Dynamic dependence and predictability between volume and return of Non-Fungible Tokens (NFTs)

The roles of market factors and geopolitical risks

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Dynamic dependence and predictability between volume and return of Non-Fungible Tokens (NFTs): The roles of market factors and geopolitical risks

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ABSTRACT

We examine the dependence between volume and returns for the NFT market and three sub-markets (Cryptokitties, Cryptopunks, and Decentraland) using both quantile cross-spectral coherency and quantile regression techniques. Results from both techniques show significant evidence of dependence between NFT return and volume. Dependence between volume and return is weakest in the Cryptopunks market. Similarly, quantile regression results show that during extreme market conditions, equity and gold markets uncertainty, business condition and term-spread are important predictors of Cryptokitties returns, while oil, equity and gold markets uncertainty and geopolitical risks significantly predict Cryptopunks and Decentraland markets returns. In all cases, increase in Bitcoin prices reduces NFT market returns.

1. Introduction

Following an auction by Christie's auction house in 2021 that sold a non-fungible token (NFT) for $69.3 million, NFT has gained significant prominence among investors, policymakers, and the general public. Descriptively, an NFT is a pure digital asset that is blockchain-enabled. Unlike classical cryptocurrencies like Bitcoin that are fungible and interchangeable, NFTs are unique and "nonfungible" and therefore cannot be exchanged like-for-like (Wang et al., 2021; Wilson et al., 2021; Dowling, 2022b). Indeed, some scholars argue that NFT is one of the most nascent revolutionary digital assets, in terms of its market trends, trade networks and the opportunity it presents (Malhotra et al., 2021; Chohan and Paschen, 2021; Nadini et al., 2021; Wang et al., 2021). Aharon and Demir (2021), for instance, note that NFT sales volume across multiple blockchains reached almost 2.5 billion dollars in the first half of 2021, while the sales volume was only around 95 million dollars in 2020.

The emergence of NFTs has yet provided market participants an alternative investment option. As an investment option, they have the added advantage of being easily transferable and tradable. They also provide an instant proof of authenticity and provenance, which eliminates counterfeit and improves market efficiency. In addition to this, they have higher returns than traditional financial assets (Kong and Lin, 2021) and provide diversification and hedging roles to conventional assets (Yousaf and Yarovaya, 2022; Ko et al., 2022; Urom et al., 2022). However, they also have challenges with the most pronounced being that they are illiquid, speculative and extremely volatile investments. A large part of this is because NFTs are still in their early stages and their value is on the presumption the token will be used in the future for something. Moreover, unlike other speculative investments, the NFTs are also not backed by commodities.

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The foregoing has led to an incipient literature on NFTs. To date, scholars contributing to this literature has predominantly focused on questions regarding the pricing behavior, risks–return characteristics, and diversification roles of NFTs (Ante, 2021; Aharon and Demir, 2021; Maouchi et al., 2021; Corbet et al., 2021; Kong and Lin, 2021; Dowling, 2022a; Karim et al., 2022; Umar et al., 2022; Dowling, 2022b). For instance, Dowling (2022a) shows that NFTs price series are characterized by inefficiency and a steady rise in value. Ante (2021) shows that Bitcoin and Ethereum prices affect the NFT market, although the NFT market does not affect cryptocurrencies. Similarly, Dowling (2022b) shows that NFT pricing relates to cryptocurrency market pricing. Karim et al. (2022) study the diversification role of NFTs and found that they offer greater diversification avenues with substantial risk-bearing potential among other blockchain markets. Aharon and Demir (2021) analyzed the return connectedness between NFTs and other financial assets (equities, gold, cryptocurrencies, currencies, oil, and bonds). Results from their static analysis showed that the majority of NFTs returns are attributable to endogenous shocks, whilst the dynamic analysis results showed that NFTs act as transmitters (absorbers) of systemic risk to some degree during normal (stressful) times.

In this paper, we contribute to this evolving literature on NFTs by examining the dependence structure between NFTs returns and its trade volume, across market conditions and investment horizons. Our analysis focuses on both the entire NFT market and three NFT sub-markets: Decentraland, CryptoKitties and Cryptopunks. To our best knowledge, whereas the dependence between return and volume has been studied for conventional cryptocurrencies (e.g. Balcilar et al., 2017; Aalborg et al., 2019; Bouri et al., 2019; Hau et al., 2021), there is no similar study for NFTs. As noted earlier, NFTs differ fundamentally from conventional cryptocurrencies due to their innate feature of being non-fungible. Extant studies also suggest the NFTs market behaves differently from conventional cryptocurrencies (Corbet et al., 2021; Maouchi et al., 2021). Hence, knowledge gained from studies focused on conventional cryptocurrencies cannot be easily generalized to NFT. The objective of the current paper is, therefore, to fill the above identified gap. The need for such analysis draws from the rising importance of NFTs as a financial asset, and the consequent need to understand its return–risk characteristics as well as the adequate trading strategies to reap the gains thereof. We pay particular attention to trade volume following several theories such as the sequential information arrival hypothesis (e.g. Copeland, 1976), asymmetry in the information endowment (e.g. Llorente et al., 2002), and information precision (e.g. Schneider, 2009) that highlight return predictability from volume.

To address our research objective, we employ the quantile cross-spectral dependence technique recently proposed by Baruník and Kley (2019). As Maghyereh and Abdoh (2021) rightly noted, this technique captures the existence of dependence at different market conditions and across various investment horizons. Hence, we take advantage of the model's innate characteristics in addressing our research objective. Inspired by past studies (e.g. Mensi et al., 2014; Nusair and Olson, 2019; Das and Kannadhasan, 2020) we also complement the quantile cross-spectral analysis with quantile regression which enables us to jointly examine the dependence and predictability of NFTs returns on trade volume and other market variables as well as an indicator of geopolitical risks across different market conditions. Unlike the tail based copula technique or multifractality technique that has been employed in the erstwhile literature on the cryptocurrency volume–return analysis (e.g., see El Alaoui et al., 2019; Naeem et al., 2020), it suffices to mention that using the quantile cross-spectral and the quantile regression methods provide a flexible framework to analyze how the dependence structure among NFTs volume and returns vary across investment horizons (i.e. short-, intermediate-, and long-term investment horizons) and market conditions (i.e., during bear, normal and bull market conditions).

The rest of the paper is structured as follows. The next section describes the research design by presenting the data sources, computation of variables, and estimation strategy. The third section presents the results, while we conclude with the fourth section.

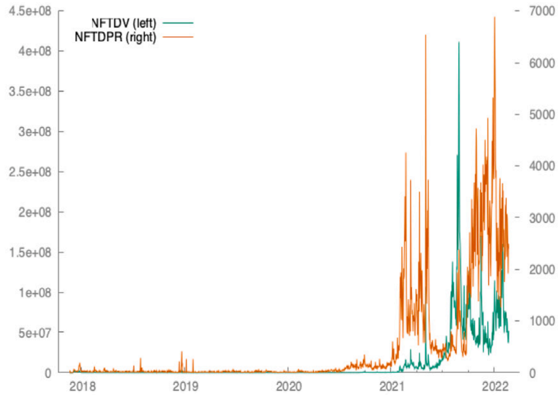
2. Data and empirical strategy

2.1. Data

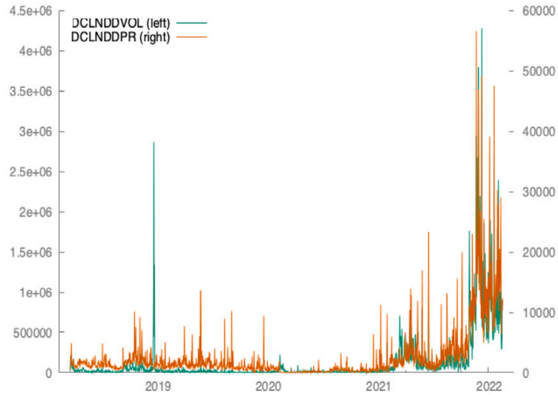
NFTs can be categorized into different groups based on their properties. Along this line, Ante (2021b) and Kräussl and Tugnetti (2022) identified five major NFTs groups including collectibles, utilities, gaming, arts, and metaverse. However, only collectibles, gaming, and metaverse have a considerable existing market size and is transforming into a full-fledged market. Hence, in addition to the aggregate NFTs market, our analysis focuses on the latter three categories, paying particular attention to Decentraland, CryptoKitties, and Cryptopunks. Specifically, Decentraland is a metaverse submarket. It is a virtual world on the Ethereum blockchain that allows users to buy NFTs (called LAND in the ecosystem) that represent the ownership of land parcels, i.e., digital real estate (Kräussl and Tugnetti, 2022). CryptoKitties is a submarket in the gaming category, serving as a collection of artistic images representing virtual cats that are used in a game that allows players to purchase, collect, breed, and sell them on Ethereum (Nadini et al., 2021). CryptoPunks is a submarket in the collectible category. In particular, it is a collection of 10,000 uniquely generated characters with proof of ownership stored on the Ethereum blockchain (Ante, 2021b).

To operationalize the NFTs indexes, we retrieve daily data of the composite NFT market as well as the three sub-markets from https://nonfungible.com/. We follow Aharon and Demir (2021) that use the mean value of transaction prices on a daily basis for the composite NFT as well as NFT sub-markets, which offers a higher number of observations for analysis.[1] Except for Decentraland which starts from March 19, 2018, our data sample spans the period from June 23, 2017 to February 11, 2022. The start periods are determined by the availability of data on the NFT market. Fig. 1 presents the time series plots of prices and volumes for the NFT market as well as the three NFT sub-markets including Decentraland, CryptoKitties and Cryptopunks.

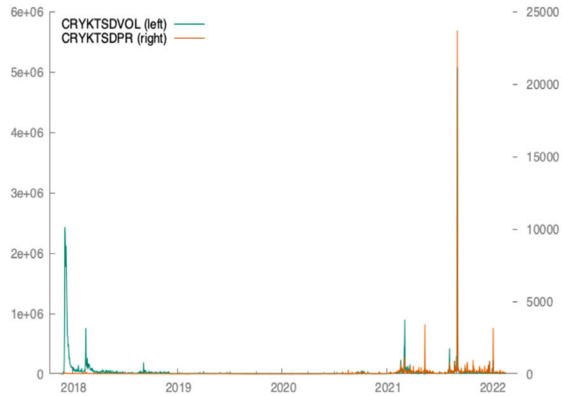
[1] For detailed discussion on the NFT market, please see Nadini et al. (2021).



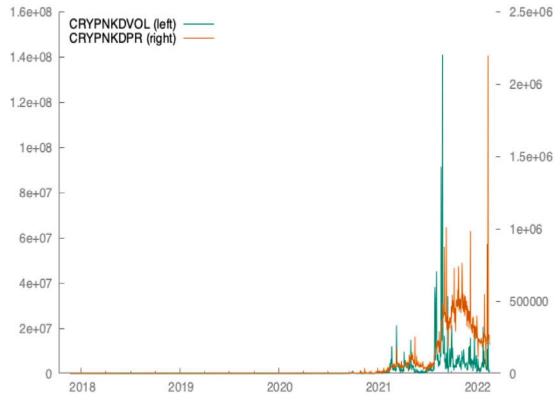
(a) NFT prices and volume



(b) Decentraland prices and volume



(c) CryptoKitties prices and volume



(d) Cryptopunks prices and volume

Fig. 1. Plots of prices and volume series for the entire NFT markets, and Decentraland, Cryptokitties and Cryptopunks sub-markets.

As noted in the introduction, we complement the quantile cross-spectral analysis with quantile regression which enables us to jointly examine the dependence of NFTs returns on trade volume and other market variables. To this end, we source additional variables from different sources to capture effects due to (un)related markets and the broader macroeconomic environments. For this objective, we particularly use the Chicago Board Options Exchange (CBOE) volatility index on S&P 500 (VIX), Oil market volatility index (OVX), Gold market volatility index (GVZ), Merrill Lynch Option Volatility Estimate (MOVE), and the U.S economic policy uncertainty index (EPU) to capture the influence of uncertainty related to equity, oil, gold, fixed income markets and economic policy on return and volatility connectedness among these markets. Additionally, we use the Aruoba–Diebold–Scotti business conditions index (ADS) of Aruoba et al. (2009), the term spread between the 10-year and 3-month U.S. Treasury bonds (Terms), and the Geo-political Risk index (GPRI) of Caldara and Matteo (2021) as proxies for the global macroeconomic and geo-political conditions. We retrieved data for these indicators from St. Louis FRED, except for ADS and GPRI that we sourced from Federal Reserve Bank of Philadelphia database and policyuncertainty.com, respectively. Also, we account for the effects of fluctuation of cryptocurrency prices on the returns of NFTs using Bitcoin price. We retrieved Bitcoin prices from the website of coinmarketcap (https://coinmarketcap.com/currencies/bitcoin/). Lastly, we use a dummy variable that takes the value of 1 for the period from January 1, 2020 to August 1, 2021, and 0 otherwise to capture the influence of the different waves of the global crisis due to COVID-19 pandemic.

2.2. Methods

To address our first research objective, we employ the Baruník and Kley's (2019) cross-spectral coherency technique. This method measures the dynamic dependence between two time series ($R_{t,j1}$ and $R_{t,j2}$) as follows:

$$\mathfrak{R}^{j_1 j_2}(\omega;\tau_1,\tau_2) := \frac{f^{j_1 j_2}(\omega;\tau_1,\tau_2)}{(f^{j_1 j_1}(\omega;\tau_1,\tau_1) f^{j_2 j_2}(\omega;\tau_2,\tau_2))^{1/2}} \tag{1}$$

where ω is the time–frequency corresponding to $\omega\ \xi\ 2\pi(1/5; 1/22; 1/250)$ respectively. Indeed, the coherency (co-dependence) across these three frequencies correspond to the short-rum (one week), the intermediate run (one month) and the long run (one year). π denotes the periodic intervals of $\omega\ \xi\ (-\pi < \omega < \pi)$; τ_1 and τ_2 are the τth quantiles of R_{t,j_1} and R_{t,j_2} (i.e. 0.5, 0.05 or 0.95, which correspond to bearish, normal and bullish market conditions) consecutively, where $(\tau_1, \tau_2) \in [0, 1]$, $f^{j_1 j_2}, f^{j_1 j_1}$ and $f^{j_2 j_2}$ represent the quantile cross-spectral density and the quantile spectral densities of processes R_{t,j_1} and R_{t,j_2} respectively generated from the Fourier transform of the matrix of quantile cross-covariance kernels denoted by $\Gamma(\tau_1, \tau_2) := (f\omega; \tau_1 \tau_2)_{j_1 j_2}$, where

$$\gamma^{j_1 j_2} := Cov\left(I\{X_{t+k,j_1} \le q_{j_1(\tau_1)}\}, I\{X_{t+k,j_2} \le q_{j_2(\tau_2)}\}\right) \tag{2}$$

For $j_1, j_2 \in \{1, \ldots, d\}, k \in Z, \tau_1, \tau_2 \in [0, 1]$, and $I\{A\}$ denotes the indicator function of event A. To generate information about serial and cross-sectional dependence, we vary K while restricting $j_1 \neq j_2$. Further, the matrix of quantile cross-spectral density kernels $f(\omega; \tau_1, \tau_2) := (f(\omega; \tau_1, \tau_2))_{j_1 j_2}$, is realized from the frequency domain where:

$$f^{j_1 j_2}(\omega; \tau_1, \tau_2) := (2\pi)^{-1} \sum_{k=-\infty}^{\infty} \gamma_k^{j_1, j_2}(\tau_1, \tau_2) e^{-ik\omega} \tag{3}$$

Quantile coherency is estimated by the smoothed quantile cross-periodogram as expressed below:

$$\hat{G}_{n,R}^{j_1, j_2}(\omega; \tau_1, \tau_2) := \frac{2\pi}{n} \sum_{s=1}^{n-1} W_n \left\{\omega - \frac{2\pi s}{n}\right\} I_{n,R}^{j_1, j_2}\left\{\frac{2\pi s}{n}, \tau_1, \tau_2\right\} \tag{4}$$

where $I_{n,R}^{j_1, j_2}$ represents the matrix of rank-based copula cross periodograms (CCR-periodograms) while W_n is a sequence of weight functions. Then, the estimator for the quantile coherency may be expressed as:

$$\Re_{n,R}^{j_1 j_2}(\omega; \tau_1, \tau_2) := \frac{\hat{G}_{n,R}^{j_1, j_2}(\omega; \tau_1, \tau_2)}{\left\{\hat{G}_{n,R}^{j_1, j_1}(\omega; \tau_1, \tau_1) \hat{G}_{n,R}^{j_2, j_2}(\omega; \tau_2, \tau_2)\right\}^{\frac{1}{2}}} \tag{5}$$

In addition to the coherency matrices for the 0.05, 0.5 and 0.95 quantiles, and their combinations of quantile levels (0.05|0.05, 0.5|0.5, 0.95|0.95), we consider a combination of the extreme quantiles (0.05|0.95), which enables us to explore the dependence structure between the lower quantile of volume and the upper quantile of returns.

Following our second objective, we rely on the QR model of Koenker and Bassett (1978) to measure the effects of NFTs sales volume, geopolitical risks and the chosen macroeconomic variables on NFTs returns across market conditions. Our QR model evolves from a traditional OLS specification as follows:

$$r_t = \beta_0 + \beta_1 X_t + \psi D_t + v_t \tag{6}$$

where rt is the return of sub-markets and the composite NFT market at time t while X_t is the set of important macroeconomic and geopolitical indicators at time t while D_t COVID-19 dummy.

The QR approach relates the conditional τth quantile of the dependent variable to a set of $\tau \in (0, 1)$. Hence, the conditional quantile model for q_t, given x_t can be expressed as:

$$Q_{q_t}(\tau/x_t) = \alpha^\tau + X_t' \beta^\tau \tag{7}$$

where $Q_{q_t}(\tau/x_t)$ is the conditional τth quantile of the dependent variable q_t while α^τ represents the intercept, which depends on τ. β^τ is the vector of coefficients associated with τth quantile while X' is as defined earlier. As in Koenker and Bassett (1978), the coefficients of the τth quantile of the conditional distribution are expressed as a solution to the minimization problem written as:

$$\underset{\hat{\beta} \in \Re^k}{min} \sum_t \rho_\tau(q_t - \alpha^\tau - x_t' \hat{\beta}^\tau) \tag{8}$$

where ρ_τ represents a weighting factor known as a check function, expressed for any $\tau \in (0, 1)$ as:

$$\rho_\tau(\xi_t) = \begin{cases} \tau \xi_t, & if \quad \xi_t \ge 0 \\ (\tau - 1)\xi_t, & if \quad \xi_t < 0 \end{cases} \tag{9}$$

where $\xi_t = q_t - \alpha^\tau - x_t' \beta^\tau$. Hence, QR technique minimizes the sum of residuals, given that the weight of τ is assigned to positive residuals while the weight of $1 - \tau$ is assigned to negative residuals. The QR model for this study, is therefore, specified as:

$$Q_{q_t}(\tau/x_t) = \alpha_0^\tau + \alpha_1^\tau X_t + \alpha_2^\tau D_t \tag{10}$$

We estimate the QR model in Eqs. (10) by specifying three quantiles: τ = 0.05, 0.50, 0.95, which to three market regimes, including bearish; normal and bullish market states, respectively. Thus, bearish(bullish) market regime denotes period of rapid decline(increase) in the performance of NFTs.

3. Results and discussion

3.1. NFTs returns dependence on volume: Quantile cross-spectra

Fig. 2 shows the results of the dependence between volume and return using the cross-spectral coherency technique. Each figure shows the results across three quantiles corresponding to the bearish (i.e. 0.05 quantiles), normal (i.e. 0.5 quantiles), and bullish (i.e., 0.95 quantiles) market conditions and time frequencies corresponding to the weekly (W), monthly (M) and yearly (Y) frequency cycles. Specifically, following past studies such as Maghyereh and Abdoh (2021), the horizontal axis displays the daily cycles over the interval, while the measures of co-dependence of volume and return of NFT market as well as the sub-markets is presented in the vertical axis. The weekly, monthly, and yearly frequency cycles in the upper label of the horizontal axis display how each pair of the time series are dependent across quantiles of the joint distribution.

Results from Fig. 2 panel i–ii indicate that the degree of dependence between the entire NFT market sales volume and return vary across market conditions and time scales. However, dependence is strongest when the NFT market is bullish but least during the bearish period. Further, the dependence between volume and return lies relatively at similar levels across time scales. Looking closely across the three NFT sub-markets i.e. Fig. 2(ii)–(iv), results show that dependence between volume and return remains strong. However, some interesting patterns emerge across market conditions and time scales. First, for Decentraland and CryptoKitties, dependence between volume and returns is significantly stronger during the bullish period but least during the bearish period across all the time's scales, especially for the CryptoKitties. There is noticeable stronger dependence between volume and return for Decentraland during the normal period for both weekly and monthly time scales.

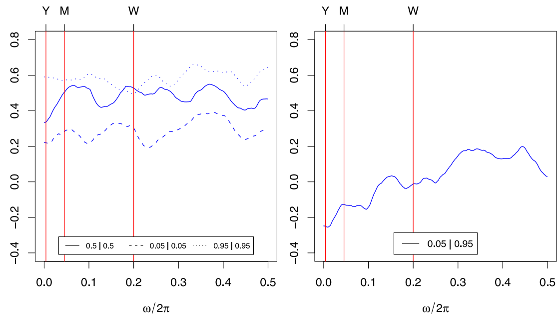
Regarding the Cryptopunks sub-market, dependence between volume and return are mixed across market conditions and time scales. For instance, normal market dependence appears to dominate dependence across both the left and right tails, especially during the weekly time scale. However, dependence under the right tail (0.95) quantile dominates the dependence under other quantiles during the monthly time scale. Interestingly, results also show that although dependence during the bearish market period is generally negative across both the weekly and monthly time scales, it becomes positive under the yearly time scale while both normal and bearish market dependence becomes positive at this time scale. This suggests that when the Cryptopunks market is in a bearish condition, an increase in volume may be followed by a decrease in returns in the short and intermediate-term while it may be followed by an increase in return in the long term. The reverse may, however, be the situation in the case of both normal and bullish periods across this time scale. Meanwhile, the cross-quantile dependence between volume and return is positive in the weekly time scale but negative in both the monthly and yearly investment horizons.

3.2. NFTs returns dependence on volume: Quantile regression

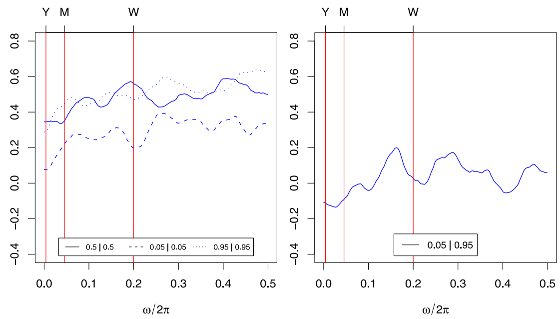
Table 1 presents the results of the quantile regression for the three quantiles corresponding to the normal (Q0.5), bearish (Q0.05), and bullish (Q0.95) market conditions respectively. Across the three quantiles, the estimated coefficients of NFT volume are positive and largely significant for the aggregate NFT market and the three sub-markets that are under study, except for Cryptopunks where the coefficient is not significant. This implies that NFT volume is a key predictor of NFT returns and therefore validates past literature such as the sequential information arrival hypothesis (e.g. Copeland, 1976), asymmetry in the information endowment (e.g. Llorente et al., 2002), and information precision (e.g. Schneider, 2009) that highlight return as a strong predictor of volume. In terms of the sizes of the estimated coefficient of NFT volume, those for Cryptopunks are the smallest implying a much lower effect which is consistent with those of the quantile cross-spectra analysis. Also, the coefficients of the COVID-19 dummy are insignificant across the three market conditions for both the NFT and the Cryptokitties markets but significant and positive for Cryptopunks (bullish market) and Decentraland (normal and bullish markets). This indicates that although the COVID-19 pandemic may not have significantly affected the aggregate NFT market as well as the Cryptokitties sub-market, it had a positive impact on the prices of Cryptopunks and Decentraland during bullish market periods as well as normal market period for Decentraland only.

Both the oil market uncertainty (OVX) and geopolitical risks negatively impact on the aggregate NFT market under the bearish market condition (0.05 quantile); business conditions index (ADS) affects it negatively under the bullish market while Bitcoin prices impact it negatively across all market conditions. Regarding the sub-markets, the predictive powers of the control variables vary across market conditions and the NFT markets. For the Cryptokitties, the estimated coefficients for equity market uncertainty (VIX) are negative and significant at the 0.05 and 0.95 quantiles. This suggests that equity market uncertainty become significant predictor of Cryptokitties during extreme downside and upside market conditions. Gold market uncertainty (GVZ), bond terms spread (Terms) and the business environment (ADS) are statistically significant only at the 0.95 quantile, implying that gold market uncertainty, bond terms spread and business environment only matter during extreme upside market condition. In particular, these indicators exert positive effects on Cryptokitties at the 0.95 quantiles, implying that increases in term spread, gold market uncertainty as well as better-than-average real business condition lead to price appreciation in the Cryptokitties market during extreme upsides market condition. On the other hand, oil market uncertainty (OVX) and geopolitical risk (GPRI) has a significant negative effects at the 0.05 quantile. This suggests that an increase in oil market uncertainty and increase in geopolitical risks lead to a depreciation of Cryptokitties market returns during extreme downside market conditions. Regarding the effects of the cryptocurrency market, the coefficient of Bitcoin prices is negative and significant across both the 0.5 and 0.05 quantiles, indicating that increase in Bitcoin prices leads to a depreciation of Cryptokitties prices.

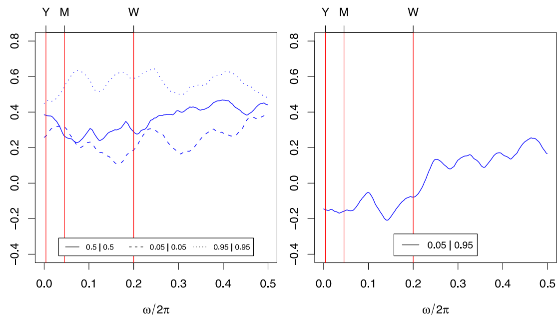
Regarding the Cryptopunks market, the coefficients of both the oil and equity markets uncertainty indexes are negative at the 0.95 quantile while those of economic policy uncertainty and term spread are negative at the 0.5 quantile. These indicate that



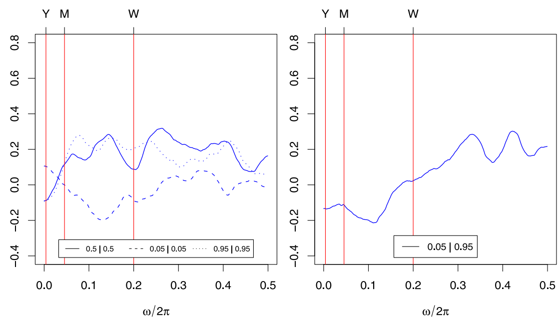
(i) NFT volume vs return



(ii) Decentraland volume vs return



(iii) CrytoKitties volume vs returns



(iv) Crytopunks volume vs returns

Fig. 2. Cross-spectral coherency estimates for the 0.05|0.05, 0.5|0.5, 0.95|0.95 and 0.05|0.95 quantiles of NFT sub-markets' volume and return.
Note: W, M, and Y denote weekly, monthly, and yearly periods, respectively. The ——, - - - and ...... lines correspond to the 0.5, 0.05 and 0.95 quantiles, respectively.

Table 1
Drivers of NFT market returns across normal, bearish and bullish market conditions.

Variables	CryptoKitties			CryptoPunks			Decentraland			NFT Market		
	1	2	3	4	5	6	7	8	9	10	11	12
	Q0.5	Q0.05	Q0.95	Q0.5	Q0.05	Q0.95	Q0.5	Q0.05	Q0.95	Q0.5	Q0.05	Q0.95
ln(VOL)	0.062***	0.160***	0.357***	0.012**	0.005	0.116***	0.272***	0.323***	0.321***	0.053***	0.083***	0.137***
	(0.012)	(0.052)	(0.051)	(0.005)	(0.009)	(0.007)	(0.024)	(0.049)	(0.037)	(0.012)	(0.021)	(0.034)
ln(VIX)	−0.024	−0.608*	−0.690***	−0.010	−0.218	−0.320***	−0.662**	−0.376	−0.739**	−0.018	0.059	−0.228
	(0.071)	(0.317)	(0.249)	(0.055)	(0.281)	(0.108)	(0.164)	(0.394)	(0.301)	(0.073)	(0.148)	(0.265)
ln(OVX)	0.067	0.612**	−0.026	0.009	0.222	−0.279***	−0.253*	−0.692	−0.840***	−0.055	−0.483***	−0.089
	(0.074)	(0.297)	(0.240)	(0.042)	(0.237)	(0.100)	(0.144)	(0.609)	(0.305)	(0.082)	(0.123)	(0.163)
ln(GVZ)	0.085	−0.029	1.094***	−0.027	0.526*	0.470***	0.824***	0.482	0.955***	0.073	0.467*	0.078
	(0.103)	(0.456)	(0.279)	(0.081)	(0.272)	(0.152)	(0.212)	(0.524)	(0.352)	(0.118)	(0.251)	(0.353)
ln(EPU)	−0.005	0.006	0.089	−0.009	−0.137**	0.103***	−0.021	−0.166	−0.014	0.0003	0.068	0.088
	(0.024)	(0.098)	(0.079)	(0.017)	(0.068)	(0.039)	(0.051)	(0.118)	(0.091)	(0.027)	(0.055)	(0.101)
ln(MOVE)	−0.022	−0.372	0.333	0.024	−0.355	−0.166	0.682***	0.737	2.299***	0.011	−0.125	0.269
	(0.132)	(0.565)	(0.296)	(0.091)	(0.249)	(0.188)	(0.262)	(0.731)	(0.511)	(0.145)	(0.260)	(0.388)
ln(GPRI)	0.042	0.298**	0.069	−0.016	0.027	0.142***	0.088	0.097	0.222**	−0.020	−0.077*	0.015
	(0.029)	(0.117)	(0.093)	(0.023)	(0.086)	(0.045)	(0.063)	(0.119)	(0.095)	(0.031)	(0.043)	(0.105)
d(Term)	−0.077	1.266	1.663**	−0.078	−0.888***	−0.212	−0.197	2.107*	−2.424***	0.067	0.211	−0.375
	(0.287)	(1.249)	(0.769)	(0.197)	(0.317)	(0.407)	(0.266)	(1.266)	(0.407)	(0.282)	(0.448)	(0.898)
d(ADS)	0.061	−0.059	0.158***	0.049	0.167	0.099	0.026	−0.226	−0.319*	−0.021	0.193	−0.126**
	(0.049)	(0.092)	(0.044)	(0.034)	(0.139)	(0.068)	(0.151)	(0.426)	(0.176)	(0.069)	(0.206)	(0.056)
ln(BTC)	−0.055*	−0.479***	0.016	−0.061*	0.227	−0.702***	−0.324***	−0.262*	−0.293***	−0.173***	−0.125*	−0.401***
	(0.032)	(0.162)	(0.087)	(0.034)	(0.733)	(0.057)	(0.058)	(0.158)	(0.102)	(0.045)	(0.075)	(0.136)
COVID	0.025	0.334	0.071	0.008	−0.053	0.306***	0.156**	0.056	0.527***	0.017	0.054	0.007
	(0.046)	(0.209)	(0.076)	(0.029)	(0.093)	(0.056)	(0.078)	(0.175)	(0.088)	(0.037)	(0.057)	(0.148)
Constant	−0.763**	0.721	−4.461***	0.646**	−1.278**	6.285***	−0.358	−0.489	−0.792	1.089***	−0.146	0.274*
	(0.347)	(1.575)	(0.975)	(0.324)	(0.567)	(0.557)	(0.637)	(1.473)	(1.165)	(0.400)	(0.708)	(1.401)

Note: Robust standard errors are presented in brackets. $Q_{0.5}$; $Q_{0.05}$ and $Q_{0.95}$ denote 0.5, 0.05 and 0.95 quantiles, which correspond to normal, bearish and bullish market conditions, respectively, for each sub-markets as well as the entire NFT market.

***Represent significance at 1% level.

**Represent significance at 5% level.

*Represent significance at 10% level.

uncertainties in both the oil and equity markets reduce Cryptopunks market returns while increases in shocks on economic policy and the term exert similar negative effects during normal market periods. Furthermore, the coefficients of gold market uncertainty exert significant effects at both the 0.05 and 0.95 quantiles, while those of economic policy uncertainty and geopolitical risks are significant at the 0.95 quantile. In both cases, their estimated coefficients are positive, implying that increase in gold market uncertainty may lead to Cryptopunks market return appreciation under the bearish and normal market conditions while this is possible due to increase in economic policy uncertainty and geopolitical risks during bullish market period only. Similar to the Cryptokitties market, the coefficients of fixed-income market uncertainty (MOVE) are not significant across all market conditions. On the other hand, the effects of the cryptocurrency market are significant across both normal and upper extreme market condition. In both cases, these effects are negative, suggesting that increase in Bitcoin prices negatively affects Cryptopunks market prices. Taken together, these results show that oil, equity, gold markets, economic policy uncertainties, geopolitical risks and Bitcoin prices are strong predictors of Crytopunks market returns, especially during upper extreme market condition.

Lastly, results for the Decentraland market indicate that the coefficients of both oil (OVX) and equity (VIX) markets uncertainty are significant and negative at 0.5 and 0.95 quantiles while those of fixed-income (MOVE) and gold market uncertainty are significant and positive under the same market conditions. This suggests that although these factors are important predictors of the Decentraland returns under normal and upper extreme market conditions, they exhibit opposing effects on Decentraland market under these market periods. In particular, increase in both oil and equity markets uncertainty decreases Decentraland market returns while increase in both fixed-income (MOVE) and gold market uncertainty (GVZ) increases it. The effects of the term spread, however, becomes significant and positive when the market condition becomes bearish. On the other hand, geopolitical risks and business conditions index also exhibit opposing significant effects at the 0.95 quantile. In particular, while the coefficient associated with geopolitical risk is positive, that of business environment is negative, suggesting that increase in geopolitical risks may lead to increase in Decentraland market returns while improvements in business conditions may lower it when the market condition is bullish. Regarding the effects of the cryptocurrency market, results show that the coefficients associated with Bitcoin prices are significant and negative across all the market conditions, indicating that similar other NFT sub-markets, increase in Bitcoin prices may lead to decrease in Decentraland prices across all the market conditions.

4. Conclusion

Given the expanding investment inflows into the NFTs market as well as their increasing relevance as a new financial asset, the need to understand its volume and return/risk characteristics has emerged. Against this background, this paper explores the dependence structure between sales volume and returns for the NFT market as well as three NFTs sub-markets including Decentraland, CryptoKitties and Cryptopunks using both the cross-spectral coherency and quantile regression techniques for the period from June 23, 2017 to February 11, 2022. For both the entire NFT market and the sub-markets, the cross-spectra analysis results show significant evidence of dependence between volume and return. Among NFT sub-markets, dependence between volume and return is weakest in the Cryptopunks market. The quantile regression results are largely in line with those of cross-spectral. Hence, our results highlight the importance of volume-based trading strategies to increase profits from NFTs, especially for the three studied submarkets: Decentraland, CryptoKitties and Cryptopunks. As our result indicates, the gains associated from strategy is independent of the market conditions. On the one hand, such a finding ameliorates doubts or concerns that the observed exponential increase in the volume of NFTs transaction may be signaling wash trading phenomena which has been highlighted in the cryptocurrency market (Le Pennec et al., 2021). On the other hand, it suggests that while information are jointly received in the studied NFT submarkets, their respective traded volumes capture the quality of information and act as a predictor of their returns. Hence, investors and market participants can initiate volume-based strategies with respect to the market performance of the aggregate NFTs market as well as the studied three submarkets, irrespective of the market conditions.

Furthermore, the results from the quantile regression show that during extreme market conditions, equity and gold markets uncertainty, business condition and term-spread are important predictors of Cryptokitties returns. The results also show that oil, equity and gold markets uncertainty and geopolitical risks significantly predict Cryptopunks and Decentraland markets returns. In all cases, increase in Bitcoin prices reduces NFT market returns. For each submarket, however, the effects of these latter factors are either limited to periods of extreme downturns or upturns. Going further, there are two potential areas of further inquiry that stand out. First, whereas our study focuses on the volume–return relationship, other studies can focus on the volume–risk relationship. Second, future studies can also examine either the volume–return or volume–risk relationship in other NFTs sub-markets that are not covered by our study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Aalborg, H.A., Molnár, P., de Vries, J.E., 2019. What can explain the price, volatility, and trading volume of bitcoin? Finance Res. Lett. 29, 255–265.
Aharon, D.Y., Demir, E., 2021. NFTs and asset class spillovers: Lessons from the period around the COVID-19 pandemic. Finance Res. Lett. 102515.
Ante, L., 2021. The non-fungible token (NFT) market and its relationship with bitcoin and ethereum. Available at SSRN 3861106.
Ante, L., 2021b. Non-fungible token (NFT) markets on the ethereum blockchain: Temporal development, cointegration and interrelations. Available at SSRN 3904683.
Aruoba, S.B., Diebold, F.X., Scotti, C., 2009. Real-time measurement of business conditions. J. Bus. Econom. Statist. 27 (4), 417–427.
Balcilar, M., Bouri, E., Gupta, R., Roubaud, D., 2017. Can volume predict bitcoin returns and volatility? A quantiles-based approach. Econ. Model. 64, 74–81.
Baruník, J., Kley, T., 2019. Quantile coherency: A general measure for dependence between cyclical economic variables. Econom. J. 22 (2), 131–152.
Bouri, E., Lau, C.K.M., Lucey, B., Roubaud, D., 2019. Trading volume and the predictability of return and volatility in the cryptocurrency market. Finance Res. Lett. 29, 340–346.
Caldara, D., Matteo, I., 2021. Measuring Geopolitical Risk. Working paper, Board of Governors of the Federal Reserve Board, 2021.
Chohan, R., Paschen, J., 2021. What marketers need to know about non-fungible tokens (NFTs). Bus. Horiz..
Copeland, T.E., 1976. A model of asset trading under the assumption of sequential information arrival. J. Finance 31 (4), 1149–1168.
Corbet, S., Goodell, J.W., Gunay, S., Kaskaloglu, K., 2021. Are DeFi tokens a separate asset class from conventional cryptocurrencies?. Available at SSRN 3810599.
Das, D., Kannadhasan, M., 2020. The asymmetric oil price and policy uncertainty shock exposure of emerging market sectoral equity returns: a quantile regression approach. Int. Rev. Econ. Finance 69, 563–581.
Dowling, M., 2022a. Fertile LAND: Pricing non-fungible tokens. Finance Res. Lett. 44, 102096.
Dowling, M., 2022b. Is non-fungible token pricing driven by cryptocurrencies? Finance Res. Lett. 44, 102097.
El Alaoui, M., Bouri, E., Roubaud, D., 2019. Bitcoin price–volume: A multifractal cross-correlation approach. Finance Res. Lett. (31).
Hau, L., Zhu, H., Shahbaz, M., Sun, W., 2021. Does transaction activity predict bitcoin returns? Evidence from quantile-on-quantile analysis. North Am. J. Econ. Finance 55, 101297.
Karim, S., Lucey, B.M., Naeem, M.A., Uddin, G.S., 2022. Examining the interrelatedness of NFTs, DeFi tokens, and cryptocurrencies. Finance Res. Lett. 102696.
Ko, H., Son, B., Lee, Y., Jang, H., Lee, J., 2022. The economic value of NFT: Evidence from a portfolio analysis using mean–variance framework. Finance Res. Lett. 102784.
Koenker, R., Bassett, G., 1978. Regression quantiles. Econometrica 46 (1), 33–50.
Kong, D.R., Lin, T.C., 2021. Alternative investments in the fintech era: The risk and return of non-fungible token (NFT). Available at SSRN 3914085.
Kräussl, R., Tugnetti, A., 2022. Non-fungible tokens (NFTs): A review of pricing determinants, applications and opportunities. Applications and Opportunities (May 17, 2022).
Le Pennec, G., Fiedler, I., Ante, L., 2021. Wash trading at cryptocurrency exchanges. Finance Res. Lett. 43, 101982.
Llorente, G., Michaely, R., Saar, G., Wang, J., 2002. Dynamic volume-return relation of individual stocks. Rev. Financ. Stud. 15 (4), 1005–1047.
Maghyereh, A., Abdoh, H., 2021. Tail dependence between gold and islamic securities. Finance Res. Lett. 38, 101503.
Malhotra, A., O'Neill, H., Stowell, P., 2021. Thinking strategically about blockchain adoption and risk mitigation. Bus. Horiz..
Maouchi, Y., Charfeddine, L., El Montasser, G., 2021. Understanding digital bubbles amidst the COVID-19 pandemic: Evidence from DeFi and NFTs. Finance Res. Lett. 102584.

Mensi, W., Hammoudeh, S., Reboredo, J.C., Nguyen, D.K., 2014. Do global factors impact BRICS stock markets? A quantile regression approach. Emerg. Mark. Rev 19, 1–17.

Nadini, M., Alessandretti, L., Giacinto, F.Di., Martino, M., Aiello, L.M., Baronchelli, A., 2021. Mapping the NFT revolution: market trends, trade networks, and visual features. Sci. Rep. 11 (1), 1–11.

Naeem, M., Bouri, E., Boako, G., Roubaud, D., 2020. Tail dependence in the return-volume of leading cryptocurrencies. Finance Res. Lett. 36, 101326.

Nusair, S.A., Olson, D., 2019. The effects of oil price shocks on Asian exchange rates: Evidence from quantile regression analysis. Energy Econ. 78, 44–63.

Schneider, J., 2009. A rational expectations equilibrium with informative trading volume. J. Finance 64 (6), 2783–2805.

Umar, Z., Gubareva, M., Teplova, T., Tran, D.K., 2022. COVID-19 impact on NFTs and major asset classes interrelations: insights from the wavelet coherence analysis. Finance Res. Lett. 102725.

Urom, C., Ndubuisi, G., Guesmi, K., 2022. Quantile Return and Volatility Connectedness Among Non-Fungible Tokens (NFTs) and (Un) Conventional Assets. UNU-MERIT Working paper No. 2022-017.

Wang, Q., Li, R., Wang, Q., Chen, S., 2021. Non-fungible token (NFT): Overview, evaluation, opportunities, and challenges. arXiv preprint arXiv:2105.07447.

Wilson, K.B., Karg, A., Ghaderi, H., 2021. Prospecting non-fungible tokens in the digital economy: Stakeholders and ecosystem, risk and opportunity. Bus. Horiz..

Yousaf, I., Yarovaya, L., 2022. Static and dynamic connectedness between NFTs, defi and other assets: Portfolio implication. Glob. Finance J. 100719.