Fertile LAND: Pricing non-fungible tokens

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Abstract

The current popularity of non-fungible token (NFT) markets is one of the most notable public successes of blockchain technology. NFTs are blockchain-traded rights to any digital asset; including images, videos, music, even the parts of virtual worlds. As a first study of NFT pricing, we explore the pricing of parcels of virtual real estate in the largest blockchain virtual world, Decentraland; an NFT simply termed *LAND*. We show a LAND price series characterised by both inefficiency and a steady rise in value.

JEL codes: G14; G12
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1 Introduction

Decentraland is one of a new generation of virtual world, popularly referred to as *metaverses*, built on the blockchain. To become a citizen, all you need is to buy LAND, a coded piece of the metaverse that translates to a 16m by 16m plot of virtual land (Ordano et al., 2017). 90,601 pieces of this LAND exist, of which 43,689 are for private use. Private LAND can be traded freely, with each change in ownership, and money exchanged, permanently recorded in an ethereum smart contract. You can use your LAND as you wish. Perhaps host a game that visitors enter and play or a shop promoting virtual or real merchandise. Maybe a venue where attendees can listen to an exclusive concert or a casino to part gullible netizens from their hard-earned cryptocurrencies. The currency that fuels all this interaction is MANA and, in early 2021, it was hovering around a $1 billion value. LAND itself trades at about $6,000 a lot.

Decentraland, and their LAND, are examples of the growth of non-fungible tokens (NFT). An NFT is a blockchain-recorded right to a digital asset. This can be anything digital; an image, a video, a song, a digital trading card of your favourite baseball player, a coded piece of virtual land, or a virtual tunic for your virtual character to wear while he explores his virtual land. NFTs primarily trade through online marketplaces, and early 2021 has seen these markets explode in popularity. A peak point (so far) was an NFT auction by Christie's auction house, which sold an NFT digital collage by artist Mike Winkelmann for $69.3 million (Crow and Ostroff, 2021), one of the highest prices ever paid for any work of art. Google Trend data shows the term NFT having virtually no interest up until January 2021, to peak

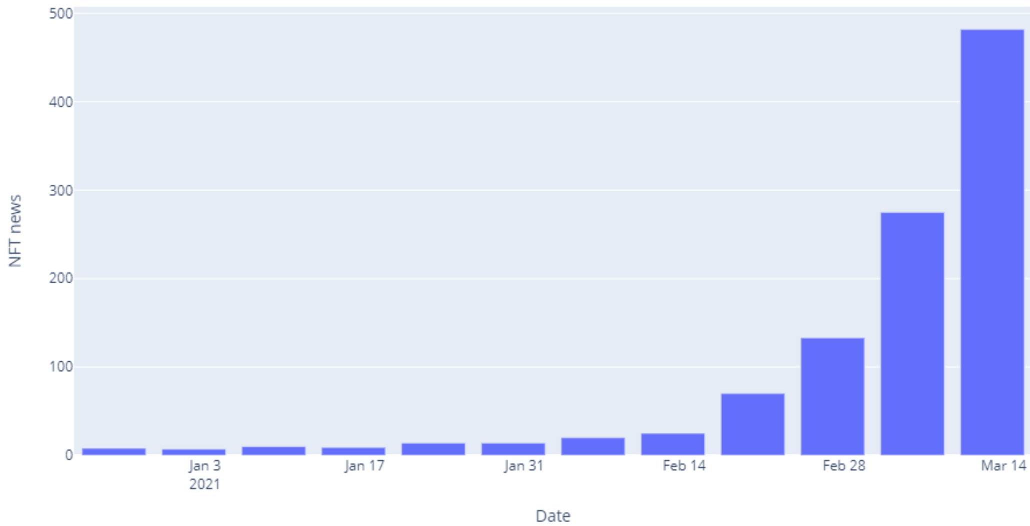

Figure 1: Weekly count of news coverage (print, online, television) mentioning 'non-fungible token' (early 2021). Source: author own calculations from LexisNexis news database.

interest currently[1]. News media interest also shows significant recent growth as seen in Figure 1. Trade in NFTs matches the news growth, with a popular transaction website[2] estimating lifetime trading volumes to 17th March 2021 at $440m, but that $200m of those sales were just in the single month up to 17th March.

No previous study has examined NFT pricing, and this is important to address given the size of this new asset market, particularly the growth rate. In this study, we provide a first exploration of how these digital assets are being traded. We take trade in Decentraland LAND NFTs as a dataset as the LAND NFT is reasonably uniform and therefore amenable to assessment as a price series. We also consider the mental association between the virtual asset LAND and the long-established asset of physical land as interesting, as traders may have implicit pricing frameworks in mind

[1] https://trends.google.com/trends/explore?date=today%203-m&q=NFT
[2] https://nonfungible.com/market/history

when trading this NFT. At this early stage in the market's development, our intent is to describe pricing and identify whether this pricing is efficient or approaching efficiency.

Our study can be related to the burgeoning cryptocurrency pricing literature. Although what we study should be considered distinct, as cryptocurrencies are conceptualised primarily as a medium of exchange, even if they show speculative asset properties (Baur et al., 2018). NFTs, on the other hand, are conceptualised as pure assets, just in digital form. Nevertheless, given NFTs are most frequently bought with cryptocurrencies as the means of payment, and are based on ethereum smart contracts, there should be some commonalities. We also expect that traders of cryptocurrencies will be the leading traders in NFTs, due to their familiarity with buying and using cryptocurrencies. Therefore, we expect some inefficiency in pricing behaviour in NFTs, similar to early cryptocurrency pricing (Cheah and Fry, 2015; Urquhart, 2016).

This study's main contribution is to act as a first investigation of the efficiency of pricing behaviour in NFTs, and to introduce that market for economic analysis. Given the size, growth, and novel specification of this new market in digital assets, such a study provides an important insight into pricing behaviour in early-stage markets (Khuntia and Pattanayak, 2018). The next section describes the data and testing approach, and the following section presents the findings.

2 Methodology

Our dataset is all secondary market trades in Decentraland LAND tokens from the period March 2019 to March 2021[3]. We have 4,936 trades of LAND in our dataset, with trades on 720 out of the 749 days in our time frame. The average LAND price is $1,311, as per the descriptive statistics in Table 1. Figure 2 shows the strong upward price trend in recent months and highlights that daily data is subject to extreme volatility. We, therefore, primarily use weekly data in our testing, something which is suited to a low transaction volume market.

Table 1: Descriptive statistics

	Daily returns			Weekly returns	Transactions	
	Overall	Year 1	Year 2		$ value	Daily count
Mean	0.0035	-0.0005	0.0074	0.0214	1,310.69	6.59
Standard deviation	0.4781	0.5012	0.4556	0.2754	2,179.74	5.99
Minimum	-1.7959	-1.7169	-1.7959	-0.5788	0.00	0.00
Maximum	2.1258	1.5977	2.1258	0.6955	74,279.40	57.00
Skewness	-0.0346	0.0354	-0.1180	0.3283	14.66	2.59
Kurtosis	2.4239	1.0118	4.3406	0.0050	372.53	11.29
Number	748	365	383	107	4,936	748

The table presents descriptive statistics for Decentraland LAND NFTs from March 2019 to March 2021. Year 1 refers to March 2019 to February 2020, Year 2 is March 2020 to March 2021.

We rely on a suite of tests informed by initial cryptocurrency markets studies by Khuntia and Pattanayak (2018) and Urquhart (2016) for our market efficiency tests. As a first step, we are interested in whether there is evidence of martingale market efficiency in LAND pricing. As a second step, we are further interested in whether the market for LAND is suggestive of adaptive market efficiency. That is, whether the market shows evidence of improvement in efficiency over time. Our tests are: a modern version of the classic variance ratio test; the *automatic variance ratio* (AVR)

[3] A starting point of March 2019 is chosen, as the size of a parcel of LAND changed from a 10m x 10m size to a 16m x 16m size in February 2019. Data is sourced from `https://nonfungible.com/market/history`.

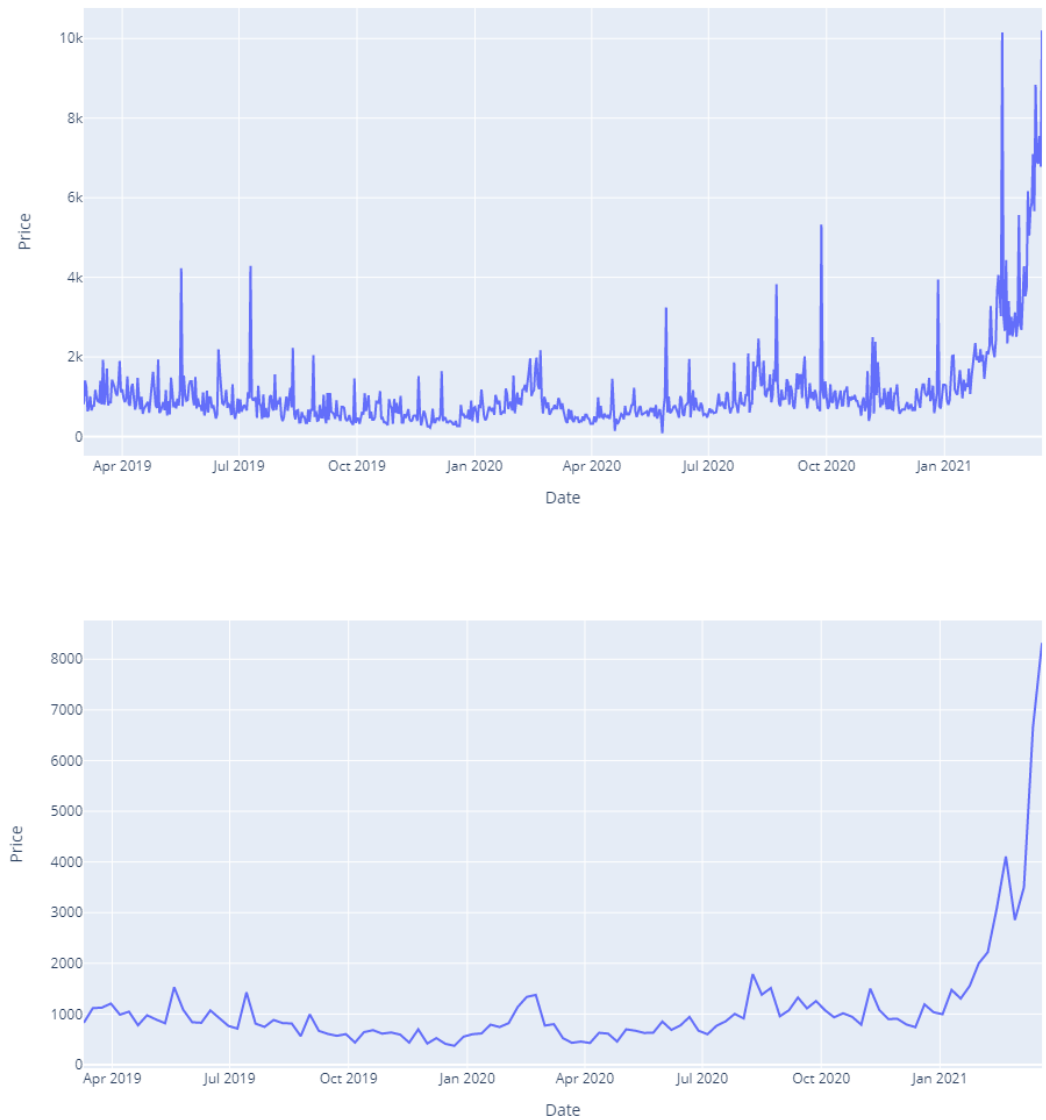

Figure 2: Daily (top) and weekly (bottom) average pricing of Decentraland LAND NFTs, March 2019 to March 2021.

test (Kim, 2009). A similar test that is more suitable for smaller data samples, such as our two years of weekly data; the *automatic portmanteau* (AP) test (Escanciano and Lobato, 2009). We also use the Domínguez and Lobato (2003) (DL) *consistent test* due to its robustness to various data non-normalities.

Lastly, we explore the memory of the time series further with Hurst exponents. We use the Weron (2002) corrected empirical components test variant of Hurst due to this test variant's suitability for smaller data samples.

3 Findings

Figure 3 reports the core market efficiency findings. These show a rolling window of p-values for the AVR, AP, and DL tests. We allow a 40-week rolling window to balance the need for sufficient data with the limited time period we have available. We also summarise, in Table 2, the results based on weekly and daily data, and for two daily sub-periods.

Table 2: Summary of market efficiency findings

	AVR	AP	DL	Hurst
Weekly overall	(0.0020)	(0.0020)	(0.0000)	(0.4780)
Daily overall	(0.0000)	(0.0000)	(0.0000)	(0.2182)
Daily, Year 1	(0.0000)	(0.0000)	(0.0000)	(0.1474)
Daily, Year 2	(0.0000)	(0.0000)	(0.0000)	(0.2773)

The table presents p-values from automatic variance ratio (AVR), automatic portmanteau (AP), consistent test (DL) tests, and Corrected Empirical Hurst Exponent scores of Decentraland LAND NFT market efficiency. Year 1 refers to March 2019 to February 2020, Year 2 is March 2020 to March 2021.

In Figure 3, times of market inefficiency are shown by the p-value being below 0.05. While there are more periods where the market is not inefficient in the second half of the chart, the picture, consistent across all measures, is that pricing is generally

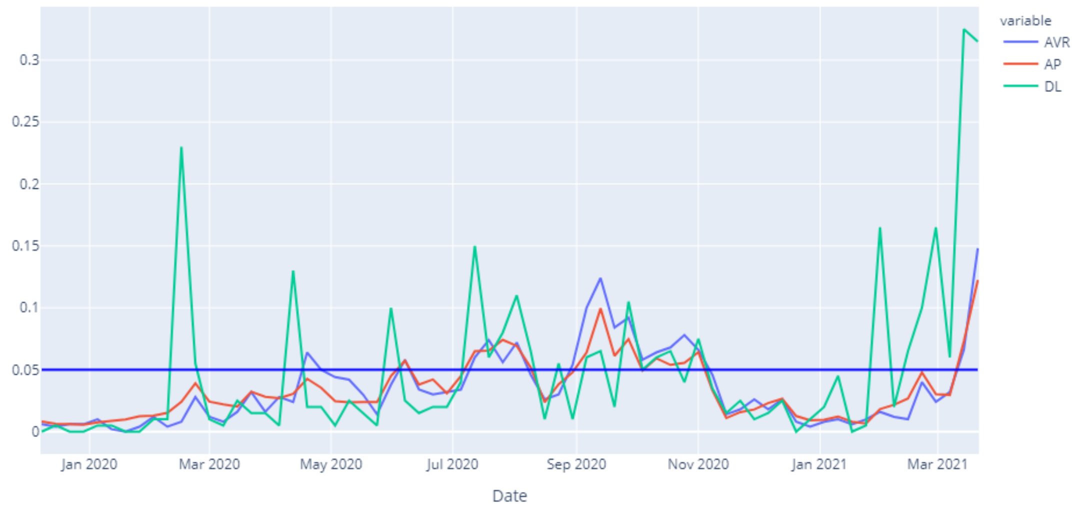

Figure 3: Rolling window (40-week) p-value results from automatic variance ratio (AVR), automatic portmanteau (AP), and consistent test (DL) tests of Decentraland LAND NFT market efficiency.

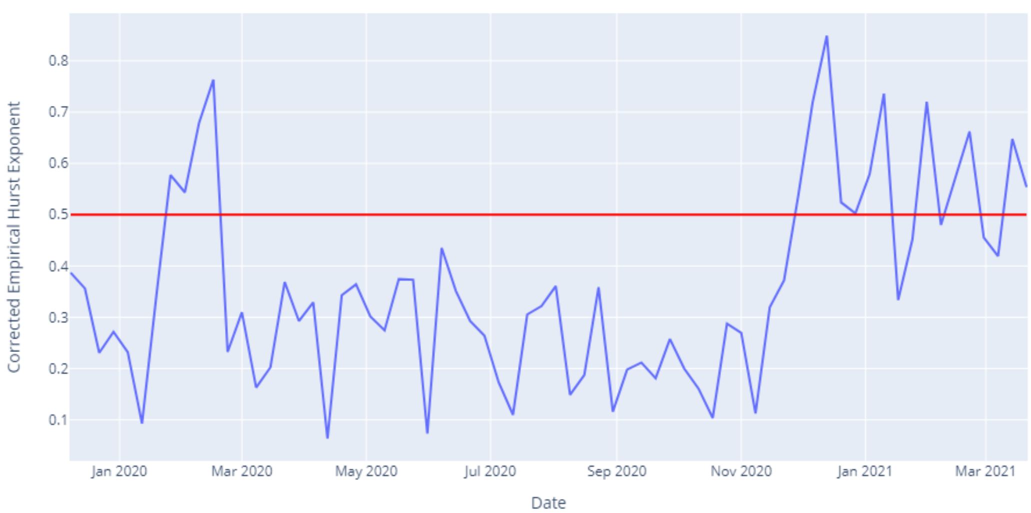

Figure 4: Rolling window (40-week) Corrected Empirical Hurst Exponent scores for Decentraland LAND NFTs.

inefficient. We also note that the AP test shows the smoothest pattern over time, perhaps because of its better suitability for smaller samples.

In Figure 4, we add to the efficiency exploration by charting Hurst scores in rolling 40-week windows. The chart shows a dividing line between above and below 0.5. A value above 0.5 indicates positive autocorrelation - that positive or negative returns tend to be followed by the same direction of return. Values below 0.5 indicate switching behaviour, with high return weeks followed by low return weeks. The findings are interesting because we see for much of the time period, switching behaviour dominated, but since the beginning of January 2021, there has been significant positive autocorrelation.

Table 2 confirms the Hurst scores as the most informative measure, with the AVR, AP, and DL tests at the aggregate level simply confirming market inefficiency. For Hurst, at the aggregate level, we see a score reasonably close to 0.5 for weekly data, but there is clear evidence of switching behaviour at the daily level.

4 Conclusions

In this exploratory study, we have introduced pricing behaviour in the rapidly growing market for NFTs. Our initial finding is of inefficiency in pricing, but despite this, a rapid rise in value. This inefficiency is not necessarily surprising. Early-stage markets tend to be driven by a volatile search for suitable pricing models and only slowly emerging market efficiency (Khuntia and Pattanayak, 2018). Our results are probably likely to even flatter on how efficient NFT markets are. The asset we track, virtual land, at least has a vivid physical world equivalent in the real estate market.

One wonders what pricing models and physical world learning can possibly apply in the currently most valuable NFT market; the CryptoPunks market of unique and absurd digital comic characters.

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