Is non-fungible token pricing driven by cryptocurrencies?

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Abstract

In early 2021, non-fungible tokens (NFT) became the first application of blockchain technology to achieve clear public prominence. NFTs are tradeable rights to digital assets (images, music, videos, virtual creations) where ownership is recorded in smart contracts on a blockchain. Given the NFT market emerged out of cryptocurrencies, we explore if NFT pricing is related to cryptocurrency pricing. A spillover index shows only limited volatility transmission effects between cryptocurrencies and NFTs. But wavelet coherence analysis indicates co-movement between the two sets of markets. This suggests that cryptocurrency pricing behaviours might be of some benefit in understanding NFT pricing patterns. However, the low volatility transmissions also indicate that NFTs can potentially be considered as a low-correlation asset class distinct from cryptocurrencies.

JEL codes: G14; G12
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1 Introduction

Non-fungible token (NFT) markets emerged to some prominence in early 2021. These new markets for digital assets grew to about $550m of lifetime total traded volume towards the end of March 2021, but over $200m of that trade happened in the month of March alone. This trade growth was matched by large growth in public discussion and traditional media coverage of NFTs (Dowling, 2021).

NFTs can be any type of digital assets. The most common types are collectibles and artworks, objects in virtual worlds, and digitalised characters from sports and other games. An NFT starts with registering ownership of a digital asset on a blockchain, usually on an ethereum network. This digital asset can then be sold, with changes in ownership and the cryptocurrency payment received registered on the blockchain.

An example of an NFT, which forms part of the data analysed in this study, are the *CryptoPunks*. CryptoPunks are the largest single traded market in NFTs at time of writing, with approximately $200m traded over its lifetime. The market started in early 2017 when 10,000 unique digital characters were created and registered as individual assets on the Ethereum blockchain. The characters were trading for $50 to $100 each until around April 2020 when they started a steady inexorable price rise, with prices then exploding in early 2021. By February and March 2021 individual CryptoPunks were trading at between $20,000 and $100,000.

NFTs, while traded through cryptocurrencies, have some very different characteristics to cryptocurrencies, and this is important to bear in mind when trying to understand them. Cryptocurrencies are intended primarily as currencies, even if they maintain some asset-like properties (Baur et al., 2018). NFTs, on the other hand, are intended as pure assets. Indeed the term *non-fungible* in the NFT name is the clue to this difference. Fungibility, or interchangeability, is one of the defining characteristics of cryptocurrencies and money in general (one bitcoin is the same as another bitcoin, and one dollar the same as another). The non-fungibility of NFTs is one of the key asset characteristics that is valued.

Having said this, anyone active in the NFT market will be aware of the strong crossover between cryptocurrency market participants and NFT market participants. This is partially because to buy an NFT you need to use cryptocurrencies as a means of payment, a non-trivial level of complexity for many people. With that in mind, our study looks at crossover effects between cryptocurrency pricing and NFT pricing. We expect cryptocurrencies to influence NFT pricing, as, in general, larger markets tend to spillover into smaller related markets (Bhattarai et al., 2020) and cryptocurrencies are a vastly larger related market to NFTs. NFT pricing might also influence cryptocurrency markets, as NFTs and their popularity shows a strong business use case for the blockchain. This, therefore, addresses an open business point about what practical uses there are for the blockchain and the cryptocurrencies built on top of blockchains (Morkunas et al., 2019; Trautman and Molesky, 2019).

With this understanding of the trader crossover between the two sets of markets, this study sets out to examine the interrelationships between cryptocurrencies and NFT markets. Moratis (2021) shows there is a large level of volatility shock transmission between cryptocurrencies, with Bitcoin dominating this transmission. Given the crossover of trading between cryptocurrencies and NFTs, and the potential leading influence of cryptocurrency pricing on NFTs, we investigate if volatility also spills over to NFT markets. To boost this investigation we further examine whether there is co-movement between cryptocurrency and NFT returns, as co-movement has been shown to be a major feature within cryptocurrency markets (Qiao et al., 2020). The discovery of links between the two sets of markets would be beneficial to researchers and practitioners alike as we could then examine trends in cryptocurrency pricing for guidance on likely trends in NFT markets.

Our study contributes to the nascent NFT pricing literature. Only one previous study has examined the pricing patterns of NFTs (Dowling, 2021). That study shows, for one NFT market, that pricing does not show signs of basic efficiency, but that there are some emerging signs of changes in pricing behaviour. Given the diversity of NFT markets, our study contributes to Dowling (2021) at a basic level by being a second study in the area and by extending testing to three NFT markets (two new markets). Our primary contribution is showing how NFT pricing relates to cryptocurrency market pricing. We find limited volatility transmission and some strong evidence of co-movement, and this gives a framework for understanding how NFT pricing might develop as the markets mature. The study at a more general level contributes to understanding of how pricing behaviour develops in new markets (Khuntia and Pattanayak, 2018).

In the next section we discuss the data and the methodology. The section after that contains the findings and analysis. Lastly, we conclude the study.

2 Methodology

Our dataset starts with data for the two largest cryptocurrency markets; Bitcoin and Ether, with the raw data obtained from coinmarketcap.com. The reason for choosing these two cryptocurrencies is the direct connection between Ether and NFTs, as NFTs are, to date, primarily registered on Ethereum smart contracts and payment is normally made through Ether. Bitcoin is selected as the market with the largest size[1] and the largest volatility transmissions to other cryptocurrencies (Moratis, 2021).

Our NFT data is secondary market trades in: Decentraland LAND tokens; CryptoPunk images; and Axie Infinity game characters. Individual trade data is sourced from nonfungible.com and we aggregate[2] from trade data to our time window. We chose Decentraland LAND, a virtual land NFT that exists in the Decentraland virtual world, for comparability with the data in Dowling (2021), and because it is the largest virtual world, and the fourth largest NFT market overall. We chose CryptoPunk as it is the largest NFT market, the original NFT market, and somewhat representative of the (quite diverse) NFT art and collectible market. We chose Axie Infinity as a market with a large traded volume unlike the other two markets, as it is a representative of the NFT gaming market, and the eight largest NFT market overall by dollars traded.

Table 1 provides the descriptive statistics for our dataset, and Figure 1 charts the pricing history of all markets. The time period is March 2019[3] to March 2021. Prices

[1]Bitcoin is about five times larger than the next largest market (Ethereum) with a market value in excess of a trillion US dollars at time of writing.

[2]we are aware that aggregation of the unique characters that inhabit, for example, the Axie Infinity universe, will be anathema to its adherents. We hope in future studies to focus on the unique aspects of the characters and the impact of this on pricing. But, for this study, given the novelty of NFT pricing research, we consider it acceptable to aggregate and average prices.

[3]The starting time period of March 2019 is determined by a major change in Decentraland LAND specifications in February 2019, and wishing to have a balanced dataset.

are in USD equivalents and returns are calculated on a weekly basis due to excessive variation in daily returns data, as trading in some of the NFTs is quite limited in the early time periods. We have 4,936 trades of Decentraland LAND, 7,578 trades of CryptoPunks, and 95,272 trades of Axie Infinity characters over the time period. We see there is three distinct price points across the three NFT markets also, with Axie Infinity characters at $61 average price, Decentraland at $1,109, and CryptoPunks as the most premium market at an average of $4,439. Figure 1 emphasises the large 2021 run up in prices for both cryptocurrencies and NFTs, although the price rise of NFTs appears more abrupt.

Table 1: Descriptive statistics

	Decentraland		CryptoPunks		AxieInfinity		Bitcoin		Ether	
	Price	Return	Price	Return	Price	Return	Price	Return	Price	Return
Mean	1108.64	0.0214	4439.30	0.0649	61.07	0.0294	13428.90	0.0252	390.41	0.0243
Median	826.48	-0.0076	269.01	0.0212	15.65	-0.0299	9537.82	0.0172	228.16	0.0169
Std Dev	1069.41	0.2754	14065.13	0.6203	117.84	0.6241	11600.17	0.0859	419.70	0.1066
Minimum	372.04	-0.5788	41.51	-1.7731	2.81	-1.5452	3898.49	-0.3174	123.55	-0.3766
Maximum	8321.89	0.6955	100753.50	1.7350	684.37	2.3206	57360.48	0.2360	1880.29	0.4289
Skewness	4.69	0.3283	4.72	0.0332	3.29	0.4346	2.48	-0.2077	2.45	-0.0949
Kurtosis	25.92	0.0050	24.99	0.3235	11.60	1.6132	5.51	1.9385	5.06	3.2186

Descriptive statistics for selected NFT and cryptocurrency markets from March 2019 to March 2021. Returns are based on weekly data. Prices are USD equivalents at time of trade. Data sourced from coinmarketcap.com (Bitcoin and Ether) and nonfungible.com (Decentraland, CryptoPunks, AxieInfinity).

In the testing we first look at volatility spillovers between the markets. We are interested in whether volatility shocks are flowing to the NFT markets or from the NFT markets. We are also interested in volatility transmission within the NFT markets. For this analysis we use the volatility spillover methodology of Diebold and Yilmaz (2009, 2012). Without wanting to over-describe this widely known technique, the technique involves constructing a matrix of Generalized Impulse Responses which are transmissions of volatility from one market to another. The popularity of

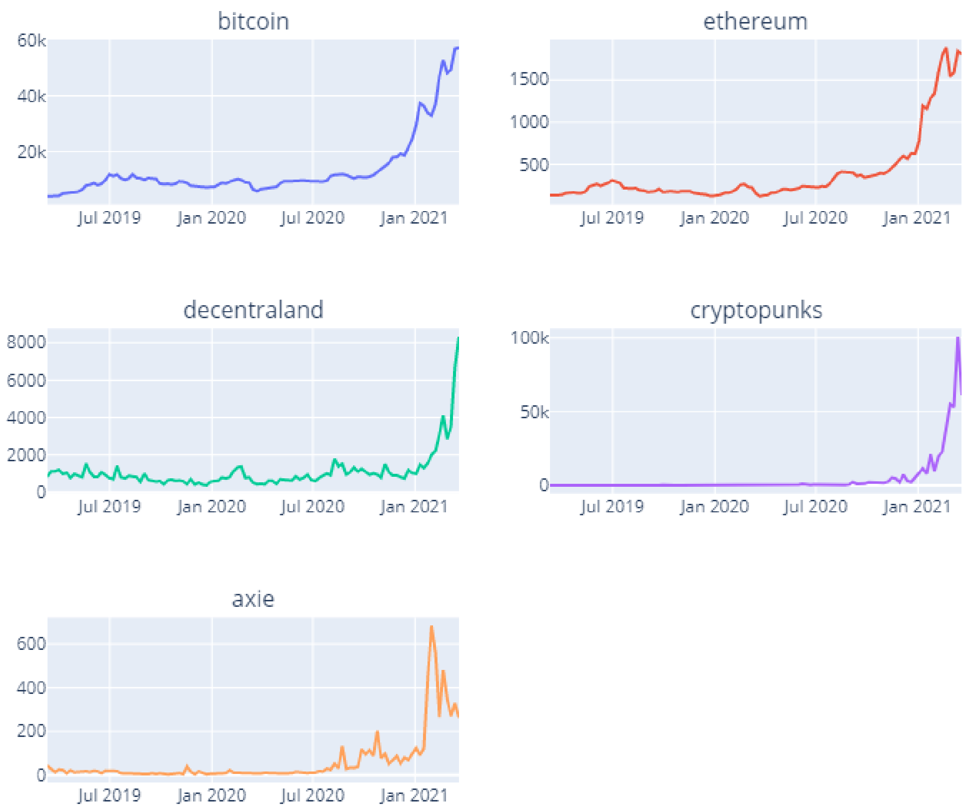

Figure 1: Weekly pricing plots as named for all NFTs and cryptocurrencies, March 2019 to March 2021.

the spillover matrix is because it allows an intuitive reading of many transmissions relationships to and from markets of interest in a single table.

The second technique we use is wavelet coherence to investigate co-movement between markets. Wavelet coherence analysis allows investigation as to whether there is co-movement between two assets (bivariate wavelets) in terms of both time and frequency. We use cross-wavelets following the approach of Torrence and Compo (1998) and as specified for a cryptocurrency analysis in Goodell and Goutte (2021). We incorporate phase positions in the wavelet analysis, which help inform on direction of influence. We discuss this further in the relevant analysis contained in the next section.

3 Findings

Table 2 reports the spillover effects for our selection of cryptocurrencies and NFTs. Immediately apparent from the results is that, compared to cryptocurrenies, there is much lower spillover from and to NFT markets. Further, even among the NFT markets there is quite limited spillover, suggesting these markets are quite distinct from each other. The Decentraland LAND token market shows the greatest connection to cryptocurrencies with returns impacted about 25% from Bitcoin and Ether lagged returns.

Table 2: Spillovers between cryptocurrencies and NFTs

	Bitcoin	Ether	Decentraland	CryptoPunks	Axie	from others
Bitcoin	50.30	33.60	10.11	4.73	1.26	49.70
Ether	30.70	45.38	13.69	5.77	4.46	54.62
Decentraland	13.57	12.75	66.88	2.49	4.32	33.12
CryptoPunks	7.61	10.79	6.59	70.83	4.18	29.17
Axie	5.44	3.43	9.20	0.49	81.46	18.54
to others	57.31	60.56	39.59	13.48	14.22	37.03

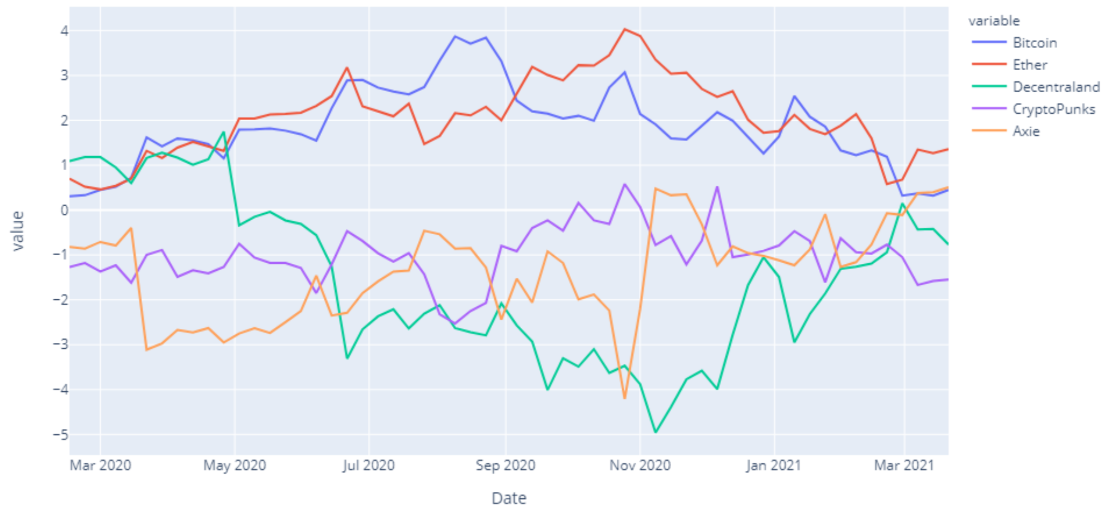

Figure 2: Rolling (50-week) net spillovers for all NFTs and cryptocurrencies, February 2020 to March 2021.

Diebold and Yilmaz (2012) volatility spillover matrix for selected NFT and cryptocurrency markets from March 2019 to March 2021 based on weekly returns.

In Figure 2 we check if there might be time variation to the spillover effects. We are limited here by our short time frame and so we choose a 50-week rolling window, meaning results are available for the last year of our sample - 2020/21. Figure 2 reports net spillover effects for each NFT and cryptocurrency, and we see that these are generally negative for NFTs and generally positive for our two cryptocurrencies. There is, however, no notable change over time and, therefore, the findings in Table 2 are appropriate.

Our last set of results is based on a wavelet coherence approach. We analyse co-movement between Ether (as NFTs are normally registered on an Ethereum

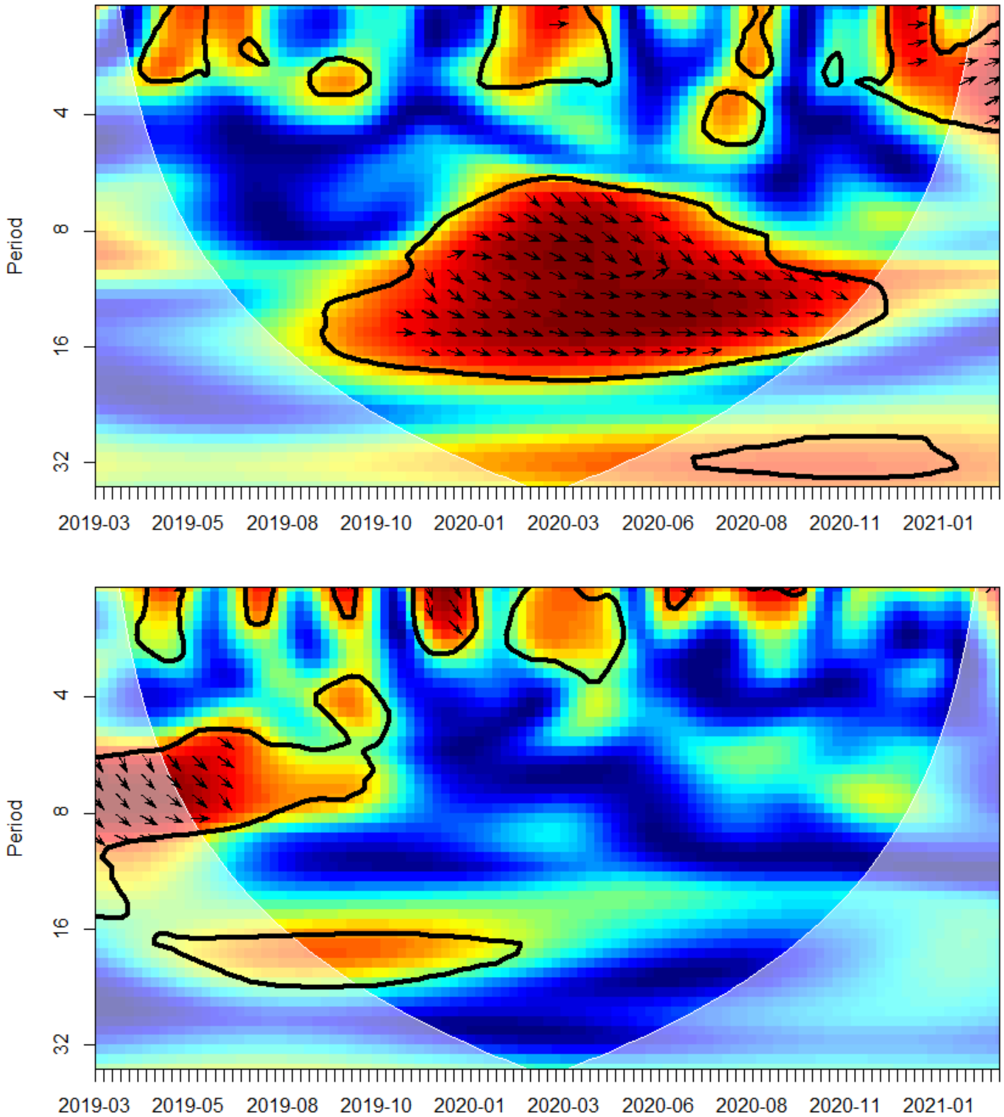

Figure 3: Wavelets (1): Wavelet coherency (WTC) for Ether and Decentraland LAND NFT (top), Ether and CryptoPunk images (bottom). Correlation is shown by the colour - hotter colours (cool blue to hot red) indicate higher absolute correlations. For the arrows, $\rightarrow$ shows positive correlation, $\nearrow$ and $\swarrow$ show Ether leads the NFT, and $\searrow$ and $\nwarrow$ show the NFT lead Ether.

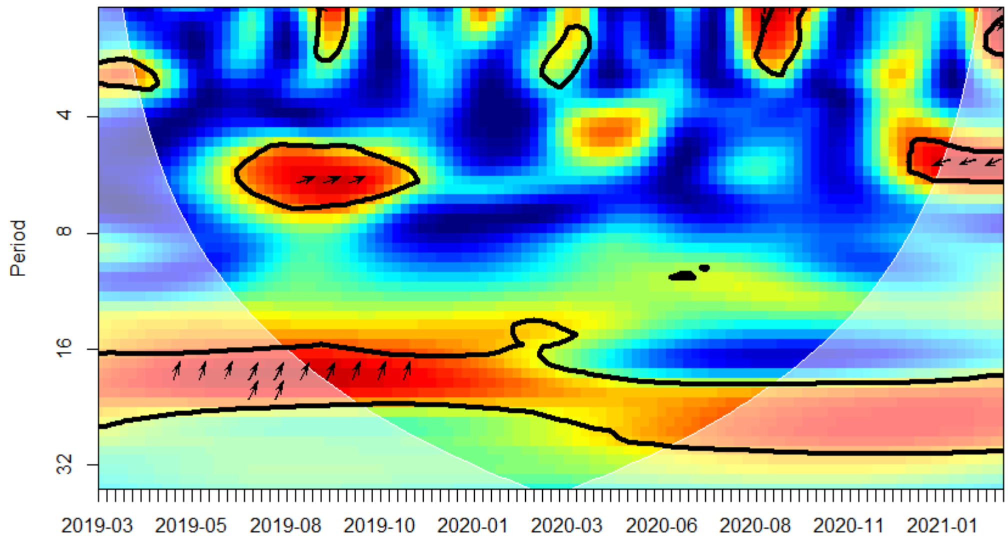

Figure 4: Wavelets (2): Wavelet coherency (WTC) for Ether and Axie Infinity characters. Correlation is shown by the colour - hotter colours (cool blue to hot red) indicate higher absolute correlations. For the arrows, $\rightarrow$ shows positive correlation, $\nearrow$ and $\swarrow$ show Ether leads the NFT, and $\searrow$ and $\nwarrow$ show the NFT lead Ether.

blockchain) and the three NFT markets. We therefore run three bivariate wavelets; Ether-Decentraland, Ether-CryptoPunks, Ether-Axie. The wavelet coherences are reported in Figures 3 and 4.

These charts show probably the most convincing co-movement for Ether-Decentraland. Based on a heat map code that red indicates strong co-movement, and that values within a black outline have significant values for correlation, we see quite a lot of co-movement between Ether and Decentraland LAND pricing. This is evident across the time period at the 1-4 week cycle and a large 8-16 week cycle that dominates the chart. A $\rightarrow$ in the phase indicates positive correlation, and this is the most common arrow direction, although in the January-March 2021 upswing we see $\nearrow$ arrows which indicates that Ether pricing is leading Decentraland pricing in these most recent months. While Ether-Decentraland shows the most clear evidence of co-movement, there is also consistent evidence of short-term (1-4 week) positive correlation cycles for the other two NFT markets.

4 Conclusions

We make two important conclusions thanks to the testing in the study. First, NFT pricing seems quite distinct to cryptocurrency pricing in terms of volatility transmission. This has interesting implications for investment portfolios, as low-correlation assets are highly desirable for their diversifying characteristics. We need further investigation of NFT pricing to other asset classes to confirm the low-correlation status of NFTs. Another interesting conclusion from the volatility spillover analysis is that there is little spillover *between* NFT markets. This is unlike cryptocurrencies (Moratis, 2021) and stock markets (Bhattarai et al., 2020) which tend to have high spillover effect among their individual markets. A possibility here is that we need to consider that NFT markets might contain multiple asset classes.

A second conclusion is that, despite the low volatility transmissions between NFTs and cryptocurrencies, wavelet coherences suggest some co-movement between the two sets of markets. This suggests there is a value to applying understanding of cryptocurrency pricing behaviour to NFT pricing. Cryptocurrency research has grown significantly in recent years, and being able to able this learning to NFT pricing and valuation can speed by knowledge development. Notwithstanding that NFTs do appear to be a distinct (and exciting) new asset class.

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