTs, or unique digital assets, stand in for ownership of a particular object or work of content, including music, art, collectibles, and more. Like cryptocurrency, each NFT is distinct and cannot be traded in for another of the same kind. Cryptography is a sort of digital money that is used to restrict the generation of new units and safeguard transactions. Cryptocurrencies are fungible, meaning each unit is interchangeable with another unit of the same value. The analysis shows that the markets for NFT, BNB, ETH, and BTC have a weak dependence structure and linkage. Copula modeling and Kendall's Tau correlation both corroborate this. Although the correlations between the returns series are weak, the copula analysis indicates fat tail dependence between them, indicating significant linkages. The model that best fits the relationships between these variables is the T-Student copula, which consistently produces the lowest AIC values in various pairs. Overall, this indicates that each market functions somewhat independently of the others and that, although there may be some interdependencies between NFT, BNB, ETH, and BTC, they are not very strong.

In conclusion, NFTs and cryptocurrencies serve different purposes, with NFTs focused on digital ownership and uniqueness, while cryptocurrencies are focused on providing a decentralized, secure and interchangeable medium of exchange. The results of this study are helpful for investors and better understand how stock markets in different countries move, which in turn helps them in taking investment decisions and develop better risk management and risk quantification models. The research's objective is accomplished by using the daily returns the copula family is used in this work to quantify the dependent structure. The tail dependency in this study is assessed using the Gaussian, student-t, and Gumbel, Clayton, and Frank copulas. The model with the lowest AIC is chosen as the best-fitting model for the copula family. Due to the asymmetry of the data, the student-t copula is selected as the best-fitting model for all pairs of data series. The student-t copula also shows the normal upper and lower tail marginal behaviour of series. The small range of time used in this study makes it impossible effortlessly to conclude about the potential of NFTs and traditional cryptocurrencies. The forthcoming part of our research will try to widen the sample that follows both directions so as to gain a deeper understanding of the type of correlation existing between the assets.

Appendix A: Indices and Variables Details

Indices

S. No.	Indices	Time Span
•	NFT	30 June 2017 to 3 June 2022
•	BNB	30 June 2017 to 3 June 2022
•	ETH	30 June 2017 to 3 June 2022
•	BTC	30 June 2017 to 3 June 2022

Cryptocurrencies with their Market Capitalization

Currencies name	Market capitalization
Bitcoin	$329.98B
Ethereum	$156.99B
BNB	$5.53B

Variables

Variable Name	Data Source	Reference
NFT	Coin market cap	By Emanuel scicluna(2022)
Cryptocurrencies (Bitcoin,Ethereum, BNB)	CoinmarketcapFinance yahoo	Ante,2021

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