Applied Economics and Finance
Vol. 9, No. 1; February 2022
ISSN 2332-7294 E-ISSN 2332-7308
Published by Redfame Publishing
URL: http://aef.redfame.com

NFTs Emergence in Financial Markets and their Correlation with DeFis and Cryptocurrencies

Khuloud M. Alawadhi & Nour Alshamali[1]

[1] Public Authority for Applied Education and Training, Kuwait

Correspondence: Khuloud M. Alawadhi, Public Authority for Applied Education and Training, Kuwait.

Received: January 7, 2022 Accepted: February 8, 2022 Available online: February 14, 2022

doi:10.11114/aef.v9i1.5444 URL: https://doi.org/10.11114/aef.v9i1.5444

Abstract

Non-fungible tokens (NFT) have been defined as digital assets that encode items such as art, collectables, and in-game goods. They are often stored in smart contracts on a blockchain and are exchanged online, frequently using Bitcoin. As NFT became increasingly popular in the last few years, decentralized financial assets (DeFi) tokens also started receiving growing attention as financial instruments that differ from NFTs and cryptocurrencies. Based on data on NFTs, DeFi tokens, and cryptocurrency daily prices between January 15th and December 6th, 2021, we examine the correlation between NFTs, DeFi tokens and major cryptocurrencies such as Bitcoin and Ethereum. Using the volatility spillover matrix approach by Diebold and Yilmaz (2012) as applied by Dowling (2021) and including DeFis into the discussion, we find that there is very limited spillover to and from non-traditional financial markets. Also, DeFi assets appear to be relatively unconnected to cryptocurrency markets. Following the methodology by Karim, Lucey, Naeem and Uddin (2021) of the quantile connectedness approach and the cross-quantilogram model of Han, Linton, Oka and Whang (2016), we determine that positive DeFi and Crypto spillovers exceeded negative NFT spillovers. This paper concludes that both NFTs and DeFi assets show significant potential in terms of portfolio diversification since they display low correlation with cryptocurrencies, especially in the case of DeFis thanks to it being disconnected from other assets in the market, based on this year's data. This has significant implications for investors who seek to diversify their portfolios by including cryptocurrency, NFTs and DeFis as assets.

Keywords: NFT, DeFi, blockchain, cryptocurrency, Bitcoin, Ethereum, volatility spillover, quantile connectedness

1. Introduction

1.1 The Emergence of NFTs and DeFi in Financial Markets

Cryptocurrencies, DeFis and NFTs are gaining popularity among investors, policymakers, regulatory agencies, and portfolio managers, with market capitalizations of \$3.05 trillion, \$93.40 billion, and \$43.08 billion, respectively (Statista, 2021a, b; Wette.de, 2021).

The technology behind NFTs is blockchain and they can be traded on marketplaces, such as OpenSea, similarly to cryptocurrencies, yet the essential difference between NFTs and cryptocurrencies or other assets that use blockchain technology is that NFTs are non-interchangeable, they are unique and cannot be replaced with another asset for an equivalent value (NonFungible.com, 2021). Cryptocurrencies, such as Bitcoin or Ethereum, or even traditional money, however, rely on the interchangeability trait (Wragg, 2021). An NFT begins with the certification of ownership of a digital asset on a blockchain, often on the Ethereum network. The digital asset that underlies the NFT may then be sold, which causes the owner to change as well as the Bitcoin payments recorded on the blockchain if this was used to pay for the asset (Dowling, 2021).

So far, NFTs have mostly been used to commodify digital objects in art, gaming, collectables, metaverse, utility and, more recently, in decentralized finance (DeFi). The first and most well-known example of an NFT is CryptoKitties, a collection of creative photos of virtual cats that are utilized in an Ethereum game that allows users to buy, collect, breed, and sell them on Ethereum (Nadini, Alessandretti, Giacinto, Martino, Aiello and Baronchelli, 2021). CryptoKitties blocked the Ethereum network in December 2017. CryptoKitties, widely regarded as a prime illustration of the irrationality that drove the cryptocurrency market in 2017, was the exclusive popular example of NFTs for over two years.

NFTs have been around for some time, approximately since 2017, however, they only became popular recently when NFT became the first application of blockchain technology to gain widespread public attention in early 2021 (Dowling, 2021). The emergence of NFTs in trade finance has been marked by the launch by XDC Network and Tradeteq of the world's first trade finance-based NFT transaction, with invoice finance firm Accelerated Payments serving as asset originator, in September 2021 (Golden, 2021).

Also, in the second half of 2021, both the number and the value of NFT sales exploded, as shown in Figure 1. Previously, at the begining of 2018, there was a significant increase in NFTs, from 23,500 in December 2017 to almost 630,000 in January 2018 (NonFungible.com, 2021). However, the number of NFT sales saw a major decline between 2018 and 2020 and only after the second half of 2021, NFT sales reached a peak of approximately 5.2 million sales in August 2021, as illustrated in Figures 1 and 2.

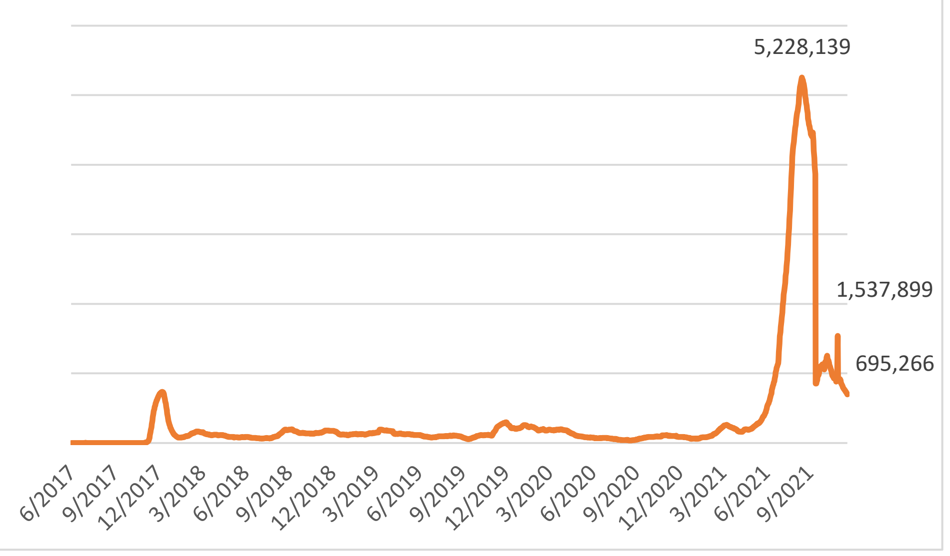

Figure 1. Total number of NFT sales since June 2017 (monthly)

Note. Data from NonFungible.com (2021)

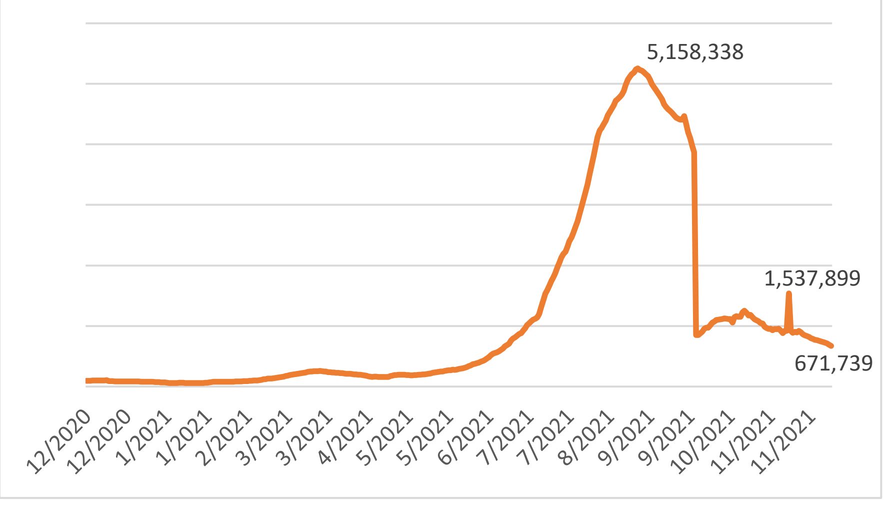

Figure 2. Total number of NFT sales in the last year, since December 2020 (monthly)

Note. Data from NonFungible.com (2021)

Regarding the value of completed NFT sales shown in Figure 3, this exceeded $4.37 billion in September 2021, which represents a huge increase from the previous year, based on monthly data from NonFungible.com (2021) database. However, the value of NFT deals exploded only after the second half of 2021 when it doubled between August and September, as illustrated in Figure 4. The value of NFT sales crashed in October 2021 and then increased by mid-November reaching $3.96 billion (NonFungible.com, 2021).

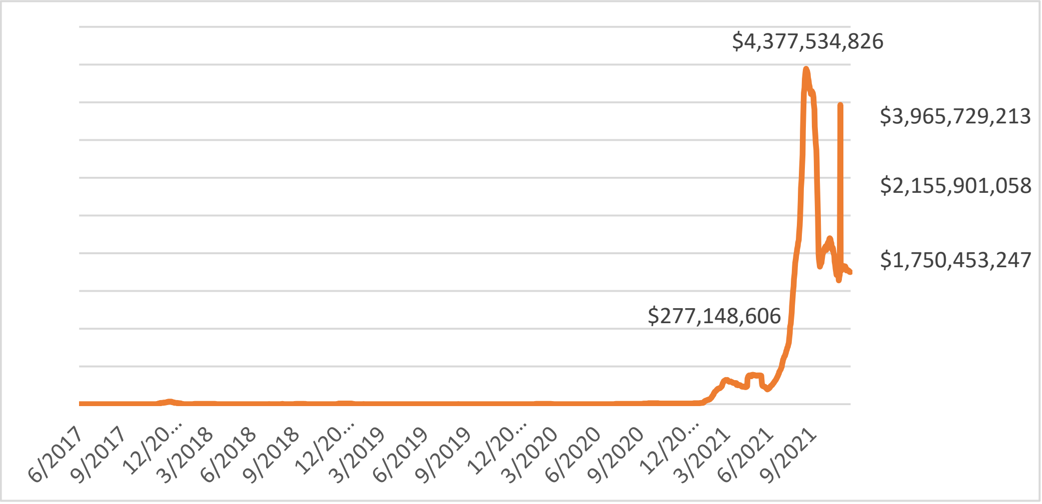

Figure 3. Total value of NFT sales since June 2017 (monthly)

Note. Completed sales based on data from NonFungible.com (2021)

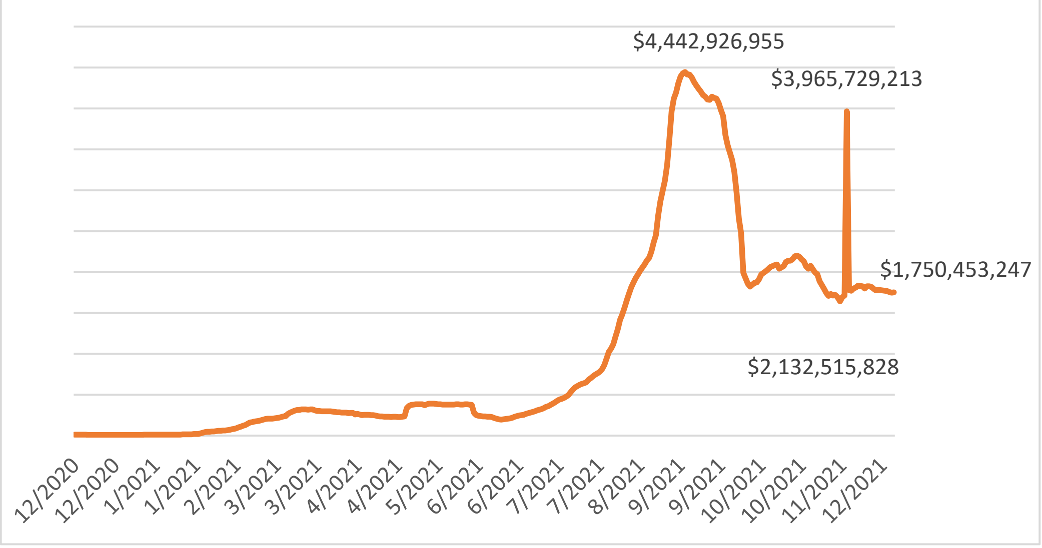

Figure 4. Total value of NFT sales in the last year, since December 2020 (monthly)

Note. Completed sales, based on data from NonFungible.com (2021)

Another important asset class included in the data analysis for this study are DeFi tokens. These have been defined by Musan (2020) as a subset of Decentralized Applications (DApps) that represent platforms with smart contracts that run on distributed computing systems. Specifically, DeFi can be defined as protocols that allow interoperable methods for solely leveraging and trading ERC-20 tokens, which in turn represent blockchain-based assets with inherent value gathered in a pool that are aggregated in a pool from which borrowers can benefit and obtain liquidity if they have posted collateral (Musan, 2020). At the moment of writing, the capital locked in DeFi tokens amounts to $105.26 billion, with Maker being the largest protocol (Defi Pulse, 2021).

Figures 5 and 6 show the total number and value of daily sales in DeFi assets, respectively, which started at the end of 2020. Deals in DeFi tokens were rare until August 2021 and then saw a sharp increase and a record high of 12,909 DeFi sales registered in just one day (NonFungible.com, 2021). The value of the DeFi sales on the 31st of August 2021 reached $3,79 billion, which is higher than the traded value on September 2021, at $3.30 billion (NonFungible.com, 2021).

By investing in NFT and DeFi assets, investors are also allowed to participate in a new type of staking that comprises pledging one's assets as collateral to tiny crypto and blockchain firms in exchange for newly created tokens (Finneseth, 2020). This explains the growing interest in DeFi since, typically, the assets would quickly develop significant value and generate yield to the stakers or farmers (Cointelegraph.com, 2021).

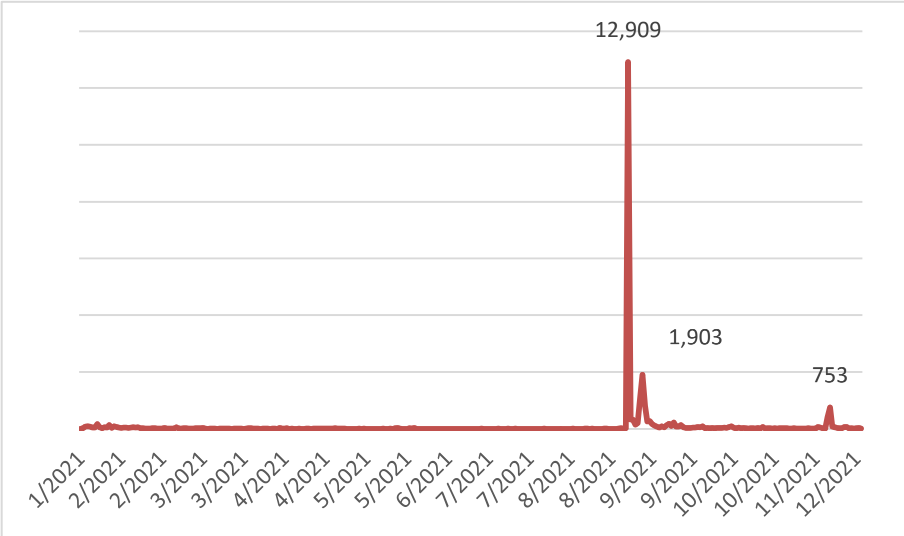

Figure 5. Total number of NFT sales in DeFi assets since January 2021 (daily)

Note. Completed sales, based on data from NonFungible.com (2021)

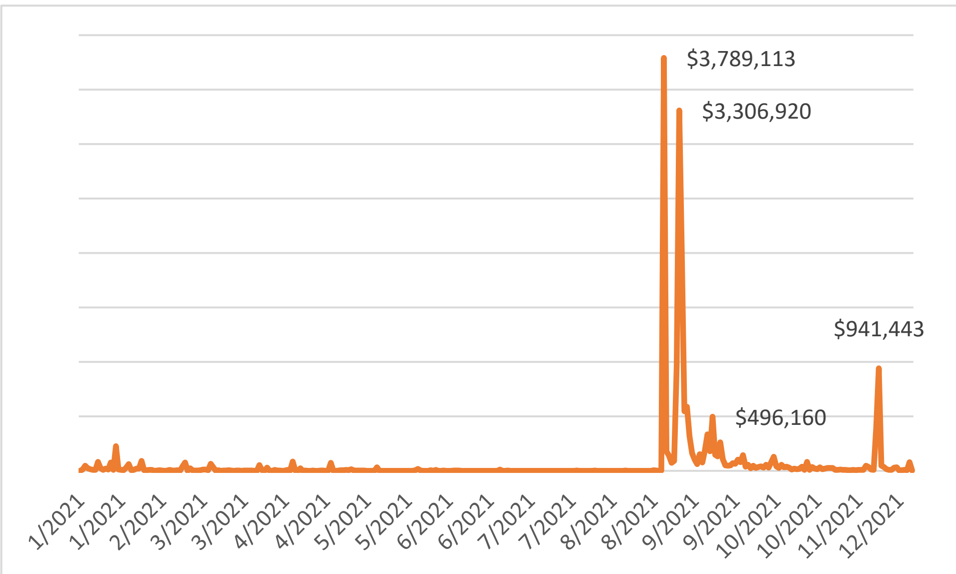

Figure 6. Total value of NFT sales in DeFi assets since January 2021 (daily)

1.2 Exploring the Importance of Mapping the Link between NFT, DeFi and Their Correlation with Cryptocurrencies

While NFTs denote a method of uniquely storing assets, DeFi essentially represents a financial system that works using blockchain technology, yet there is a strong link between the two, as recently shown by Yousaf and Yarovaya (2021) who demonstrated that there is a dynamic return and volatility spillover from NFTs and DeFi assets and Bitcoin transmitted towards more traditional assets such as gold and oil. Meanwhile, the findings reveal that NFTs and DeFi assets have limited static return and volatility spillovers to chosen markets, indicating that these new digital assets are still largely dissociated from established asset classes and Bitcoin (Yousaf & Yarovaya, 2021). As the authors argued, it is crucial to analyse these relationships since, within the lines of modern portfolio theory, when markets are weakly correlated, portfolios offer more diversification advantages (Fabozzi, Gupta and Markowitz, 2002). As a result, it is valuable to investigate the possible diversification of these new digital assets and help determine whether it is possible to diversify portfolios of other asset classes by including NFTs and Defi assets (Yousaf & Yarovaya, 2021).

It is, therefore, crucial for the advancement of current research that we map the interaction between DeFi and NFTs to understand the opportunities around financial assets that are traded on platforms built on blockchain technology and that can be tokenized (Iredale, 2021). Such an example is represented by real estate assets, which are illiquid and can generate high value for companies and individual investors if these opportunities are unlocked (Iredale, 2021).

1.3 Literature Review

The extant literature on NFTs, and specifically on DeFi tokens, is rather limited mainly due to the newness of the NFT concept especially as a financial instrument that can be traded alongside other more traditional asset classes but also because of its complexity and the blockchain technology pre-requisites.

Dowling (2021) examined three NFT markets, namely the *CryptoPunks*, which is currently the largest trading market in NFTs, Decentraland LAND tokens, and Axie Infinity game characters. The author sought to determine whether the prices of cryptocurrencies such as Bitcoin and Ethereum influence the NFT prices and find that there are relatively minor volatility transmission effects between cryptocurrencies and NFTs, based on the volatility spillover index (Dowling, 2021).

Also focusing on spillover effects involving NFTs, yet coming from various financial assets such as equities, bonds, currencies, gold, oil and Ethereum, and taking into consideration the COVID-19 crisis, Aharon and Demir (2021) found that NFTs are mostly immune to shocks from conventional asset classes, including its close relative, Ethereum.

Corbet, Goodell, Gunay and Kaskaloglu (2021) analysed DeFi tokens attempting to discover fundamental driving variables that differentiate DeFi tokens from traditional cryptocurrencies. Their findings based on the Supremum Augmented Dickey-Fuller, Hacker-Hatemi-J modified Wald, and Diebold-Yilmaz return and volatility spillover tests, as well as the Diebold-Yilmaz return and volatility spillover analysis, show that the DeFi market should be regarded as a distinct asset class from traditional cryptocurrencies, despite the significant correlations between certain DeFi tokens and Bitcoin (Corbet et al., 2021). Also, the most prominent DeFi tokens (Mkr and Link) behave the most like traditional tokens, as shown by the authors who argued that since groups of cryptocurrencies appear as distinct asset classes, the operational process of portfolio design must include DeFi tokens to maximize diversity (Corbet et al., 2021).

Lastly, the study by Karim et al. (2021) is central to this study since the authors also focused on the diversification opportunities presented by NFTs, DeFis and cryptocurrencies and examined the risk transmission. The authors identified considerable risk spillovers in block-chain markets with a high degree of disconnection of NFTs (Karim et al., 2021). Nevertheless, diverse unequal economic conditions were defined by time-varying characteristics. Ultimately, among other block-chain markets, NFTs provide higher diversification channels with the significant risk-bearing ability to shield investments and prevent severe hazards, according to Karim et al. (2021).

1.4 Research Questions and Their Correspondence to Research Design

Drawing from the extant literature on NFT, DeFi and their relationship with conventional cryptocurrencies, this study aims at expanding the literature and analyse whether and how NFTs and DeFi correlate with each other and with Bitcoin and Ethereum, which are still the top traded cryptocurrencies on the market (CoinMarketCap, 2021a; 2021b). We expect NFT and DeFi pricing to have an impact on cryptocurrency markets, as both NFT and DeFi assets provide a strong corporate use case for blockchain (Dowling, 2021).

By examining these questions, this paper contributes to the current literature by providing evidence from new asset classes such as NFT and DeFi to the modern portfolio theory. Moreover, this study will assist investors and portfolio managers in allocating funds across various traditional and digital assets and producing more suitable portfolio management decisions.

In the next section, we discuss the research method and the data collection procedures as well as the research hypotheses formulated for this study.

2. Method

2.1 Data Sourcing and Sampling

Data on NFT and DeFi assets have been gathered from the NonFungible.com platform and sampled as daily volumes and prices of NFT and DeFi contracts in USD between 15th January 2021 and 6th December 2021 since this was the largest timeframe for DeFi assets. Individual trade data have been aggregated for NFTs to our time window, following the approach by Dowling (2021). Data for NFT includes prices for tokens such as Bored Ape Yacht Club, The Sandbox, CryptoPunks, Art Blocks, Decentraland to name but a few, while data for DeFi refers to the Cometh asset, which uses

MUST token in liquidity mining (NonFungible.com, 2021).

The caveat we built using this method is that by aggregating the various DeFi assets we are conscious of the fact that the various traits and idiosyncrasies of each asset are lost in calculating averages, yet taking into consideration the newness of NFT research in finance and the objective of this research study that seeks to understand market movements, we find that it is acceptable to work with aggregates and average prices, as supported also by Dowling (2021).

Our dataset also includes prices for the most popular cryptocurrencies at the moment, Bitcoin and Ethereum. The two cryptocurrencies have been selected not only due to their cryptocurrency market share but also because they have registered the largest spillover effect to other cryptocurrencies (Dowling, 2021; Moratis, 2021). The data have been sourced from CoinMarketCap (2021a, 2021b) as the daily close price for the same timeframe, 15th January and 6th December 2021. Table 1 includes the descriptive statistics for aggregated NFTs and DeFis included in the NonFungible.com database as average daily sales in USD and for Bitcoin and Ethereum included and traded on CoinMarketCap as daily close prices from January to December 2021.

Table 1. Descriptive Statistics

	NFTs	DeFi	Bitcoin	Ethereum
Mean	1,818.36	854.60	46,964.40	2,647.15
Median	1,415.20	377.51	47,260.22	2,403.54
Std Dev	1,373.19	1,437.92	10,143.15	995.52
Minimum	181.08	0	29,807.35	1,121.57
Maximum	7,381.11	16,435.57	67,566.83	4,812.09
Skewness	1.48	5.78	0.04	0.43
Kurtosis	2.46	51.12	-1.27	-0.97

Note. For NFTs and DeFi, the data points have been calculated as daily average sales in USD across all tokens and assets traded on each specific day between January 15th and December 6th, 2021. For Bitcoin and Ethereum, the data points are daily close prices.

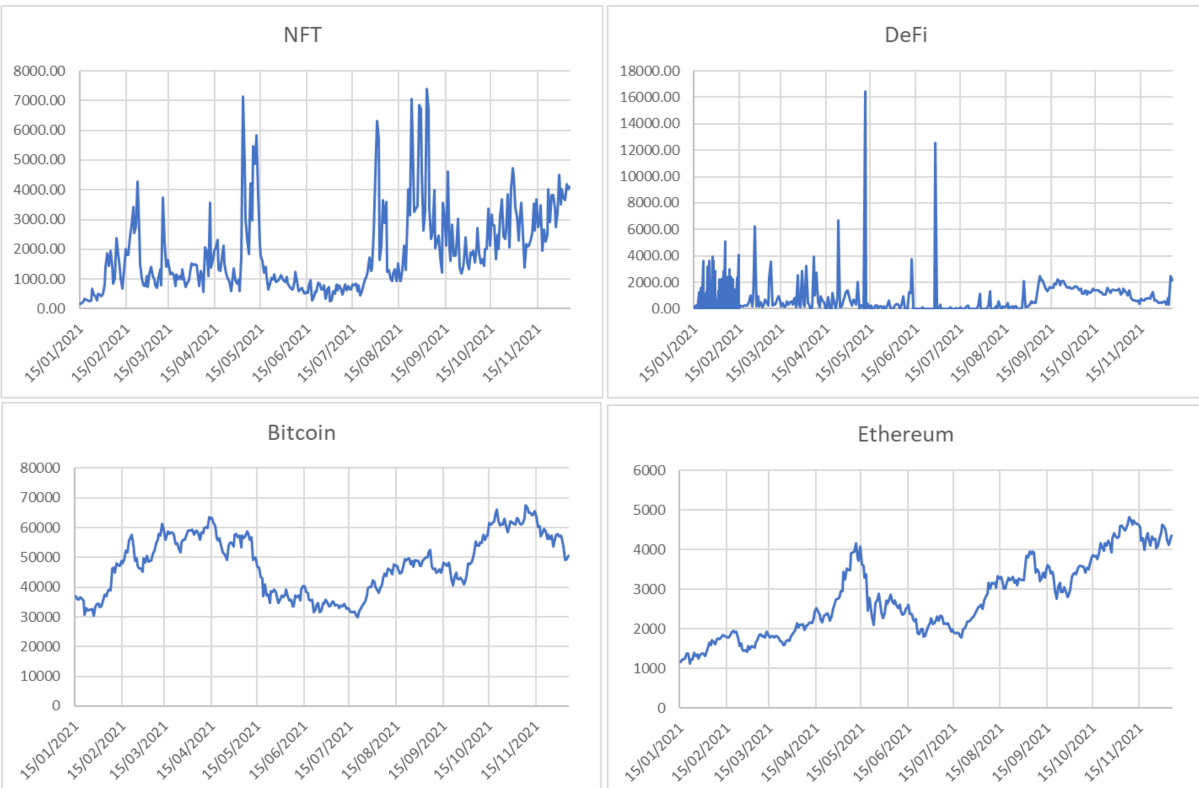

Figure 7. Daily pricing plots for NFT, DeFi, Bitcoin and Ethereum, January to December 2021

Note. Average daily prices in USD for the January 15th – December 6th timeframe from Nonfungible.com (2021) and CoinMarketCap (2021a, 2021b)

2.2 Research Method

Building on the studies by Dowling (2021), Karim et al. (2021) and Yousaf and Yarovaya (2021) we use a similar method with Dowling (2021) in terms of exploring the correlation and co-movement between NFTs and cryptocurrencies, yet focusing equally on DeFi and NFT. For the analysis of the volatility spillover matrix, we use the approach by Diebold and Yilmaz (2012) which was also used in the study by Dowling (2021).

While avoiding going into too much detail about this well-known approach, the method by Diebold and Yilmaz (2012) entails generating a matrix of Generalized Impulse Responses, which consist of volatility transmissions from one market to another (Pesaran & Shin, 1998). The spillover matrix's appeal stems from its ability to provide an intuitive interpretation of multiple transmissions linkages to and from marketplaces of interest in a single table Dowling (2021).

As shown in Table 1 and Figure 7, we have different price movements for NFTs, DeFi and the two selected cryptocurrencies, Bitcoin and Ethereum. Although Bitcoin and Ethereum have followed slightly similar trends, displaying three peaks, one in April-May, one in September and another one in November of this year, the average NFT prices showed a peak in May and another one in September but have struggled to recover in the following months. The price movement for DeFi assets also showed a peak in May but then it had a distinct behaviour from the other tokens in that it reached another high level in July and declined to more modest values in the fourth quarter of 2021. All pricing plots, however, are similar with regards to the through period between June and August 2021, except for the peak price of DeFi assets in July, as mentioned earlier.

The second method we use is the quantile connectedness approach at the median (50^{th} quantile) volatility condition, as done by Karim et al. (2021) based on the methodology of Ando, Greenwood-Nimmo and Shin (2018). In contrast with Karim et al. (2021) who also analyzed the volatility spillover effect at the extreme low (5^{th}) and extreme high (95^{th}) quantiles to observe the changes in times of uncertainty, such as the COVID-19 pandemic, we are going to limit the analysis to the median quantile. The reason for this is that the dataset includes only price points since January 2021, so it does not include a relevant timeframe corresponding to the pandemic, plus we wish not to shift the focus of this paper which is the spillover effect of NFTs, DeFis and cryptocurrencies in the last year.

We, therefore, estimate the dependence between NFTs and DeFis, on the one hand, and Bitcoin and Ethereum, on the other hand, by using the structures of y_t and x_t at different quantile levels $\tau[\tau \in (0,1)]$ through the pth order conditional distribution of y_t/x_t for the n-variable of the quantile VAR process, with y_t expressed through the equation (1):

$$y_t = c(\tau) + \sum_{i=1}^{p} Bi(\tau) y_{t-i} + et(\tau), t = 1, \dots, T \tag{1}$$

For the spillover indices at the various quantiles selected, we go back to the Diebold and Yilmaz (2012) approach, where equation (1) can be written as:

$$y_t = \mu(\tau) + \sum_{s=0}^{\infty} A_s(\tau) e_{t-s}, t = 1, \dots, T \tag{2}$$

We assume that the shocks are non-orthogonalized and for the identification, we use the vector moving average from the model, $\sum_{s=0}^{\infty} A_s(\tau) e_{t-s}$. Based on this assumption, we employed the generalized forecast error variance decomposition (GFEVD) of a variable that was subjected to a variety of shocks, following Karim et al. (2021), which can be written as:

$$\theta_{ij}^{g}(H) = \sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2 / \sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i) \tag{3}$$

We then calculate the total connectedness index (TCI) for the specified quantiles, τ, which calculate the proportion of risk spillovers among different blockchain marketplaces to total prediction error variance as:

$$TCI(\tau) = \sum_{i=1}^{N} \sum_{j=1, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(\tau) / \sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(\tau) * 100 \tag{4}$$

Then, the net connectedness can be written in equation form as:

$$NC(\tau) = C_{\cdot \to i}(\tau) \left[\sum_{i=1}^{N} \sum_{j=1, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(\tau) / \sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(\tau) * 100 \right] - C_{\cdot <-i}(\tau) \left[\sum_{i=1}^{N} \sum_{j=1, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(\tau) / \sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(\tau) * 100 \right] \tag{5}$$

A VAR lag of order 1 is chosen based on the Bayesian information criterion (BIC), and a 10-step forward forecast variance decomposition is used for connectedness calculations.

Also, we follow the cross-quantilogram approach by Han et al. (2016) whereby the correlogram of 'quantile hits' is used to assess predictability in different sections of the distribution of a stationary time series.

Assuming $\{(y_t, x_t): t \in \mathbb{Z}\}$ is a strictly stationary time series with $y_t = (y_{1t}, y_{2t})^T \in \mathbb{R}^2$ representing the NFT time series, for instance, and $x_t = (x_{1t}, x_{2t}) \in \mathbb{R}^{d_1} \times \mathbb{R}^{d_2}$ representing the DeFi assets time series, and

$x_{it} = \left[x_{it}^{(1)}, \ldots, x_{it}^{(d_1)}\right]^T \epsilon\, \mathbb{R}^{d_i}$ with $d_i \epsilon\, \mathbb{N}$ for $i = 1, 2$. Then, $F_{y_i|x_i}(* \mid x_{it})$ conditional distribution function of the series y_{it} given x_{it} with density function $f_{y_i|x_i}(* \mid x_{it})$ and the conditional quantile function defined as per equation (6):

$$q_{i,t}(\tau_i) = inf\{v: F_{y_i|x_i}(v|x_{it}) \geq \tau_i\}\, for\ \tau_i\ \epsilon\ (0,1), where\ i = 1, 2 \tag{6}$$

Let τ be the range of quantiles used for evaluating the directional predictability. We consider an indicator of serial dependence between the two events for an arbitrary pair of $\tau = (\tau_1, \tau_2)^T \epsilon$ T. The cross-quantilogram is defined as the cross-correlation of the quantile-hit process as per equation (7) below, where the quantile-hit is $\{y_{2,t-k} \leq q_{2,t-k}(\tau_2)\}$:

$$\rho_\tau(k) = \frac{E[\psi_{\tau_1}(y_{1t} - q_{1t}(\tau_1))\psi_{\tau_2}(y_{2,t-k} - q_{2,t-k}(\tau_2))]}{\sqrt{E[\psi_{\tau_1}^2(y_{1t} - q_{1t}(\tau_1))]}\sqrt{E[\psi_{\tau_2}^2(y_{2,t-k} - q_{2,t-k}(\tau_2))]}} \tag{7}$$

for $k = 0, \pm 1, \pm 2, \ldots$, where $\psi_a(u) \equiv 1[u < 0] - a$. The cross-quantilogram depicts the serial dependency of the two series at various conditional quantile levels. In the case of a single time series, the cross-quantilogram is transformed into the quantilogram suggested by Linton and Whang (2007).

In this study, we use three cross-quantilograms to test each of the three pairs the cross-correlation between NFTs and DeFis, between NFTs and cryptocurrencies and between DeFis and cryptocurrencies.

2.3 Research Hypotheses

The following research hypotheses have been formulated corresponding to each of the two research questions of this study:

H1. There is a strong link between NFT and DeFi assets.

H2. There is a low correlation between NFTs and cryptocurrencies.

H3. There is a low correlation between DeFi and cryptocurrencies.

The hypotheses have been based on the extant research by Karim et al. (2021) who found that there is a significant risk spillover within blockchain markets of the same kind (e.g., within cryptocurrency, NFT markets, etc.) but there is a prominent separation from a risk transmission perspective between NFTs and cryptocurrencies.

Also, the current study formulated these hypotheses in accordance with the findings by Dowling (2021) who determined that volatility transmission effects between cryptocurrencies and NFTs are low. However, the authors also found that there is co-movement between the NFTs and cryptocurrencies.

The next section includes the results of the statistical analysis focusing on the connectedness and the spillover effects between NFT and DeFi assets and cryptocurrencies.

3. Results

Following the research method detailed above, we present the results based on the Diebold and Yilmaz (2012) volatility spillover matrix, as applied by Dowling (2021) and the volatility connectedness using the approach by Ando et al. (2018), which was applied by Karim et al. (2021). These methods were applied to the data sampled for this study which seeks to determine whether NFTs and DeFi assets display any opportunities for portfolio diversification for investors by analysing the spillover effects to and from NFTs, DeFis and cryptocurrencies. The sections below follow the two approaches and present the results of this study.

3.1 Spillovers between DeFi, NFTs and Cryptocurrencies

Table 2 includes the spillovers between NFT, DeFi and cryptocurrencies Bitcoin and Ethereum. The results show that, as compared to cryptocurrencies, there is substantially less spillover from and to NFT markets. Also, DeFi assets seem to be relatively disconnected from cryptocurrency markets, as the volatility spillover values are significantly lower to and from DeFi versus the other assets. Moreover, among cryptocurrency markets, there is high transmission, as shown in Table 2 through the increased levels of volatility spillover between Bitcoin and Ethereum daily prices, in both directions. There is also significant influence to and from other factors in the case of both cryptocurrencies, as well as NFTs and DeFis.

Table 2. Synthesis of results linked to the literature

	NFT	DeFi	Bitcoin	Ethereum	from others
NFT	74.80	36.12	10.36	11.56	15.09
DeFi	1.03	3.66	5.45	8.49	36.02
Bitcoin	6.33	1.22	48.36	35.40	46.21
Ethereum	8.12	6.23	36.49	39.02	51.23
to others	26.96	16.39	50.36	80.56	25.20

Note. The volatility spillover matrix has been obtained following the Diebold and Yilmaz (2012) approach, based on daily prices for selected cryptocurrencies, Bitcoin and Ethereum, NFTs and DeFi assets from January 15th to December 6th, 2021.

Figure 8 illustrates the rolling net spillovers for the aggregated NFTs, DeFi assets and cryptocurrencies. We investigate whether the spillover effects vary over time. Because of the short time frame, we chose a 48-week rolling window, which means findings are accessible until January 2021. Figure 8 shows the net spillover effects for NFTs, DeFis and cryptocurrencies, which are usually negative for NFTs and DeFis and positive for our two cryptocurrencies. However, there is no discernible change over time, suggesting that the findings in Table 2 are correct. This confirms the findings by Dowling (2021) on the net spillovers for NFTs and the same two cryptocurrencies, Bitcoin and Ethereum.

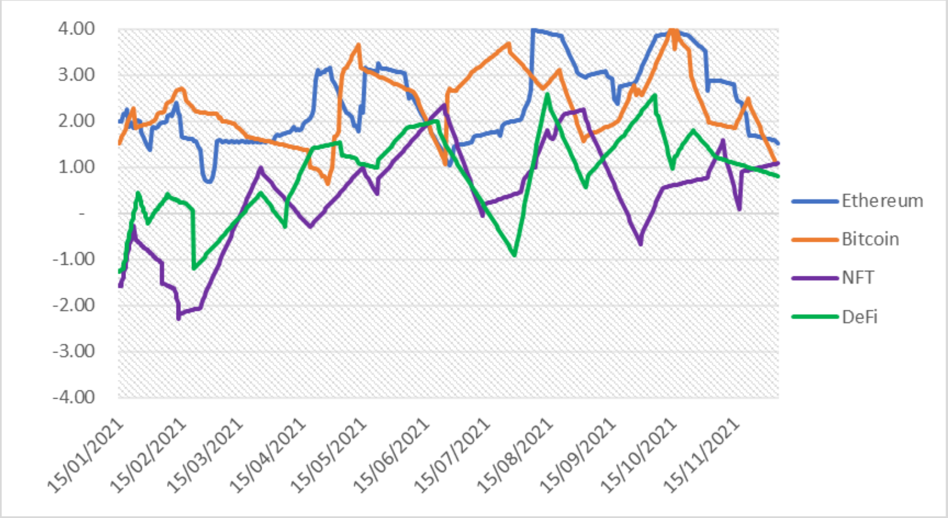

Figure 8. Rolling net spillovers for NFTs, DeFis, Bitcoin, Ethereum

Note. Data is based on daily prices between January 15th and December 6th

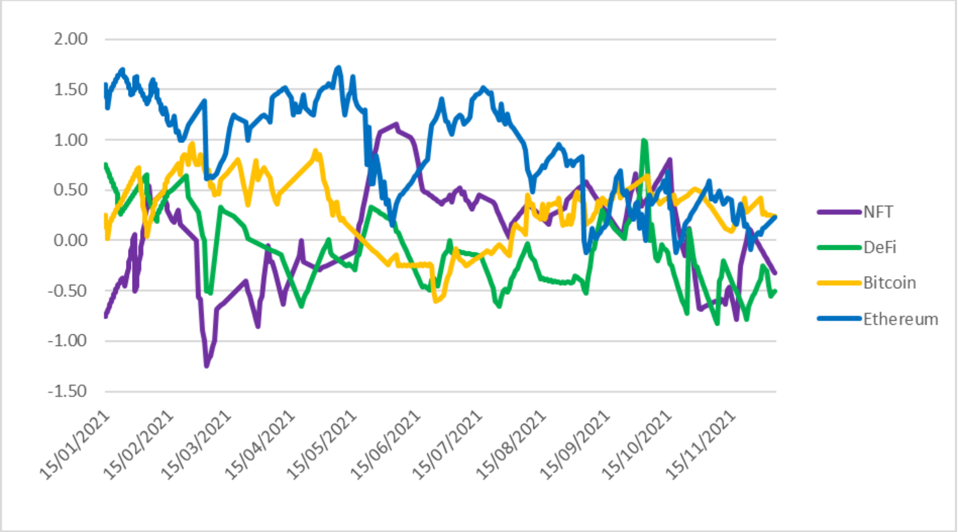

Figure 9. Net directional risk spillover for NFTs, DeFis, Bitcoin, Ethereum at median quantile

3.2 Quantile Volatility Spillovers

Figure 9 illustrates the net directional risk spillovers at the median (50^{th}) quantile for NFTs, DeFis, Bitcoin and Ethereum. At median volatility conditions, positive spillovers of DeFi and Cryptos outweighed negative spillovers of NFT, indicating that NFT has the capacity for diversification and hence outperforms our results in network risk connectivity.

3.3 Risk Spillovers between the NFT and DeFi Markets

While 117nalysing the spillover effects from NFTs to cryptocurrencies, from DeFi assets to cryptocurrencies, on the one hand, and from cryptocurrencies towards NFTs and DeFis, on the other hand, we could also observe the transmission from NFTs to DeFis and from DeFis to NFTs. As shown in Table 2 as well as in Figures 8 and 9, there is significantly higher spillover from DeFi assets to NFTs than the other way around, which could be explained through the fact that the DeFi assets analysed in this study are embedded in the NFT market, yet NFTs go beyond the Comet token included here and encompass other tokens too.

This demonstrates that while DeFis are slightly disconnected from cryptocurrencies, they display some co-movement with NFTs which was expected, as explained above, and which influences the portfolio diversification strategies involving DeFi assets.

3.4 Cross-quantilogram Testing

As detailed above, we apply the bivariate cross-quantilogram approach by Han et al. (2016) to measure the predictability of distinct quantiles of a stationary time series distribution. The statistical test employs as the null hypothesis, $H_0: \rho_\tau(1) = \cdots = \rho_\tau(p) = 0$, which is tested against the alternative hypothesis, $H_1: \exists k, \rho_\tau(1) \neq 0, k = 1, 2, \ldots, p$, where we examine the directional predictability from the event $\{x_{2,t-k} \leq q_{2,t-k}(\tau_2): k = 1, 2, \ldots, p\}$ to the event $\{x_{1,t} \leq q_{1,t}(\tau_1)\}$. As suggested by Han et al. (2016) and also implemented by Baumöhl and Lyócsa (2017) based on data from the US stock market and the gold index, we use a Ljung-Box test statistics, calculated based on the formula in equation (8) below:

$$Q_\tau^*(p) = T(T+1) \sum_{k=1}^{p} \frac{\rho_\tau^{*2}(k)}{T-k} \tag{3}$$

We consider the dependency between all pairs of quantiles supplied by 0.05, 0.10, …, 0.95 in our study, meaning we construct 361 levels of dependence for a specific pair of time series and p-value. The results indicate some quantile dependence between NFTs and DeFis and but no quantile dependence between any other pair of assets, which confirm the findings from the volatility spillover analysis.

4. Discussion

4.1 Discussion and Interpretation of Results

Based on the findings of this article, which have been included in Table 3 and compared to the results of the most relevant research in the extant literature, we can draw inferences from the correlation and co-movement of NFTs, DeFis and cryptocurrencies. This helps not only investors but also researchers and policymakers make informed decisions with respect to the emerging financial instruments that have gained increased attention in the last few years.

Regarding the hypotheses formulated earlier in this study, we found that there is a significant correlation between NFTs and DeFis, corresponding to the first hypothesis. Also, the study highlighted the low spillover effect to and from NFTs and cryptocurrencies, which helps test the second hypothesis, against the alternative hypothesis that there is a significant correlation between the two types of assets. Finally, the findings are consistent with verifying the third hypothesis too which states that there is a low correlation between DeFi assets and cryptocurrencies.

Based on the findings in this study that suggest advantageous investment profiles of instruments in blockchain markets, we can advise policymakers, regulators, and risk-seeking investors to pay attention to NFTs and DeFis. This is because significant volatility underpins cryptocurrencies and DeFis, allowing investors to earn bigger returns in a shorter period of time. For risk-averse individuals, portfolio managers, and institutional investors, investing in NFTs can mitigate the risk of DeFis and cryptocurrencies.

Furthermore, a crucial implication of these findings is that the advantageous investment aspects impact not only investors in block-chain markets but also legislators who seek to understand and regulate the mechanisms behind allowing investors to earn bigger returns in a shorter period of time, while also protecting consumers and the wider economy.

This research study also closes the gap in the literature around the NFT correlation with DeFis and cryptocurrencies by focusing on the spillover effects to and from NFTs and DeFis, on the one hand, and cryptocurrencies, on the other hand.

Moreover, the study updates the findings of previous research by basing the data on the most recent timeframe, namely the period between January 15th and December 6th.

Table 3. Synthesis of results linked to the literature

Findings	Corresponding findings in the literature
We discover far less spillover from and to non-traditional financial markets. Both NFTs and DeFi assets appear to be relatively uncorrelated to the cryptocurrency markets.	Dowling (2021) found that in terms of volatility transmission, NFT pricing appears to be fairly separate from the Bitcoin price. This has intriguing implications for investment portfolios, as low-correlation assets are highly valued due to their diversification properties. To establish the low-correlation status of NFTs, we need to look into the price of NFTs concerning other asset classes.
Negative NFT spillovers were outweighed by the low positive DeFi and Crypto spillovers.	Karim et al. (2021) investigated extreme risk transmission was among NFTs, DeFis, and Cryptos at the median, extreme low, and extremely high volatility levels and found considerable volatility connection among block-chain markets. Time-varying features indicated explainable patterns of TCI at each quantile, although net directional risk spillovers showed significant overlaps in block-chain markets. When compared to DeFis and Cryptos, NFTs exhibited a larger potential for diversification.

4.2 Limitations of the Study

Some important limitations that we must acknowledge include the fact that there are sources of potential contagion from other asset classes as well as spillovers between countries. As Claeys and Vašíček (2014) demonstrate, to identify whether there is any risk of contagion, Qu and Perron's (2007) multivariate structural break test can be performed which detects substantial rapid changes in shock transmission. The findings by Claeys and Vašíček (2014), albeit on different asset classes than NFTs, DeFis or cryptocurrencies, show significant spillover, particularly amongst EMU nations.

Moreover, the research method selected does display some measurement imprecisions especially around the accuracy of identifying the directionality of the proposed method by Diebold and Yilmaz (2012). As Urbina (2013) argues, the directional spillovers of Diebold and Yilmaz (2012) are only possible provided the researcher has a theoretical foundation for the Cholesky decomposition. Once the researcher discovers the directionality and applies the orthogonalization, they are already able to assert directionality in the spillover spread, thus directional spillovers make sense; otherwise, directional spillovers are not attainable when directionality is not reachable (Urbina, 2013). To this point, in the current study, we assume that the shocks are non-orthogonalized, and we utilize the vector moving average from the model for identification. Based on this premise, we used the generalized forecast error variance decomposition (GFEVD) of a variable subjected to a range of shocks by Karim et al. (2021).

Also, the timeframe selected is relatively limiting, compared to other studies on the subject which may hinder the applicability and generalizability of the findings in different market contexts. However, the findings based on data between January 15th and December 6th are highly valuable when compared to previous years and could guide further research into the field by offering a starting point of the initial interactions between the new asset classes represented by NFTs, DeFis and cryptocurrencies.

4.3 Concluding Remarks and Recommendations for Further Research

To conclude this study on the topic of volatility spillover between NFTs, DeFis and cryptocurrencies, the low correlation between NFTs and cryptocurrencies as well as between DeFis and cryptocurrencies offer insights into the early developments of the token market and their emergence into the financial markets. As Harvey et al. (2021) argue, the potential represented by non-fungible tokens and decentralized finance is growing and it is still in its incipient form. The high potential of DeFi and NFT to play a crucial role in the financial system in the upcoming years is supported by the fact that these assets are true “Internet of money” tools, as stated by Harvey et al. (2021). Through them, the Internet demonstrated the power of a global, open network for information while the concept of a similarly open, worldwide network for value transmission will appear clear after 40 years, making this a fact hidden in plain sight today, as Harvey et al. (2021) demonstrate.

The findings in this study confirm the importance of continually examining the co-movement of the NFTs, DeFis and cryptocurrencies, as relatively new assets that can display changing behaviours, as the investment strategies must keep up with these changes and adapt to them to avoid creating bubbles that can potentially cause serious effects like those we saw during the 2008-2009 global financial crisis. The theoretical significance of the outcomes of this study, therefore, includes the fact that both NFTs and DeFis play a crucial role in supporting the modern portfolio theory by providing strategies of diversification for investors.

A problem that remains unsolved, however, is the regulation aspect and the risks associated with investing in NFTs and DeFis. Specifically, the jurisdictional ambiguities, regulatory gaps, and standards deficiencies could cause investor damage and financial system instability. The existing regulatory gaps are most prominent around third-party intermediates and custodial services provided as a single point of contact for risk transfer and investor transaction volume (Clements, 2021). By addressing them, the regulator's actions will provide clarity, stability, and credibility to a previously vulnerable part of an industry that is experiencing a surge in investor interest (Clements, 2021).

Acknowledgements

The author would like to thank the two reviewers for their useful and constructive remarks; nevertheless, the author is solely responsible for any remaining errors.

References

Aharon, D. Y., & Demir, E. (2021). NFTs and asset class spillovers: Lessons from the period around the COVID-19 pandemic. *Finance Research Letters,* 102515. https://doi.org/10.1016/j.frl.2021.102515

Ando, T., Greenwood-Nimmo, M., & Shin, Y. (2018). *Quantile Connectedness: Modelling Tail Behaviour in the Topology of Financial Networks.* Available at SSRN 3164772

Baumöhl, E., & Lyócsa, S. (2017). Directional predictability from stock market sector indices to gold: A cross-quantilogram analysis. *Finance Research Letters, 23*, 152-164.

Claeys, P., & Vašíček, B. (2014). Measuring bilateral spillover and testing contagion on sovereign bond markets in Europe. *Journal of Banking & Finance*, *46*, 151-165. https://doi.org/10.1016/j.jbankfin.2014.05.011

Clements, R. (2021). Emerging Canadian Crypto-Asset Jurisdictional Uncertainties and Regulatory Gaps. *Banking and Finance Law Review, 37*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3891809

CoinMarketCap. (2021a). Bitcoin. Historical Data. Retrieved December 7, 2021, from https://coinmarketcap.com/currencies/bitcoin/historical-data/.

CoinMarketCap. (2021b). Ethereum. Historical Data. Retrieved December 7, 2021, from https://coinmarketcap.com/currencies/ethereum/historical-data/.

Cointelegraph. (2021, December 23). 2020’s DeFi craze: The best, worst and fishiest projects in crypto. *Cointelegraph.* Retrieved December 12, 2021, from https://cointelegraph.com/news/2020-s-defi-craze-the-best-worst-and-fishiest-projects-in-crypto.

Corbet, S., Goodell, J. W., Gunay, S., Kaskaloglu, K. (2021). Are DeFi Tokens a Separate Asset Class from Conventional Cryptocurrencies? *Available at SSRN 3810599.*

Defi Pulse. (2021). *Total Value Locked (USD)*. Retrieved December 7, 2021, from https://defipulse.com/

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57-66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Dowling, M. (2021). Is non-fungible token pricing driven by cryptocurrencies? *Finance Research Letters, 102097,* 1-6. https://doi.org/10.1016/j.frl.2021.102097

Fabozzi, F. J., Gupta, F., & Markowitz, H. M. (2002). The legacy of modern portfolio theory. *The Journal of Investing, 11*(3), 7-22. https://doi.org/10.3905/joi.2002.319510

Finneseth, J. (2020, December 23). 2020’s DeFi craze: The best, worst and fishiest projects in crypto. *Cointelegraph*. Retrieved December 7, 2021, from https://cointelegraph.com/news/2020-s-defi-craze-the-best-worst-and-fishiest-projects-in-crypto.

Golden, P. (2021, October 26). Trade finance embraces the art of the NFT. *Euromoney.* Retrieved December 6, from https://www.euromoney.com/article/298kk209i03jjab28pzi8/treasury/trade-finance-embraces-the-art-of-the-nft.

Han, H., Linton, O., Oka, T., & Whang, Y. J. (2016). The cross quantilogram: Measuring quantile dependence and testing directional predictability between time series. *Journal of Econometrics*, *193*(1), 251-270. https://doi.org/10.1016/J.JECONOM.2016.03.001

Harvey, C. R., Ramachandran, A., & Santoro, J. (2021). *DeFi and the Future of Finance*. John Wiley & Sons. https://doi.org/10.2139/ssrn.3711777

Iredale, G. (2021, September 15). Understanding the use of NFT in DeFi. *101 Blockchain*. Retrieved December 7, 2021, from https://101blockchains.com/nft-and-defi/

Karim, S., Lucey, B. M., Naeem, M. A., & Uddin, G. S. (2021). *Examining the Interrelatedness of NFT's, DeFi Tokens and Cryptocurrencies.* Available at SSRN 3967960. https://doi.org/10.2139/ssrn.3967960

Linton, O., & Whang, Y. J. (2007). The quantilogram: With an application to evaluating directional predictability, *Journal of Econometrics*, *141*, 250-282. https://doi.org/10.1016/j.jeconom.2007.01.004

Moratis, G. (2021). Quantifying the spillover effect in the cryptocurrency market. *Finance Research Letters*, *38*(C), 101534. https://doi.org/10.1016/j.frl.2020.101534

Musan, D. I., William, J., & Gervais, A. (2020). NFT. Finance Leveraging Non-Fungible Tokens. *Meng Individual Project, Imperial College London, Department of Computing.*

Nadini, M., Alessandretti, L., Di Giacinto, F., Martino, M., Aiello, L. M., & Baronchelli, A. (2021). Mapping the NFT revolution: market trends, trends networks, and visual features. *Scientific Reports, 11*(20902), 1-11. https://doi.org/10.1038/s41598-021-00053-8

NonFungible.com. (2021). *Market History*. Retrieved December 6, 2021, from https://nonfungible.com/market/history

Pesaran, M. H. & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, *58*(1), 17-29. https://doi.org/10.1016/S0169-2070(03)00068-2

Qu, Z., & Perron, P. (2007). Estimating and testing structural changes in multivariate regressions. *Econometrica*, *75*(2), 459-502. https://doi.org/10.1111/j.1468-0262.2006.00754.x

Statista. (2021a). Overall cryptocurrency market capitalization per week from July 2010 to November 2021. October 22 [Graph]. In *Statista.* Retrieved December 8, 2021, from https://www.statista.com/statistics/730876/cryptocurrency-maket-value/

Statista. (2021b). Amount of cryptocurrency held in decentralized finance, or DeFi, worldwide from August 2017 to October 15, 2021 (in million U.S. dollars) [Graph]. In *Statista*. Retrieved December 8, 2021, from https://www.statista.com/statistics/1237821/defi-market-size-value-crypto-locked-usd

Urbina, J. (2013). Financial Spillovers Across Countries: Measuring shock transmissions. *Universitat Rovira i Virgili, Department of Economics, Centre de Recerca en Economia Industrial i Economia Pública (CREIP).* Retrieved December 10, 2021, from https://mpra.ub.uni-muenchen.de/75756/1/MPRA_paper_75756.pdf

Wette.de. (2021, November 22). NFT Google Searches Increase 100x in 12 Months. Retrieved December 8, 2021, from https://www.wette.de/news/nft-google-searches-increase-100x-in-12-months/

Wragg, E. (2021, July 21). NFTs in trade finance: the next frontier or bad idea? *Global Trade Review*. Retrieved December 7, 2021, from https://www.gtreview.com/news/fintech/nfts-in-trade-finance-the-next-frontier-or-bad-idea/

Yousaf, I., & Yarovaya, L. (2021). *Static and dynamic connectedness between NFTs, DeFi and other assets: portfolio implication.* Available at SSRN 3946611. https://doi.org/10.2139/ssrn.3946611