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Characterizing the Initial and Subsequent NFT Sales Market Dynamics: Perspectives from Boom and Slump Periods

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Abstract

The NFT phenomenon has disrupted the traditional notion of digital ownership. As distinct digital assets, NFTs serve as proof of ownership for crypto assets, for example, art, music, trading cards, or in-game items. The NFT market experienced unprecedented growth in 2021, with NFTs solidifying their position as a transformative technology in the digital realm. The market growth peaked during the boom period in January 2022, and has since declined, experiencing a major slump in June 2022. The market is not yet commonplace for everyone. Within the market, the initial sales market is more challenging to enter than the subsequent sales market since the former requires a higher seller entry cost. This paper decouples the initial and subsequent sales markets on the largest NFT market platform, OpenSea, and examines the markets across the two distinct periods in the NFT market history: the boom period of January 2022 and the slump period of June 2022. For the study dataset, sales transaction records are extracted from Opensea. This study discovers many properties which are invariant between the boom and slump: higher pricing in subsequent sales than in initial sales, rapid market movement (more in the initial sales), skewed revenue generation, and statistically strong regressors from Linear Discriminant Analysis (LDA) to distinguish between different resale return types, ranging from *large loss* to *large profit*. The finding indicates that the initial and subsequent sales markets are not identical. However, the composition and behaviour of the markets listed prior would be scale-free to the markets' economics stages. When we simulated a resale return with a zero hidden cost, the number of profit returns in resale inflated, suggesting that hidden costs should be surfaced and/or minimised to improve an investor's experience in the subsequent sales market. Our study sheds light on the dynamics of the NFT initial and subsequent sales markets across the boom and slump periods. By evaluating the two market types separately, we contribute to demystifying the subsequent sales market, which can be veiled without the market type distinction due to the initial sales market's over-representation. Ordinary people, who are generally incapable of affording a seller's entry cost in the initial NFT sales market, would notably benefit from this study. Since the study covers the two extreme periods, its finding will provide certainty, even in an atypical period.

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I. Introduction

A non-fungible token (NFT) is a digital asset residing on a blockchain that represents an object, usually digital, such as art, music, trading cards, or in-game items [1]. Because an NFT is stored on a public ledger – the blockchain – this acts as undeniable proof of ownership, and transactional records can be traced back to the initial creation (minting) of the NFT. The NFT market took off in 2021, reaching a total sales volume of $USD24.9B, over 250 times that of 2020 [2]. Investors flooded the market during this time, attracted largely by the prospect of realising extraordinary returns, and, by August 2022, blockchain wallet users numbered 68 million [3]. A high-profile example of large returns is *Beeple*'s record sale of his NFT artwork *The First 5000 Days* for $USD69M in March 2021 [4], which garnered considerable publicity. In addition, the sale of *CryptoPunk #7523* for $USD11.8M in June 2021 [5] fueled the hype and the NFT market began to flourish in August 2021, with total sales for the month of over $USD3.4B [6]. Following this boom period, the NFT market entered a slump in June 2022 [7], which has continued into the start of 2023. A (market) boom is defined as the expansion and peak phases of a business cycle [8], and a (market) slump is defined as a period of drastic economic decline[9].

The global reaction to the slump of June 2022 was mixed. Some believed it was confirmation that NFTs were a short-lived fad, whilst others saw the slump as simply a flow-on effect of tightening monetary policy and the Terra LUNA crash [10][11]. After the exceptional returns experienced during the boom phase, there was concern as to whether NFTs could even be profitable during the slump, as transaction volume fell from $USD2.6B in May to $USD695M in June, as shown in Fig. 1. Whilst comparatively low trading volume continues in the NFT market after the slump, there are still a million transactions per month and a large number of active traders [7]. This indicates the need for more insights into the market for the period.

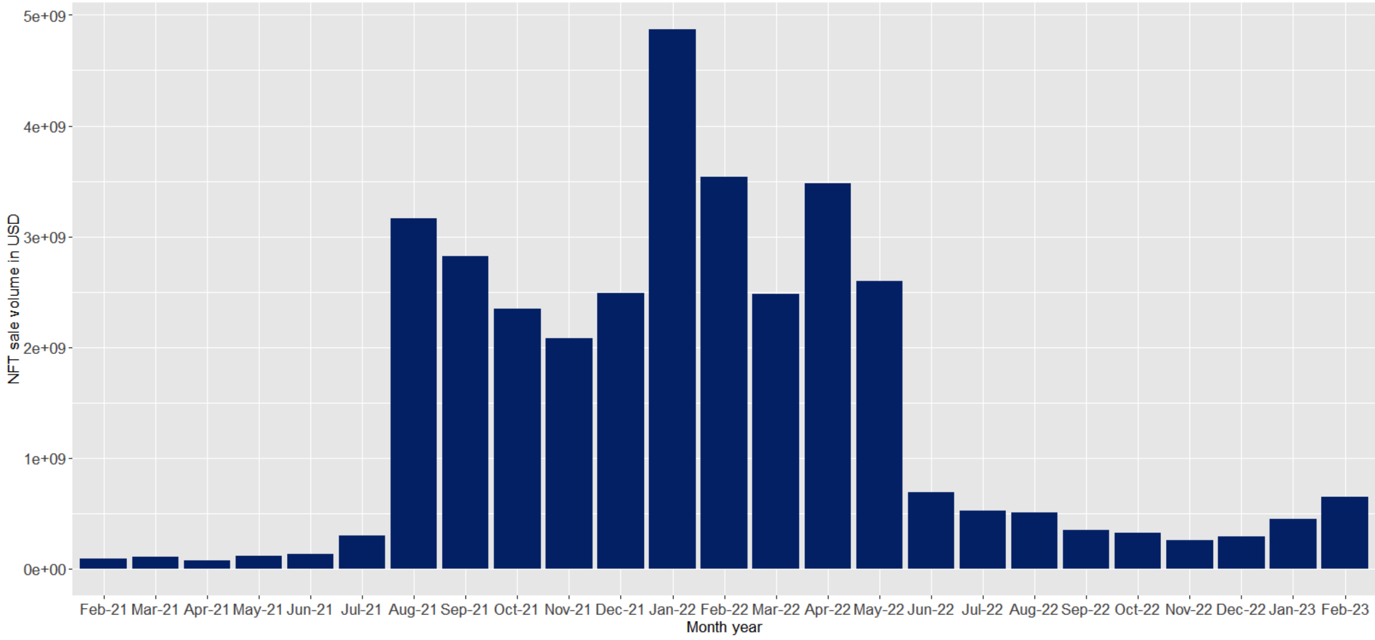


Figure 1. OpenSea monthly volume chart

The initial and subsequent sales markets on an NFT market platform are different, and understanding the latter market would be especially useful. The initial sales market is where an NFT is sold for the first time on an NFT market platform, and the subsequent sales market is where any subsequent sale of the NFT happens on the platform. The initial sales market has a higher entry hurdle for a seller since the seller must have a skill in at least one of these areas: 1. minting or 2. research to find an NFT creator's pre-NFT sale which is not through an NFT market platform. Hence, the subsequent sales market has more potential in attracting ordinary people who do not necessarily have one of the aforementioned skills. *Buy and hold* behaviour is typical in the NFT market as a whole[12]. Hence, the subsequent sales market proportion is undoubtedly smaller compared to the initial sales market. Due to this under-representation, if the NFT market is assessed as a whole, we would not have the opportunity to reveal the unique characteristics of the subsequent sales market.

We have chosen January 2022 and June 2022 as the primary examples of a boom and slump period, respectively. January 2022 represents the all-time monthly high for sales volume and June 2022 represents the greatest decline in sales volume, falling over 73% on the previous month and signaling the beginning of the slump period [7]. Ethereum is by far the most popular blockchain for creating and trading NFTs [13], with a total marketplace volume of over $USD40B[14]. As OpenSea accounts for over 82% of this volume, we elected to use OpenSea transactions for our data collection and subsequent analysis. It is the most representative source of data for the market and is not known to have significant wash trading volume,[1] as is the case with its largest competitor, LooksRare[15]. First, we sourced the data for January 2022 and June 2022 directly from the OpenSea API [16]. Next, within the dataset, we tried verifying whether a sale record is for an initial or subsequent sale of an NFT. If the record was for a subsequent sale, its previous sale information was mined from the dataset. When the verification was impossible or the previous sale information was unobtainable within the dataset, an extra OpenSea API call was made for the NFT in question to fill in the missing information.

The findings from this study highlight that the initial and subsequent sales markets are not identical while these contain characteristics invariant across the boom and slump. NFT pricing in the subsequent sales tends to be higher than one in the initial sales, and it is more resilient from a market crash. Despite the median NFT price plummeting in the slump, the median creator royalty rate increased from the boom to the slump. This could be motivated by an NFT creator trying to compensate for their lost sale revenue by increasing the creator's royalty. The market movement is very fast in both initial and subsequent sales markets, for example, the majority of sales occur within 24 hours of listing. From very low revenue seller to very high revenue seller group, the median number of active days increases per market and period. The activity frequency decreased from the boom to the slump. Skewed market behaviour is observed in NFT sale revenues among seller and buyer groups per market and period. Nevertheless, such behaviour is observed among collection groups in the slump only. The factors which strongly differentiate between resale return types ranging from large loss to large profit in both periods, are the number of days a collection made a sale, previous price, median price of a collection, profit-to-loss ratio in a collection, and creator royalty rate. When a resale return was estimated without hidden costs, the profit count multiplied in both periods. This finding hints that many investors could be ill-informed of the costs or often forget about these.

Various stakeholders will benefit from this study. Regulators can assess the profitability of investing in the NFT market. This can inform the drafting of future taxation laws to govern the market and aid in determining the amount to be taxed. The actual resale return calculation that includes hidden costs can help guide on such a tax regulation. This research will help retail investors determine whether it is still profitable to engage in the NFT market during a slump and it will also offer insight into what behaviours tend to result in a high resale return and what behaviours tend to result in a lower resale return. NFT marketplaces may benefit from this work through increased exposure. If there are still returns to be made in the market during a slump, this information could help to encourage investors back to the marketplaces or bring in new investors. This paper also helps researchers by contributing to the literature explaining market participant behaviour during the slump and acting as a reference point on the slump period for research going forward, as the market continues to evolve.

The remainder of the paper is organised in the following way: Section II provides background on NFTs and the NFT market, as well as its sale types; Section III discusses related works; Section IV describes our data collection and analysis methodology; Section V explains our results and the insights that can be drawn from them; Section VI looks at the bigger picture, discussing the significance of the results and the benefit they provide to stakeholders; Section VII concludes the paper.

II. Background

This section delves into the structure of the NFT market and participant behaviour. Furthermore, we will detail the transactional flow of an NFT, from its creation to its exchange on an NFT marketplace.

A. The process of producing NFTs

An NFT is a digital asset that has been written to the blockchain. It represents ownership of a given item. Typically, these items are also digital, such as virtual art, trading cards, game assets, and collectibles. However, NFTs can also be used to represent ownership of physical items [17].

An NFT is created by a smart contract, which is a programme that has been deployed to the blockchain that responds to specific events. As well as creating NFTs via a process called minting, the smart contract also facilitates NFT transactions and the transfer of ownership between a buyer and a seller [18].

B. The mechanics of NFT markets

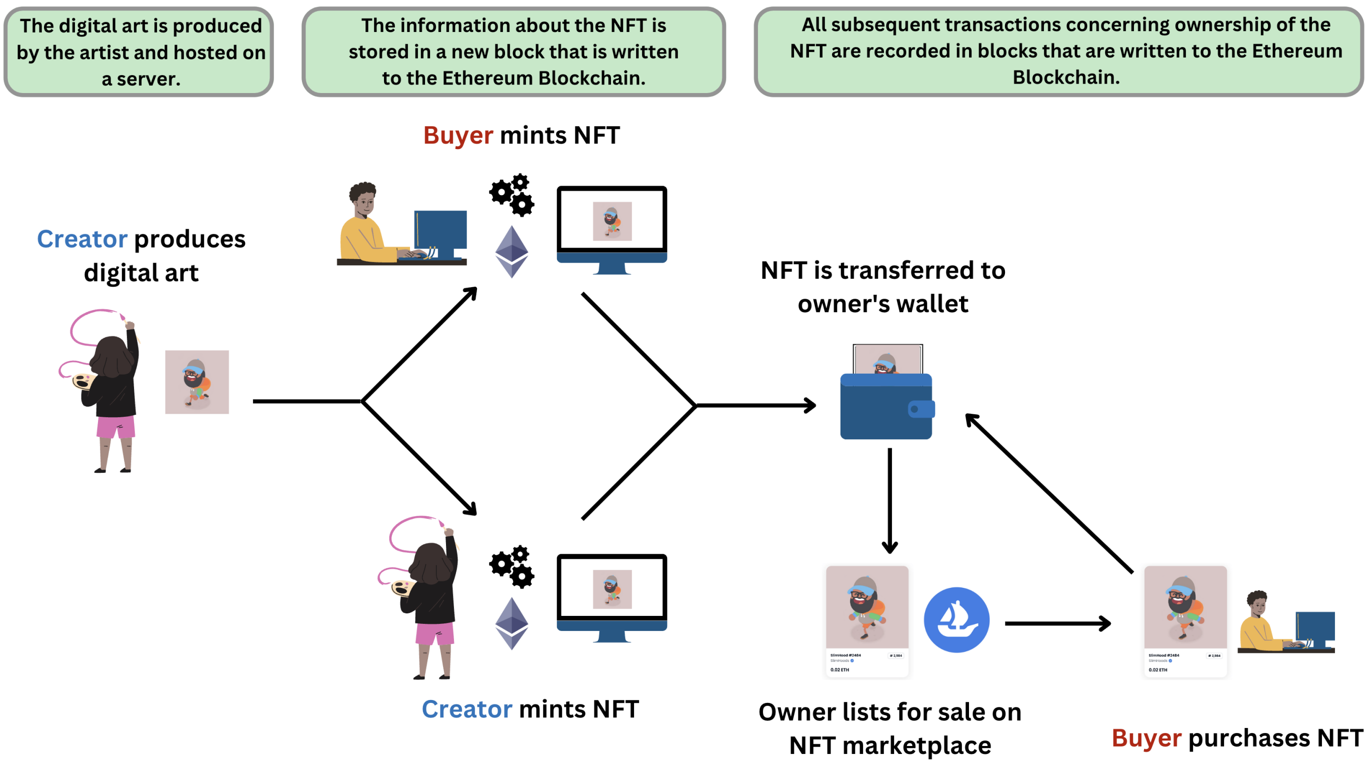


Figure 2. Typical transactional flow of an NFT

NFT market participants consist of creators, buyers, and sellers. As shown in Fig. 2, creators produce the original digital content that is to be represented by the NFT and, generally, upload the content to a file hosting server, such as cloud storage or the InterPlanetary File System (IPFS) [19]. They can then sell this NFT in one of two ways. The first method is by minting the NFT into their digital wallet and then selling it to a buyer. The second method is to set up a minting process via a smart contract and allow buyers to mint the NFTs directly to their wallets, in exchange for a set amount of cryptocurrency. After an item has been minted, either by the creator or the first buyer, it is then able to be sold on an NFT market platform, such as OpenSea. The owner of the NFT can then choose to list it, and a buyer can purchase it. These stages represent the typical transactional cycle for an NFT trade on an NFT market platform.

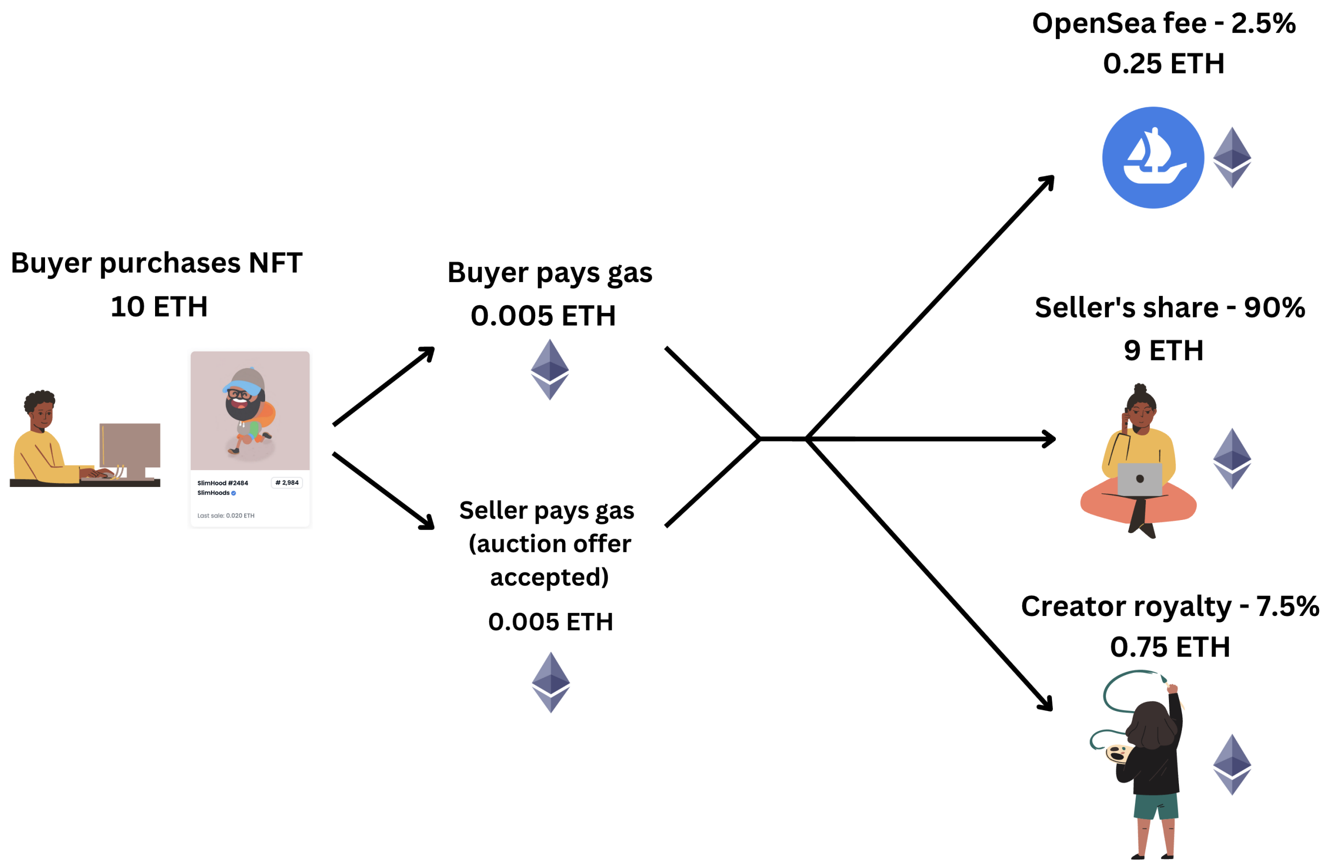


Figure 3. Distribution of purchase amount to relevant stakeholders

When the sale of an NFT occurs on an NFT marketplace, there are additional hidden costs beyond the sale price of the asset. Fig. 3 shows the flow of value between stakeholders at the point of sale on OpenSea. Although the buyer purchases at a given price, there are other fees, including gas, marketplace commission, and creator royalty, that reduce the seller's returns. In the example, a creator royalty fee is 7.5%, and the marketplace charges a fixed fee of 2.5%. A seller gas fee is omitted, assuming that the sale was at a fixed price, not on auction. Gas fees are blockchain transaction fees paid to network validators and these vary greatly, based on network traffic. Listing an NFT for sale is gas-free on OpenSea. However, in cases where the seller accepts an offer on their NFT, they must also pay a gas fee for selling. When calculating the net return on an NFT sale, the seller must also include not only the price they paid to purchase the NFT but also the price of the gas fee associated with the initial transaction.

C. The types of NFT sellers

When analysing our data, sales are classified into two different groups: *initial sales* and *subsequent sales*. Initial sales were defined as the initial (first) sale of the NFT on OpenSea marketplace. Subsequent sales were defined as any sales that occurred after the initial sale of the NFT on the market platform, i.e. the second, third, fourth sales, etc. This process afforded additional insights into market participant behaviour based on whether they were the first owner of the NFT or a subsequent owner.

The market type decoupling benefits more people because the subsequent sales market has more potential sellers. The subsequent sales market offers a lower barrier to entry for a seller as it does not necessitate the process of minting or the ability to search for and purchase a pre-mint NFT from an original artist's website before it is sold out. In contrast, one or both of these skills are mandatory for a seller in the initial sales group. Separating these two markets would facilitate uncovering insights on the subsequent sales market, which would be buried otherwise due to its under-presentation in the total NFT market.

III. Related Work

Prior studies have examined the dynamics of the NFT market by investigating various components, including pricing, sale, market participant behaviour, market skewness, primary market, secondary market and resale return.

A. Pricing characteristics of NFTs

Vasan et al. [20] argued that a first-mover advantage was a phenomenon in NFT pricing. The study conjectured that it could be easier for early NFT adopters to establish themselves as successful NFT artists or collectors by asking for a high price. The average NFT price appeared stable in the primary sales on Foundation platform between early February and mid-June in 2021 [20]. Whereas, White et al.[21] and Nadini et al. [1] showed that pricing median, trend, and volatility varied across NFT categories. Some high pricing volatility occurrences in the studies could be due to their data spanning a longer duration. Nadini et al. [1] remarked that an NFT collection's median price had strong predictive power for an NFT's price, whereas the visual features, sale probability within a collection, and centrality were rather weak predictors. Dowling [22] argued that NFT pricing was inefficient and such inefficiency was common in an early-stage market.

B. Sales properties of NFTs

Vasan et al. [20] found that the daily listing count was fairly consistent across different period partitions (1. Innovator's adoption, 2. Early bird's adoption, 3.Emergency of the majority, and 4. Laggards' adoption); however, the proportions of listed NFTs sold were 74.1% in the innovator period, but only 13.3% in the laggard period. This over-supply phenomenon was also observed in by Jiang and Liu [23]. White et al. [21] demonstrated that the average number of NFTs purchased per buyer decreased over time, too. Ante [24] showed that the sale count from one collection can impact the sale count in another collection. For example, the sale count in *CryptoPunks* has a significant impact on the ones in *CryptoKitties*, *CryptoVoxels*, *Somnium Space*, *The Sandbox*, and *Art Blocks*). The impact can be positive or negative depending on the collections. The relationship between *CryptoPunks* and *CryptoKitties* was mutually positive. Contrarily, *Somnium Space* negatively Granger-caused other older collections. Bitcoin price, but not NFT wallet count or Ethereum price, significantly causes the sale count [25]. Bitcoin price also has a positive correlation with the volume of Google searches on NFT[13]. Fazli et al. [26] observed a very prompt unlist-relist behaviour, e.g 41% of the occurrences were within one hour of their previous listings. The study argues that such a behaviour is to surge the chance of exhibiting on the market platform's homepage.

C. NFT market participants

The number of buyers was always higher than the number of sellers per year, meanwhile, the growth of the buyer count outpaced the one for sellers [21]. Nadini et al.[1] and White et al.[21] showed that the graph network with NFT market participants as nodes and sale transactions as links had a close to zero assortativity. This would mean that the participants do not connect based on their similarity in connection patterns. On the other hand, when Jiang and Liu [23] experimented with measuring it in different stages (1. the primer, 2. the rise, 3. the fall, and 4. the serenity), it varied across the stages, for instance, negative in the primer, but close to zero in the rise. According to Ante [25], Ethereum price causes an increase in the number of NFT wallets significantly.

D. Connections between NFT market participants

Skewness in NFT sale count is observed in several studies. In other words, NFT sales are concentrated around a few individuals or components in the NFT market. Casale-Brunet et al. [27] detected power law with Zipf's distribution among in-degrees and out-degrees for most collections where market participants were nodes and links were sales. Meanwhile, {*Decentraland*} collection showed a relatively poor fit in the study. Nadini et al.[1] also noticed Zipf's distribution power law, but among NFT assets and collections. In contrast, White et al. [21] remarked Laherrere distribution power law in the NFT sales among the seller, buyer, and collection ranks. Vasan et al. [20] demonstrated a higher Gini coefficient in sale count between NFT buyers and high-reputation sellers than between NFT buyers and low or medium-reputation sellers. The study also showed clear segregation between the communities of rich NFT artists' and poor NFT artists in the artist social network where artists were nodes and invitations were links. Buying power was concentrated to a few hubs in the graph network of collectors as nodes and bids on the same NFTs as links. Jiang and Liu [23] observed the explosion of Gini coefficient with the flood of market participants and upward trending in the coefficient over time.

E. NFT market behaviour in primary or secondary markets

Most studies assessed the NFT market as a whole or the primary or secondary market only; however, some studies compared the primary and secondary markets. The secondary sale market was minor to the primary market [1][12][26]. Nadini et al. [1] measured the proportion of the secondary sale market as approximately 20% of the NFT sales between June 2017 and April 2021. Barabasi [12] measured it as 9% in March 2020, but 36% in the same month in the subsequent year. The small proportion could be due to the immaturity of the NFT market or a store-of-value investment as a popular strategy for an NFT [12][21].

Franceschet et al. [28] argued that the limited emergence of the secondary market could be due to an abundant offering of NFTs, “over-tokenisation” or “artwork hyperinflation”. Not only the secondary market share, but the secondary sale price also increased over time [1]. The secondary sale price was likely to be lower than the primary in 2017, but higher in 2021.

A graph network with NFTs as nodes and being owned by the same collectors at any time as links appeared more compact for the secondary market than the primary [12]. The auction success rate was 36.10% but only 3.97% for the primary and secondary, respectively [26]. The secondary market listing price tends to be higher than the primary market settle price. Fazli et al. [26] suggested that this is because an NFT investor considers their target profit in deciding their NFT resale listing price.

F. Hidden costs in NFT sales

NFT resale return is investigated by various studies with different estimation formulae. Yousaf and Yarovaya[29] and Pinto-Gutiérrez et al. [13] estimated NFT return as $R_t = ln(P_t/P_{t-1})$ where R, t and P are return, time (day in the former and week in the latter) and NFT average price, respectively. Conversely, Jiang and Liu [23] formulated *CryptoKitties* NFT return in a more detailed manner, counting various costs including a breeding fee, renting fee, and different gas fees.

Yousaf and Yarovaya [29] showed asymmetric spillovers between NFT return and volume, indicating that an investor should implement different strategies between normal and extremely bullish and extremely bearish NFT market periods. Their study also suggested that the volume would be a strong regressor for predicting the return at extremely bullish and bearish NFT market conditions.

Vasan et al. [20] demonstrated that the number of followers on Foundation platform was a strong indicator of a seller's earnings, but Twitter follower count was not. The earning of a new seller was similar to their inviter's. Casale-Brunet et al. [27] argued that when an NFT sale is made during minting or just after minting, the probability of making a profit by reselling the NFT is greater. Jiang and Liu [23] argued that experiencing a profit generation would be important in the NFT market for players' participation because, without it, the player's enthusiasm can decline and thus opt-out. On the other hand, in the study by Pinto-Gutiérrez et al. [13], NFT return appeared insignificant to the volumes of Google searches on the terms 'CryptoPunk' and 'Decentraland'.

G. Summary

The literature review is summarised in the below table, with one row per paper. The table is in chronological order of a study dataset's end date.

Table 1. Literature review summary table

Reference	Dataset	Objective	Result Highlights
Jiang and Liu [23]	Transactions in CryptoKitties from 23rd November 2017 to 19th May 2020	Analyse CryptoKitties' entire player activity history and find the reasons for the rise and fall of CryptoKitties game mania.	An extremely high price for a special kitty led to an explosion in the game's popularity. Afterward, the popularity shrank due to: 1. oversupply, 2. loss of profit in trading a game prop, 3. the increasing gap between players in wealth distribution, and 4. limitations of blockchain.
Dowling [22]	Secondary market trades in Decentraland LAND tokens from March 2019 to March 2021	Investigate the efficiency of pricing behaviour in NFTs.	NFT pricing appears inefficient from the dataset. It could be because, at the time of the study, the NFT market was still in an early stage, still in search of suitable pricing models.
Barabasi [12]	SuperRare platform from 5th April	Examine NFT market's hidden structure to reveal the unseen patterns of relationship that	In a graph network with NFTs as nodes and links having the same collectors, no isolation cluster is observed. The network is an extraordinarily

	2018 to 15th April 2021	can help explain how the market works and why.	small world. The network for the secondary market is more concentrated than the primary market version.
Nadini et al. [1]	6.1 million NFT trades from 23rd June 2017 to 27th April 2021; obtained from four open-source APIs: CryptoKitties sales, Gods-Unchained, Decentraland, and OpenSea	Provide a comprehensive quantitative overview of NFT market based on a big dataset.	Power law is observed in the number of sales and size of collections. The most specialised traders have either few or many transactions. Collections well represent the underlying network of traders. NFTs in a large collection tend to be bought in series. The same is not observed for a small collection. Visual features were extracted. The median price of a collection with a small window is the best regressor for a price prediction.
Ante [25]	Daily data between January 2018 to April 2021	Investigate interrelationships between NFT sales, NFT users, Bitcoin price, and Ether price.	Bitocin and Ether pricing have significant impact to the NFT market, but not the other way around.
Ante [24]	Data of 14 NFT collections from June 2017 to May 2021	Assess the causality between NFT collections.	The success or adoption of a younger collection and that of a more established collection influence each other.
Fazli et al. [26]	Almost 65,000 auction data from Foundation platform from February to July 2021	Explore the possibility of undisclosed agreements in trade. Analyse NFT transfer and pricing.	There is possible collusion, selling an NFT for granting the platform invitation to the buyer. The NFT community is a very sparse and small-world graph. The interval between a successful auction and NFT relisting is usually short. The success rate of the NFT secondary sales is low; however, its pricing is generally higher. The price variation among visually similar NFTs is within 1 Ether.
Vasan et al. [20]	Primary sale data only from Foundation platform from about February to June in 2021	Find reproducible patterns to characterise the features, mechanisms, and networks enabling the success of individual artists. Provide a better understanding of the NFT ecosystem.	An artist who entered the market early has earned more than a latecomer. A collector who joined early has spent more than a late adopter. An artist-collector tie plays a crucial role in the earnings of the artist. Twitter follower count is a weak indicator but a follower count on Foundation platform is a strong indicator of an artist's earnings.
Pinto-Gutiérrez et al. [13]	Google search activities on NFT related keywords between 1st December 2017 and 30th July 2021. Bitcoin, Ether, VIX index, S&P 500 index, and gold prices and NFT sales in USD for the same period.	Examine the factors that explain investor attention to NFT.	Google search activity on NFT topics and specific NFT collections are positively associated with major cryptocurrency returns. Bitcoin and Ether returns are significant drivers for attention to NFT.
Casale-Brunet et al. [27]	Eight collections from their creation dates to 15th July 2021; Ethereum blockchain only without a specific NFT platform selection	Propose a systematic analysis of the dynamics governing the evolution of NFT communities in terms of their interaction graphs and associated properties.	Directed graph networks with traders as nodes and links as token transactions generated for the eight collections separately and all together, show mean distance around five, almost zero clustering and reciprocity coefficients. Power law is observed, except for Decentraland collection. Assortativities observed are weak or neutral.
Yousaf and Yarovaya [29]	Daily data of volume and prices of THETA, Tezos, and Enjin Coin NFTs from 17th January 2018 to 20th November 2021	Examine the quantile connectedness for returnsvolume and volatility volume pairs of THETA, Tezos, and Enjin Coin NFTs.	Trading volume is strongly connected to the returns and volatilities at extremely bullish market conditions compared to the other quantiles. The connectedness is time-varying.
White et al. [21]	OpenSea sale data from 1st January 2019 to 31st December 2021	Study across a wide range of collections and categories to better understand the NFT market.	Art and Collectible categories dominate in sale counts. The growth of buyers has outpaced the growth of sellers. Power law Laherrere distribution is found in sale counts by buyer, seller, and collection. A heavy hitter is observed. NFT price is volatile. The NFT community is very sparse.
Franceschet et al. [28]	Not applicable	Provide a collection of viewpoints on crypto art from various roles within the system: artists, collectors, gallerists, art historians, and data scientists.	An artist obtains a greater control in their work compared to the gallery-centralised approach. Crypto art would be most appealing to a broader and younger cohort of potential artists and collectors. Oversupply is present in crypto art. This may prevent users and buyers to experience, digest and eventually buy artworks before a flood of new creations arrives.
This study	OpenSea sale data for January and June 2022	Investigate the initial and subsequent NFT sales markets in a boom and a slump.	The initial and subsequent sales markets are unequal. The markets have properties which are consistent across the boom and slump. For instance, some regressors strongly differentiate between resale return groups in both boom and slump periods.

H. Comparison with prior work

Our work separates the NFT market into two categories: the initial and subsequent sales markets. The motivation behind this approach is that the subsequent sales market is easier to enter as a seller. Unlike the initial sales market, the subsequent sales market does not require any special skill besides buying a listed NFT and willingness to resell it. Our study assesses pricing, creator royalty, market movement, a market player's participation, and market skewness in each market type, especially to unveil the characteristics of the subsequent sales market, which still has a smaller market share compared to the initial sales market.

This study selects OpenSea as a dataset source. The prior studies are usually on one or a few NFT collections or/and an exclusive platform, such as Foundation or SuperRare. To be an NFT's initial seller/creator on Foundation, they must be invited by an existing NFT artist in the platform or get approval from the platform [20]. SuperRare is selective on an NFT submission based on the quality of the NFT and does not accept a meme-style NFT [30]. Because our interest has been providing insights that have implications for a wide audience, we selected OpenSea, the largest NFT platform, for our study [31].

Moreover, this study's dataset covers two extreme periods: the boom and slump periods. By exposing the intrinsic characteristics of the NFT markets in these extraordinary periods, this study aims to provide a level of certainty to investors across any intense period.

IV. Methodology

This section describes how our data were collected, resale returns were calculated and different elements (players, collections and resale returns) were grouped. Next, the section provides the data overview. Lastly, the section explains Lavalette Rank function used to assess Power Law behaviour and how Linear Discriminant Analysis (LDA) is modeled in this study.

A. Data Collection

We used OpenSea sales transactions for our data collection, as OpenSea is the largest and most representative source of data for the NFT market, accounting for over 82% of the total volume for Ethereum-based NFTs [7]. The OpenSea API events endpoint was used to obtain all successful sales transactions for January 2022 and June 2022. We then processed the data to ensure that there were no transactions that had been performed on other marketplaces, such as LooksRare. OpenSea no longer provides sales transaction data via the API. Hence, we make our dataset[2] publicly available for use by researchers and practitioners.

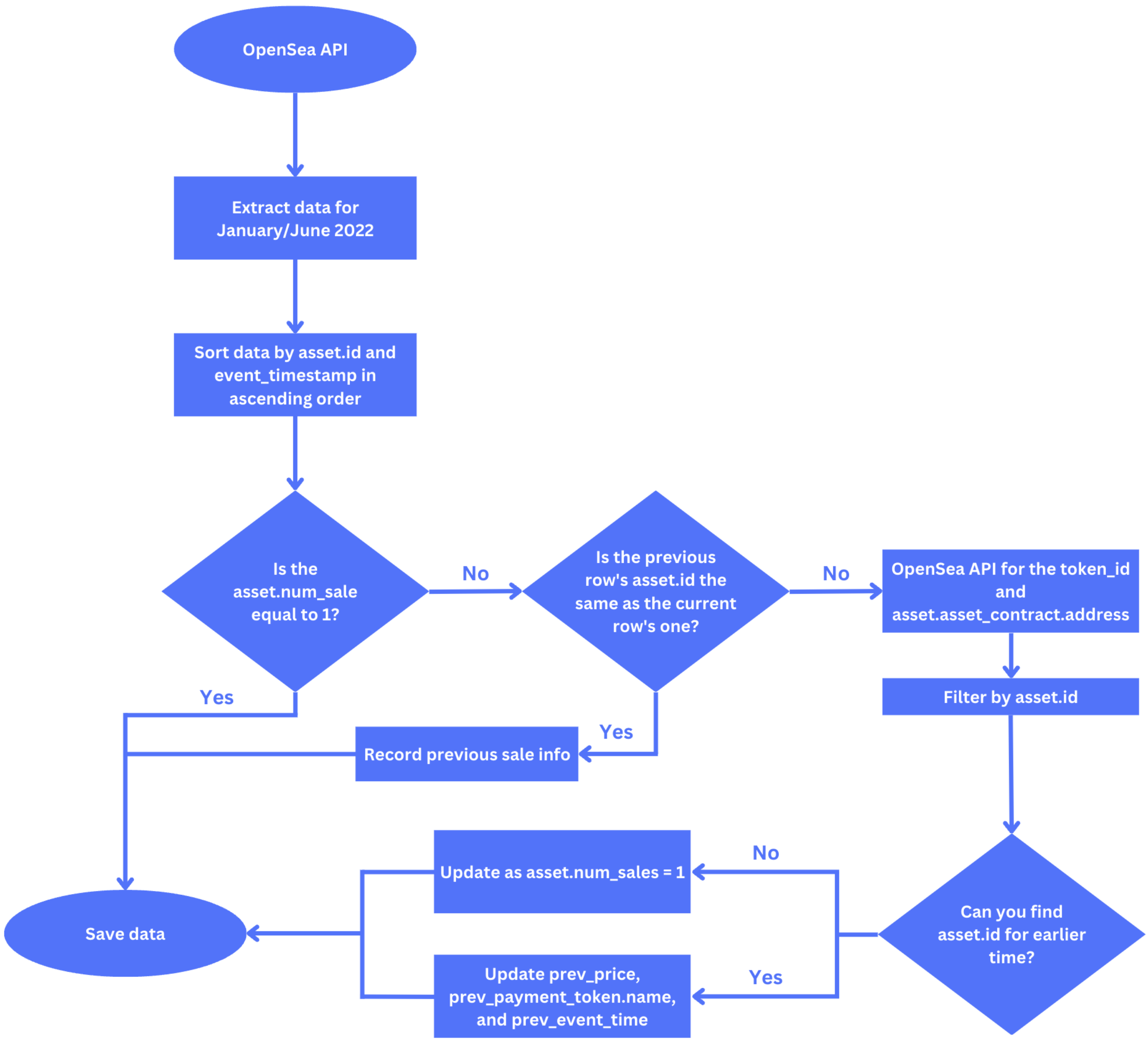


Figure 4. Data collection flow diagram

The step-by-step description of the data collection and transformation is illustrated in Fig. 4. After transforming all of the JSON data returned by the OpenSea API into a single dataframe, we sorted the dataframe by asset.id and event_timestamp in ascending order. We then saved any transactions where asset.num_sales equals one across the final dataset. Once a record was added to the final dataset, it is removed from the initial dataframe. New fields called prev_asset_id, prev_price, prev_payment_token.name, and prev_event_time were created to record the corresponding information from previous rows. For the remaining data, we assessed whether asset.id is the same as the previous asset.id. When these are different, NA is inserted into the new fields because a previous record does not represent a previous sale. When a record's previous sales data can be obtained from the dataframe, it is added to the final dataset.

For the remaining records in the dataframe, i.e. those withasset.num_sales not equal to one and without previous sales data, a call to the OpenSea API is made for each record to ascertain the sale type and previous sale information. An NFT can be uniquely identified by `asset.id` or a combination of `asset.token_id` and `asset.asset_contract.address`. Because the API call does not accept `asset.id` as a parameter, using the latter is chosen. In each extra API call, `asset.num_sales` of a record in question is updated to one if no prior sale record is found. This is because the original `asset.num_sales` shows the total number of sales of an NFT at the time of the API call, not at the time of the sale event. When a record in question has previous sales returned from the API call, it is verified as resale, and its previous sale information is obtained from the transaction that came before it.

We obtained the conversion rates for Ether to $USD from Yahoo Finance[32]. The average between each day's high and low is used for the day's conversion rate. To standardise the transactions, item (bundle) sales and token payments not in Ether or Wrapped Ether are omitted. Based on the June data, single-item sales account for 99.997% of transactions, and Ether or Wrapped Ether token payments account for 99.980%. Hence, the exclusion would have an imperceptible effect.

B. Resale Return Calculation

The NFT prices recorded in the dataset are converted to $USD. In the data, the total price shows an NFT price in Wei (the smallest denomination of Ether). To convert from Wei to Ether, we simply divide the value by 10^{18}. We then convert Ether to $USD using the Yahoo Finance prices as mentioned above. We call this variable conversion factor *ether_to_usd*. Therefore, to convert Wei to $USD, we use the following equation:

$$\frac{total\ price}{10^{18}} \times ether\_to\_usd \qquad (1)$$

The total cost of an NFT resale includes the price from the previous sale, marketplace service fee, creator royalty, gas fee for purchase, and gas fee for the sale if an offer was accepted. The last cost item is only applicable if the seller accepts an offer made by a buyer, whereas a regular transaction is when a buyer pays a price set by a seller.

OpenSea charges a seller 2.5% commission on the sale price[33]. The creator of an NFT can set up a creator royalty rate for the NFT and modify the rate at any time. This is a percentage fee charged to the seller – on OpenSea it can vary from 0% to 10%, however, in the past, the upper limit was higher. Hake [34] argues that the average gas fee per transaction is approximately $USD 185. This study, therefore, assumes the gas fee paid by both buyers and sellers is $USD 185.

Using the above, NFT resale return in $USD for OpenSea is estimated as:

$$R_t = P_t - C_t \qquad (2)$$

$$R_t = P_t - P_{t-1} - P_t \times 0.025 - P_t \times F_t - g_{t-1} - G_t \qquad (3)$$

$$R_t = (0.9975 - F_t) \times P_t - P_{t-1} - g_{t-1} - G_t \qquad (4)$$

The notations are defined in Table 2. Note that g is assumed to be 185. On the other hand, G is zero if a buyer paid a price set by a seller. Otherwise, G is 185 if a seller accepted a WETH offer on their NFT.

Table 2. Resale Return Formula Notation

Notation	Definition
R	Resale return with all costs counted
t	Sale time orde
P	NFT price
C	Total cost
F	Creator fee rate
g	Gas fee for buying
G	Gas fee for selling
W	Resale return without a hidden cost

This calculation assumes that a free lunch does not exist. This means that when a new seller's account of an NFT does not match the previous buyer's account for the NFT, the last price is still counted as a cost to the new seller. The discrepancy between the seller's and buyer's accounts would be due to a transfer of the NFT between the accounts owned by the same market participant. Multiple account ownership is allowed in OpenSea as long as multiple wallets are created [35].

All costs except an NFT's purchase price can be considered hidden because they are not disclosed up-front. On the OpenSea marketplace, an NFT's purchase price is immediately visible but the other costs are not. For example, to find a creator royalty rate, a navigator needs to click the details pane and scroll to find it. This means that if a market player is negligent or naive, a perceived resale return calculation may count only the current and previous prices of an NFT. An NFT resale return formulation for such a scenario is given below:

$$W_t = P_t - P_{t-1} \qquad (5)$$

Again, the notations from Table 2 are used. The only cost in W is an NFT's last purchasing price.

C. Grouping of Player, Collection, and Resale Return

Buyers, sellers, and collections are grouped based on their ranks by sales volume in $USD. For the two separate groups – initial sales and subsequent sales – sale volume in $USD is aggregated at a buyer level. Then, the ranks of the aggregated sale volumes are partitioned into five groups, which have about equal numbers. The five groups are named: very high buyer, high buyer, medium buyer, low buyer, and very low buyer. By the same approach, sellers are categorised into: very high seller, high seller, medium seller, low seller, and very low seller. Equally, collections are classified as very high collection, high collection, medium collection, low collection, or very low collection.

Resale returns for the subsequent sales category are categorised by two profile levels. Firstly, they are categorised into: loss, break even, and profit. Secondly, similar to the approach above, the loss type is partitioned into three groups: large loss, medium loss, and small loss. Similarly, the profit type is broken into large profit, medium profit, and small profit. The break-even type stays the same in the second-level profiling.

D. Data Overview

Table 3. Overview count

	January 2022		June 2022	
Count	**NFT Initial Sales**	**NFT Subsequent Sales**	**NFT Initial Sales**	**NFT Subsequent Sales**
Sale	1,318,009	592,683	982,494	615,018
Buyer	283,514	200,810	194,176	161,864
Seller	179,065	119,934	202,142	158,272
Collection	5,102	2,241	8,760	5,366
Private Sale	1,820	2,860	2,090	713

Table 3 shows the initial and subsequent sales split, including the count of public and private sales, unique buyers, sellers, and collections across January and June 2022. In January 68.98% of total sales were from the initial sales group, and in June, 61.50% of total sales were from the initial sales group. Interestingly, the number of buyers in June is lower than the number of sellers in the initial sales group; meanwhile, the opposite is observed in the subsequent sales group.

NFTs are initially sold from a wider variety of collections than they are subsequently sold. Private sale is unpopular in both market types, which is less than 1% of the total sales.

Table 4. Summary of NFT price in $USD

	Market Group	Min	1st Quartile	Median	Mean	3rd Quartile	Max
January 2022	Initial Sales	0.0	232.6	486.8	1,454.5	1,131.3	1,393,075.9
	Subsequent Sales	0.0	411.3	871.7	2,572.9	2,084.7	612,236.3
June 2022	Initial Sales	0.0	17.6	47.5	227.8	153.0	360,716.1
	Subsequent Sales	0.0	52.1	140.7	629.6	364.8	1,201,752.9

A statistical summary of NFT prices in $USD for each group is shown in Table 4. NFT prices tend to be higher in the subsequent sales group than in the initial sales group. Interestingly, some NFTs have been traded at zero price. The NFT price median is smaller than the NFT price mean, indicating that the price distribution is right skewed. The maximum values in the table show that the NFT price can reach seven figures.

Table 5. Summary of NFT resale return in $USD

	January 2022			June 2022		
Count	**Profit**	**Breakeven**	**Loss**	**Profit**	**Breakeven**	**Loss**
Sale	227,334	491	364,858	67,846	279	546,889
Buyer	100,423	485	157,798	35,177	274	151,646
Seller	73,882	465	91,389	38,621	269	143,366
Collection	1,352	219	2,141	1,442	97	5,277
Private Sale	325	0	2,535	148	0	565

Table 5 summarises counts per NFT resale return type. Here, resale returns are calculated by Equation 4. Since the returns can only be calculated after resale, the table only relates to the subsequent sale group. A profitable sale is uncommon in June (11.03%), compared to loss sales (88.92%). In January however, profitable sales were three times more common, at 38.36%, with loss sales accounting for 61.56%. This highlights the need for a better strategy by a seller in the subsequent sales market during a slump period. Market equilibrium states that more buyers lead to more competition and, thus, a higher market price [36]. Nevertheless, during June, there are fewer buyers than sellers in the profit sales but the opposite is observed in the loss sales. Around 63% of sellers in the profit sales group also made loss sales in June. Hence, a loss sale should be considered a trial and error transaction instead of a reason to exit the NFT market.

E. Power Law Behaviour

Power law is assessed against sales volume in $USD by buyer, seller, and collection. Power law means one variable is proportional to a power of other variable. In this study, for both the initial sales and subsequent sales groups, NFT buyers' unique sales volumes in $USD are ranked. Then, the log of the unique sales volumes is plotted against the log of the ranks. The same is experimented on for sellers and collections. There are different power law rank-frequency distributions, including Zipf's law, Discrete Generalised Beta distribution, and Lavalette distribution [37]. Since nearly all our output graphs show a straight diagonal line first and then a sharply falling tail at the end, goodness-of-fit is tested between the Lavalette distribution and the empirical output. The formula for the Lavalette rank function is:

$$x_{[r]} = C\left(\frac{N+1-r}{r}\right)^{a} \qquad (6)$$

where x is the quantity of interest, r is rank, C is the normalisation factor, N is the maximum rank, and a is the parameter that is associated with power law behaviour.

F. Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is a model which aims to reduce dimension while preserving a difference between categories [38]. It populates new variables called discriminant functions (or canonical variates) that are linear combinations of original regressors. This study uses LDA when maximising the F-statistics in Equation 7. No scaling on original regressors is required before the LDA since it aims to maximise the F-statistics, not variance.

$$\frac{\textit{Between Group Variability}}{\textit{Within Group Variability}} = \frac{\sum_{i=1}^{K} n_i \left(\bar{X}_i - \bar{X}\right)^2 / (K-1)}{\sum_{i=1}^{K} \sum_{j=1}^{n_i} \left(X_{ij} - \bar{X}_i\right)^2 / (N-K)} \tag{7}$$

The LDA is used to identify an important factor to distinguish between different resale return types. The second level return profile (described in Section IV-C) is the dependent variable. Since the break-even return type is rare compared to the other return types, it is omitted from the analysis. The regressor candidates for the analysis are data-engineered (i.e. generated by transforming the original data):

- `btc_mid`: Daily Bitcoin to $USD conversion rate. This rate is generated in the same approach as Ether to $USD (refer to Section IV-B)
- `creator_royalty`: A creator royalty rate of an NFT that is charged to a seller when the NFT is resold.
- `median_nft_price_buyer`: Median NFT price in Ether from the price(s) that a buyer has paid.
- `ether_to_usd`: Daily Ether to $USD conversion rate.
- `prof_loss_ratio_collec`: % of profit sales out of all sales per collection.
- `median_nft_price_collec`: Median NFT price of a collection.
- `no_nfts_sold_collec`: The number of NFTs sold per collection.
- `total_price_usd`: NFT price in $USD.
- `pre_price`: A previous price of an NFT in $USD.
- `no_days_collec_sell`: The number of days between collection creation and selling.

V. Results

This section examines various NFT market features: pricing, creator royalty, market movement, player participation, market skewness, and lastly, resale return. Each feature is investigated per NFT market type and period wherever possible.

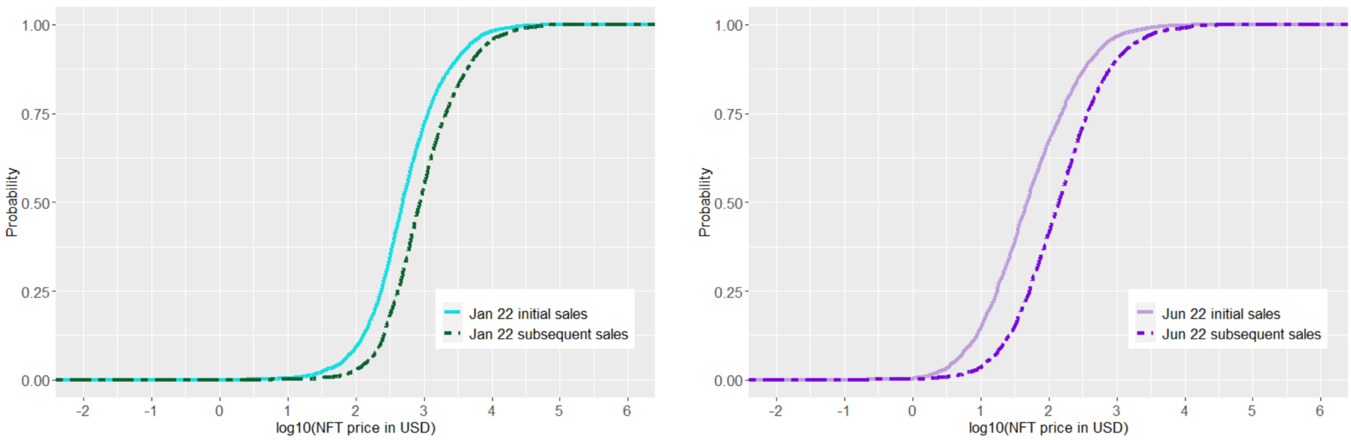
A. Higher Pricing for Subsequent Sales

Price is a determinant of demand in a market[39]. Hence, investigation of NFT sale pricing in different scenarios would prompt a better understanding of the demand for an NFT in those situations.

Higher pricing is observed in the subsequent sales market than in the initial sales market. Fig. 5 shows the cumulative distribution of the log price of NFTs in $USD for January and June 2022. In January, the median initial sale price was

$486.80 and the median subsequent sales price was $871.70. Whereas, in June, the median prices were $47.50 and $140.70 for the initial sales and subsequent sales, respectively. In both periods, NFT market participants have the propensity to price subsequent sale NFTs higher than initial sale NFTs. Fazli et al. [26] observed similar behaviour and argued that this is because an NFT investor would include their target profit in the resale price formulation. Additionally, we conjecture that the higher pricing is due to better information on pricing history. Initial sales are made by participants who have minted the NFT, and so they have limited information regarding the price that the market will value the NFT. Therefore, minters tend to set a conservative lower price, to secure a profit and cover their initial investment. In contrast, subsequent buyers tend to pay more because they are drawing on a greater price history to better determine the value of the NFT.

The price plummets from January to June are supported by the fall in the value of Ether over this period against $USD [32] and also the fall of average prices of NFTs due to investor uncertainty and the lack of confidence around the value of NFTs [40]. The median initial sale price declined to one-tenth of the price, and the median subsequent sale price to one-sixth of the price. As a result, the price gap between the initial and subsequent prices is wider in June. This may suggest that subsequent sale pricing is more resilient to a market crash than initial sale pricing.



(a) January 2022

(b) June 2022

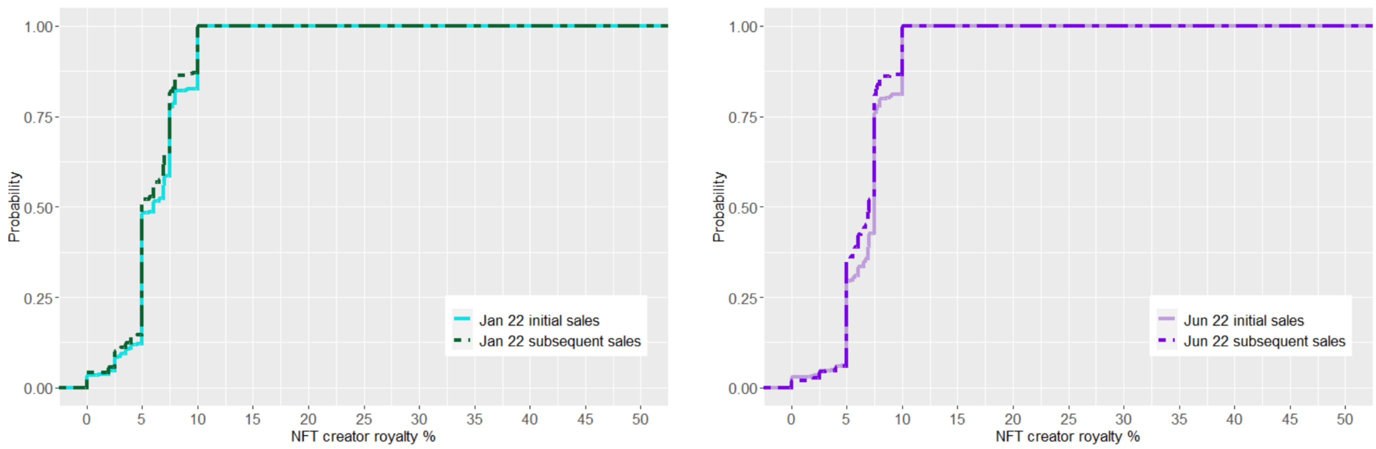
Figure 5. CDF of log10(NFT price in $USD)

Takeaway: An investor has the tendency of including a target profit when formulating their listing price. An initial sale seller may be more conservative in their NFT price setting due to missing information on the NFT's price history. The subsequent sale pricing seems more resilient to the slump. Hence, the initial sales market would be more for a high-risk investment, but the subsequent sales market for a risk adverse investment

B. Higher Royalties for Initial Sales than Subsequent Sales

NFT creator royalty is a revenue source to an NFT creator, but a cost to an NFT investor in an NFT resale[28]. The NFT creator would want to maximise the royalty, meanwhile the investor would desire the opposite. NFT creator royalties from sales transactions reflect where the forces from the two parties cross.

Unlike the plummet in pricing in the slump, creator royalty increased. Fig. 6 shows the cumulative distribution of the creator royalty rates of NFTs sold in January and June 2022. In January, about 50% of the NFTs had a creator royalty rate of 5% or lower, and around 35% of the NFTs had 7.5% or higher. Nevertheless, in June, only 32% of the NFTs had a creator royalty rate of 5% or lower. The proportion of the creator royalty rates equal to or greater than 7.5% increased to 50%. The median creator royalty rates are 6% and 5% for initial sales and subsequent sales, respectively, in January. On the other hand, in June, the median creator royalty rates are 7.5% for initial sales and 7% for subsequent sales. The rate tends to be higher in initial sales than in subsequent sales by a very small margin.



(a) January 2022

(b) June 2022

Figure 6. CDF of creator royalty rate

Despite the price plummeting from January to June, the creator royalty rate increased. This could be due to an investor's attempt to mitigate a loss from the price drop. A collection creator generates money off their collection after the mint from royalty fees on the sale of each NFT. The return for the collection creator per NFT sold is calculated with the following formula:

$$F_t \times P_t - G_t \qquad (8)$$

where the same notations from Section IV-B are used. A collection creator can increase their return in two ways. The first is when sales volume increases, and the second is to raise the creator royalty rate. The difference in royalty rates between January and June indicates that as sales volume has decreased across the NFT market, collection creators have had to increase the royalty rates per NFT sold to ensure higher returns, as they can no longer rely on high sales volumes to provide the desired return.

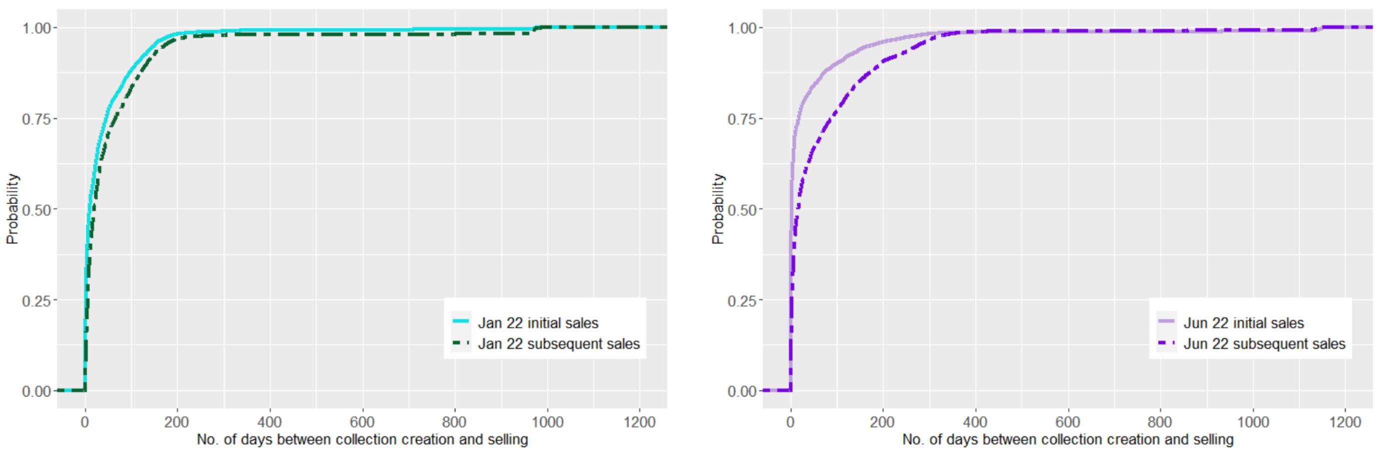
Compared to the digital music streaming industry, the creator royalty rate in the NFT market tends to be lower. The average creator royalty rate in the digital music streaming industry is around 10.5%, and main music platforms (Spotify, Apple, Amazon, YouTube, and Pandora) agreed to gradually increase the rate to 15.35% during the 2023 - 2027 period [41]. The median NFT creator royalty rate increased from January to June for both initial and subsequent sales. It would be interesting to monitor whether the creator royalty rate in NFTs will ever catch up with that of the music industry, and, if yes, how quickly.

Takeaway: An investor should be mindful of that a creator royalty rate seems higher in initial sales than in subsequent sales by a very small margin. This means that an investor should consider purchasing an NFT with reasonably cheaper creator royalty to increase its selling power in its resale. An NFT creator may use creator royalty as a mechanism to mitigate their revenue loss during a slump.

C. Rapid Turnover of Products in High-Speed Market

In describing the NFT market, terms such as the following have often been used: "unprecedented speed", "artwork hyperinflation" and "over tokenisation" [28]. This subsection assesses the market speed from the study dataset by measuring the time interval between different market activities.

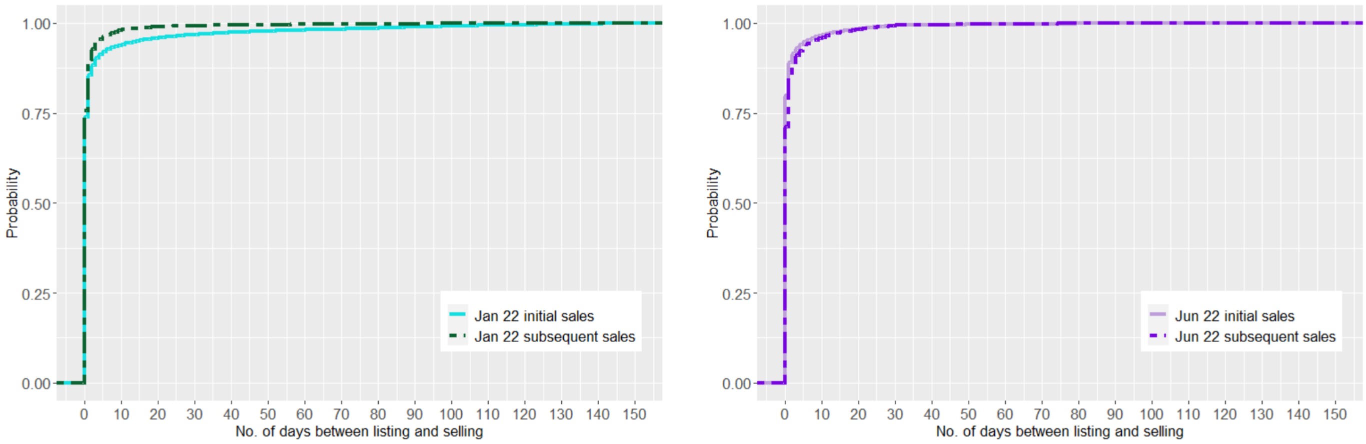
An NFT sale occurs very soon after other activities, such as the NFT collection creation, listing, or its previous sale. Fig. 7 shows the time between a collection's creation date and the sale date of an NFT, using a cumulative distribution function. In January, nearly 50% of both initial and subsequent sales occurred within a day of the collection's creation. In June, the proportion increased in the initial sales (approximately 60%), but reduced in the subsequent sales (around 30%). This indicates a slowing down for the subsequent sales market although the initial sales market in June did not experience a marked change over January.



(a) January 2022 (b) June 2022

Figure 7. CDF of day(s) between NFT collection creation and sale

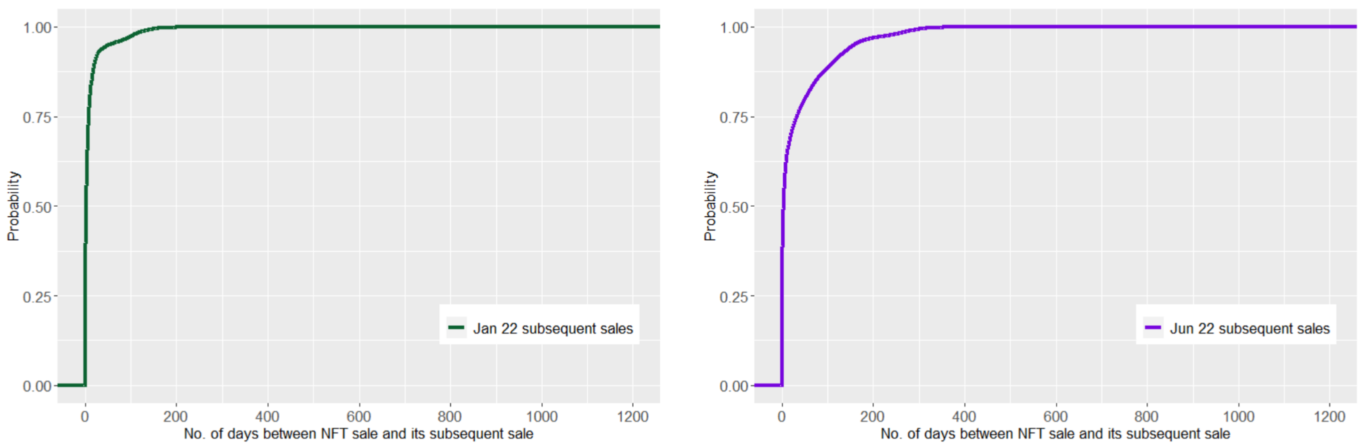
In January, around 83% of both initial and subsequent sales were occurring within a day of listing, however, in June, only around 70% of initial and subsequent sales were occurring within a day of listing. This would mean that if an NFT is meant to be sold, it is likely to be sold on the day of its listing. If an NFT is not sold within 24 hours, a seller should assume that the probability of sale is a lot lower unless it is relisted. The typical time gap between the listing and selling is short compared to the housing market – on average, a house is on market for 22 days in the United States [42]. Fazli et al. [26] observed 41% of unlist-relists within one hour. They argued that unlist-relist was to increase the chance of the NFT being displayed on an NFT market platform's homepage and thus the likelihood of a successful sale. The alleged fraud by Chastai, a former OpenSea employee, in 2021 is related to the importance of featuring on the homepage [43]. He was in charge of selecting which NFTs to exhibit on the homepage. U.S. prosecutors claimed that he bought about 45 NFTs before they appeared on the homepage. After featuring on the homepage, he is believed to have sold the NFTs at between two to five times the purchase price.



(a) January 2022 (b) June 2022

Figure 8. CDF of day(s) between listing and sale

In Fig. 9, the number of days between NFT sales has increased considerably between January and June, shown by the steeper curve in January. The median number of days between the NFT sale and its subsequent sale is three in January and four in June. On the other hand, the distribution of the measure is more right-skewed in June. The mean is 10.49 in January, but 31.48 in June.



(a) January 2022 (b) June 2022

Figure 9. CDF of day(s) between NFT sale and resale

Takeaway: The NFT market moves extraordinarily fast. Across the sale types and periods, an NFT is typically sold on the day of its listing. A buyer may promptly respond to a listing, especially one on an NFT market platform's homepage. An NFT sale follows its previous sale within four days across the boom and slump. Based on such a momentum, fail-fast approach would be appropriate to the market.

D. Fast Action and Interaction of Market Participants

Buyers and sellers shape a market. Thus, the NFT market participants are profiled into different groups. Then, their market participation frequency and interactions are investigated.

Market participation frequency rises from the very low revenue group to the very high revenue group. Fig. 10 represents the market participation frequency of seller types using subsequent sales data in January and June. The initial sale version resembles the figure. The very high seller groups participate the most in the market in both January and June for both initial and subsequent sales. This means that to be a high revenue-generating seller, it may be more important to make multiple sales across different days instead of focusing on making one big-price sale. There is a notable decline for the very high sellers, and there have also been declines in the other groups between these two months. This shows there has been an overall decrease in market participation days from the boom to the slump. If the level of profits experienced in the boom is no longer there to be made during the slump, then market participants may not want to invest as much of their time. A heavy hitter is a player who participates every day in the market during a given period. There are 634 heavy hitter buyers and 556 heavy hitter sellers in the initial sales in January. In contrast, there are much fewer heavy hitters in the subsequent sales in the same month: one heavy hitter buyer and 13 heavy hitter sellers. In June, there are two heavy hitter buyers and no heavy hitter sellers per sale type. Our results reaffirm the heavy hitter behaviour observed by White et al. [21] during varied market conditions.

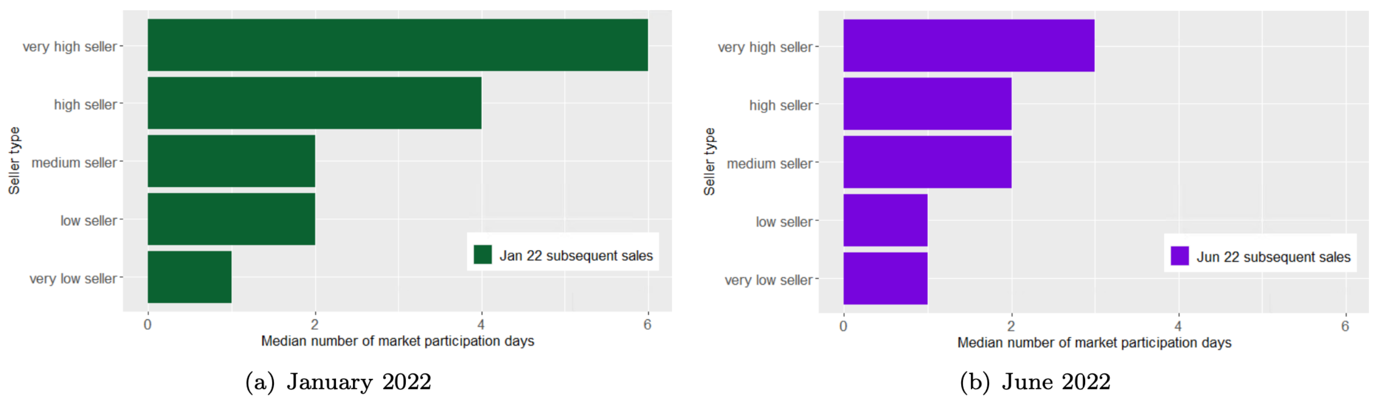


Figure 10. Seller's market participation frequency for subsequent sales

Revenue dominating player groups associate with each other the most. Fig. 11 analyses the network of buyer and seller types, which groups interact most frequently with which other groups, and what size collections ($USD sales volume) they interact with. We can see very similar results between January and June, which indicate that the interactions that exist are largely consistent between a boom and a slump period. In both months, there is a frequent interaction between very high buyers and very high sellers, indicating the NFT market may consist of several big players who are buying and selling amongst each other. Very high seller group's revenue is mostly from very high collection group. Big players' clustering is also observed in the study by Vasan et al. [20] as a distinctive community among rich NFT artists. On the other hand, a link continues to exist between each different buyer/seller group, so no group is trading in isolation. When the same Sankey diagrams were populated for initial sales, the output resembled Fig. 11.

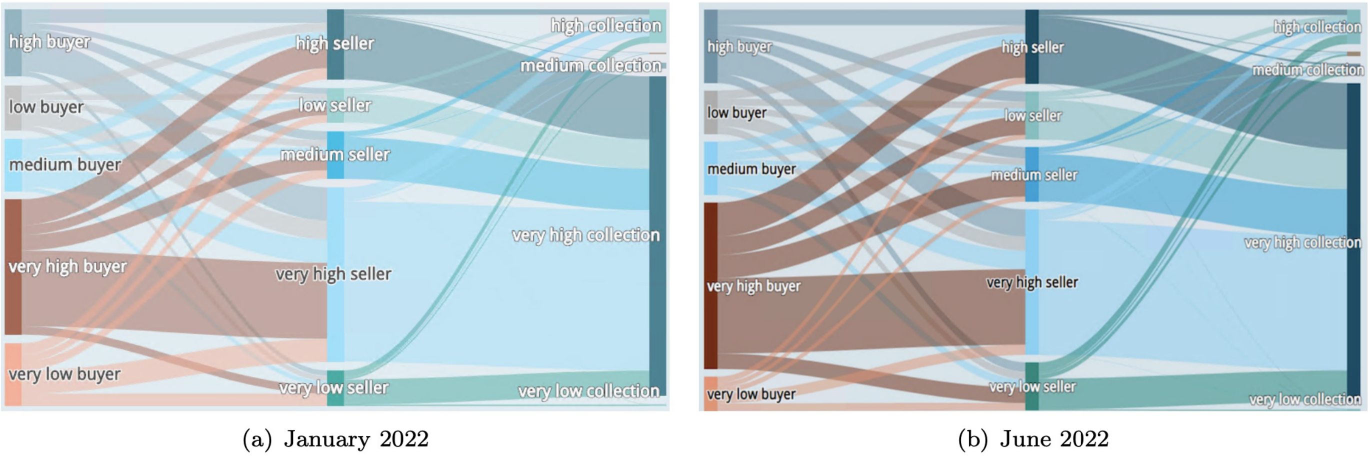


Figure 11. Relationship between buyer, seller and collection types in terms of sale transaction for subsequent sales

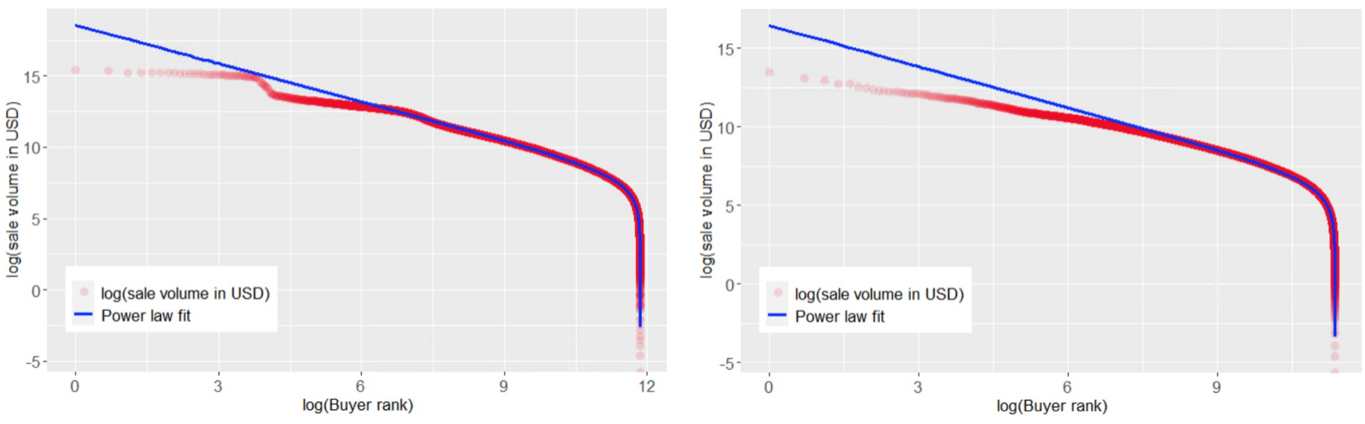
Takeaway: In both boom and slump, sale activity frequencies tend to increase from very low seller to very high seller per sale type. Hence, frequently participating in the market is highly recommended. Revenue is generated mostly by the interactions between very high buyer and seller groups, and also between very high seller and collection groups. The NFT market regulators should consider formulating a policy to encourage interactions between various types of sellers, buyers and collections.

E. Prevalence of Power Law Distribution

The skewness of revenue distribution is tested by Power Law. This assessment verifies whether revenue is highly concentrated to a few market participants or collections.

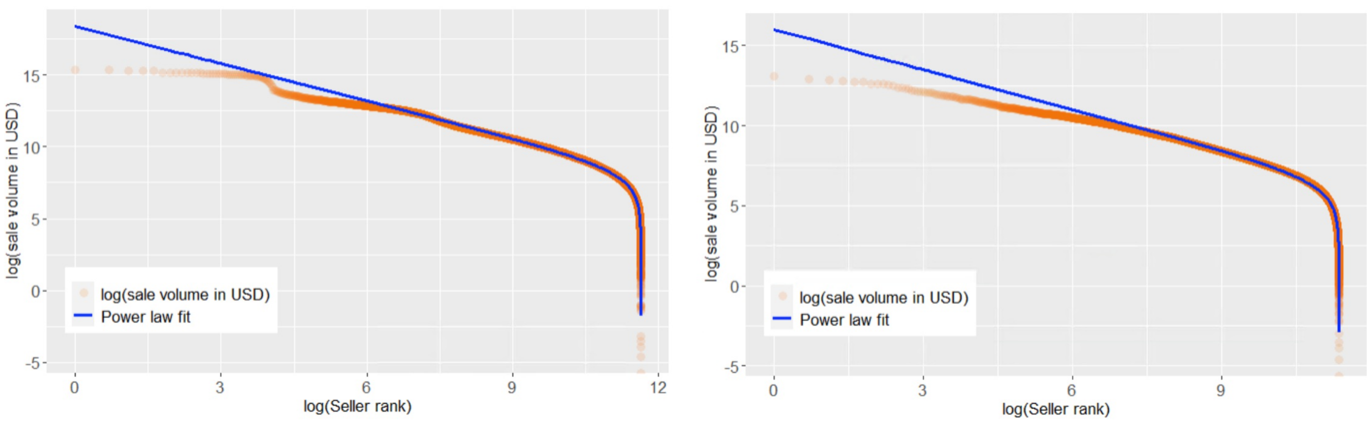
Power law is observed in the groupings of buyers, sellers, and collections in the NFT initial and subsequent sales for both periods, except for the collection groupings in January. Fig. 12 represents buyers for initial sales for January and June respectively. The red scatter points represent the log of sales volume (in $USD) against the log of buyer rank in the initial sales, whilst the blue line shows the Lavalette function's fit on the data. Fig. 12's subsequent sale equivalent is almost identical. The rank distributions for the seller groupings also resemble their corresponding buyer versions (refer to Fig. 13). The fits are weak at high group ranks in both Fig. 12 and 13, probably due to a small number of points. However, the fits are very strong from the mid-x-axis point. The minimum R^2 observed among the buyer and seller groupings from $log(rank) = 6$ is 0.9432. On the other hand, the fits for the collection groupings in June are reasonably high, even when all points are counted: R^2 = 0.6533 for the initial sales and R^2 = 0.7337 for the subsequent sales (refer to Fig. 14). Power law is absent in the collection groupings in January. There is a negligible discrepancy in the R^2 fits between the initial and subsequent sales for each scenario tested, less than 0.1.

While Lavalette distribution is present in all our power law scenarios, Zipf's distribution power law is detected in the study by Casale-Brunet et al. [27] and Nadini et al. [1], and Laherrere distribution power law in the study by White et al.[21]. One difference between our study and their studies is that sale revenue in $USD is used for ranking in this study, but sale count in the other studies. Casale-Brunet et al. [27] showed power law among market participants for all their target collections except *Decentraland* collection. On the other hand, when we test power law among collections, it is absent in January. We conjecture that in the boom, people were more optimistic about experimenting with an NFT from a lesser-known collection. A high number of buyers could be not yet sufficiently skilled in pinpointing a successful collection due to the young age of the market. However, over time, those repeatably unsuccessful ones could have departed the market [23]. Hence, in June, people's investments could be more information-driven, less experimental, and thus concentrated more on a few famous collections.



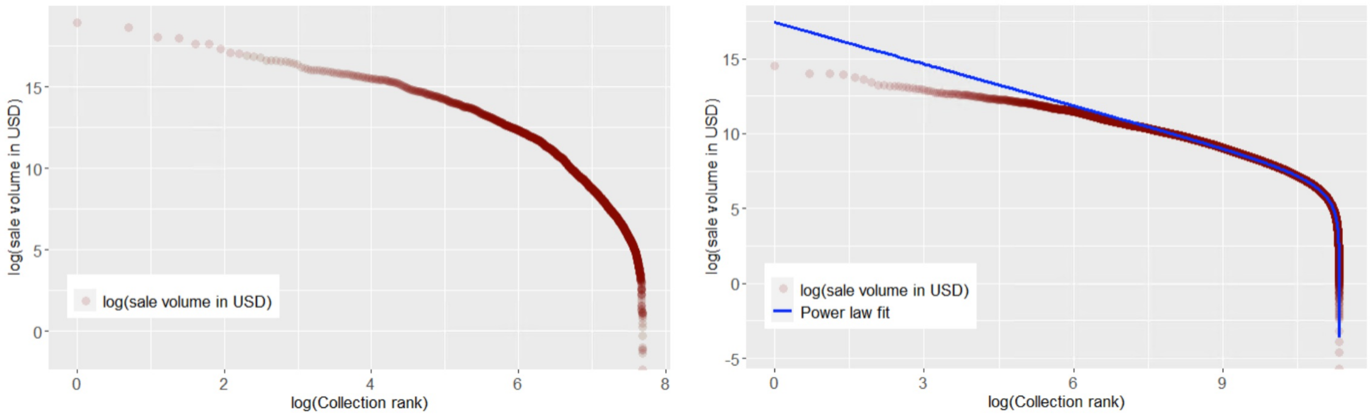
(a) January 2022 (b) June 2022

Figure 12. Buyer rank by sale volume in $USD for initial sales



(a) January 2022 (b) June 2022

Figure 13. Seller rank by sale volume in $USD for initial sales



(a) January 2022 (b) June 2022

Figure 14. Collection rank by sale volume in $USD for initial sales

Takeaway: The Lavalette Rank power law was observed in sale revenue among buyers and sellers in both June and January. Surprisingly, the power law was only present among collections in June and not in January. This could be because the market was still new in January, and buyers were more experimental with their collection selections during the boom. In contrast, by June, remaining players had become more skilled, resulting in more information-driven collection selections and greater overlap among them.

F. Higher Pricing Leads to Higher Margin, Accounting for Hidden Costs

Here, we identify factors to distinguish between various resale return types. Per subsequent sale record, a resale return is estimated by using Equation 4, and its type is categorised based on Section IV-C. The Linear Discriminant Analysis (LDA) is executed to predict a resale return type after short-listing our regressor candidates (refer to Section IV-F) per period. From the LDA, strong regressors are identified.

The regressors `btc_mid` and `ether_to_usd` have a very high correlation with one another, 0.9911 in January and 0.9919 in June. This may be consistent with the finding by Ante [25] on Ethereum price's significant Granger-causality on Bitcoin price. High correlation is also observed between `median_nft_price_collec` and `total_price_usd`: 0.8610 and 0.8010 for January and June, respectively. Hence, `ether_to_usd` and `total_price_usd` are omitted from the regressor list for modelling the LDA.

The LDA loading results are listed in Table 6 for the boom and 7 for the slump. Statistically significant predictors for the return types in both periods are: `no_days_collec_sell`, `pre_price`, `median_nft_price_collec`, `prof_loss_ratio_collec`, and `creator_royalty`. Nonetheless, `median_nft_price_buyer` has high explanatory power in January only, meanwhile `no_nfts_sold_collec` in June only. `btc_mid` appears unimportant in both periods, although it showed a significant impact on sale count by Ante [25] and on the count of Google searches on NFT by Pinto-Gutiérrez et al.[13].

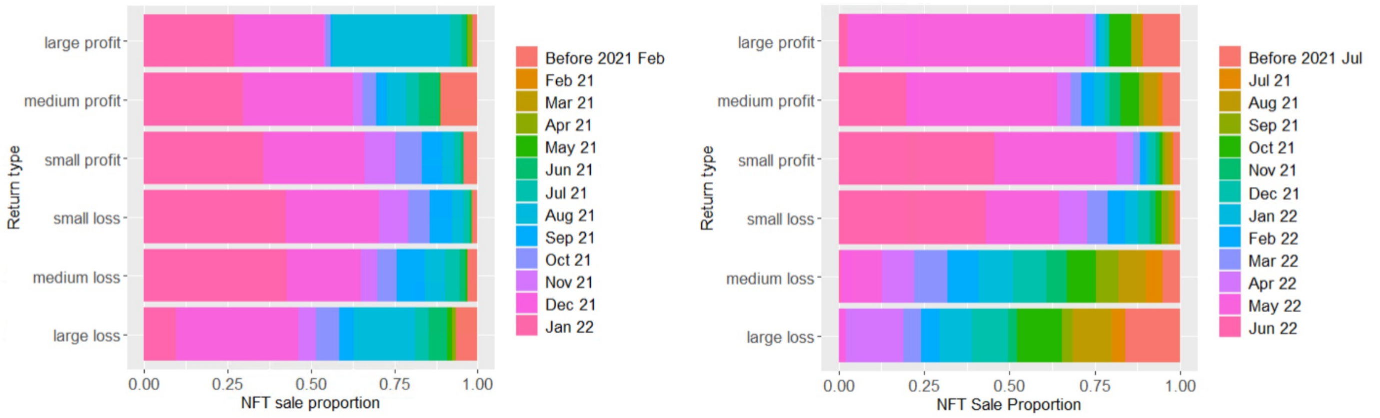
Table 6. LDA loading: identify important factor to return type in Jan

Regressor	LD1	LD2	LD3	LD4	LD5
no_days_collec_sell	-0.13	0.13	0.38	-0.21	-0.65*
pre_price	-0.02	-0.05	0.13	-0.56*	-0.36
no_nfts_sold_collec	-0.38	0.40	0.22	0.07	0.20
median_nft_price_collec	-0.80**	-0.55*	0.00	-0.15	0.13
prof_loss_ratio_collec	-0.79**	0.54*	0.16	-0.06	0.03
median_nft_price_buyer	0.69*	-0.38	-0.23	0.41	-0.36
creator_royalty	0.14	-0.11	0.66*	0.42	0.15
btc_mid	-0.07	0.22	-0.41	-0.17	-0.01

Table 7. LDA loading: identify important factor to return type in Jun

Regressor	LD1	LD2	LD3	LD4	LD5
no_days_collec_sell	0.15	0.31	-0.09	-0.83**	0.30
pre_price	0.08	0.20	0.41	-0.16	-0.61*
no_nfts_sold_collec	0.20	-0.59*	0.71**	0.11	0.13
median_nft_price_collec	0.65*	0.67*	0.20	0.21	0.13
prof_loss_ratio_collec	0.85**	-0.49	-0.05	-0.04	-0.15
median_nft_price_buyer	0.47	0.44	0.12	0.24	0.42
creator_royalty	-0.13	-0.12	-0.18	0.61*	-0.05
btc_mid	0.14	-0.27	0.13	0.22	0.37

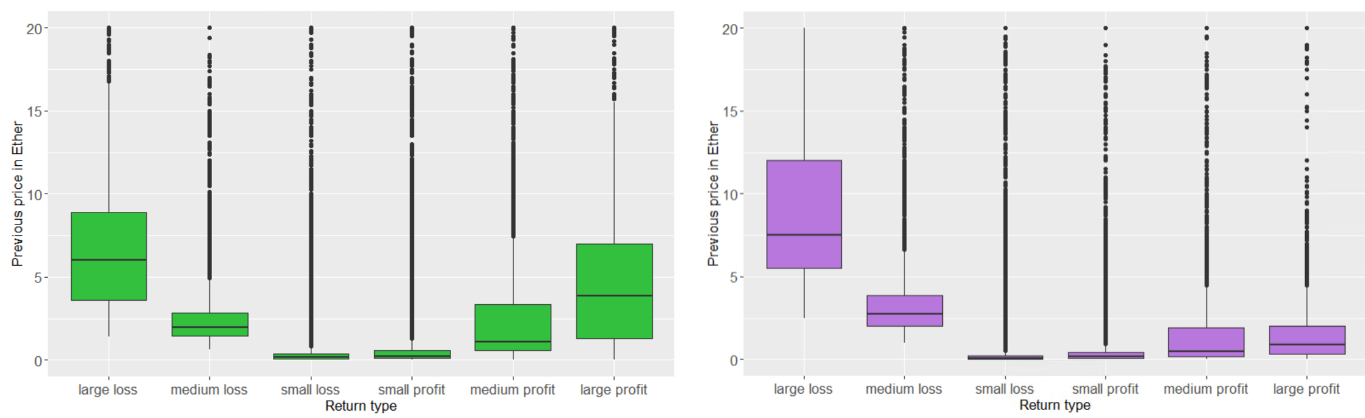
Fig. 15 represents the composition of resale return types by the age of the collections that the sales were made from. In January, the majority of medium profit through to medium losses were made on NFTs from collections that were new to two months old. We can see from the large profit and large loss categories, that collections from five months old were responsible for a large portion, particularly for a large profit. This shows that, in some cases, holding NFTs long term, e.g. Bored Ape Yacht Club [44] can lead to a very large gain or large loss - high risk investment. In June, profits existed more consistently for one to two-month-old collections, whilst losses existed more for the older collections, the majority being from four-month-old collections and onwards. This shows that, where it may have been profitable to hold or buy and sell older collections in January during the boom, the slump meant this behaviour led to a higher chance of losses. It appears that in a slump, purchasing an NFT from a very young (less than two months) collection and selling it within two months can minimise loss or increase the chance of making a profit.



(a) January 2022 (b) June 2022

Figure 15. Collection age % and return type

Fig. 16 shows how the previous price distribution varies across different resale return types. Minimising a cost is one possible strategy for profit maximisation. However, such a strategy may not be applicable in the NFT subsequent sale market. Interestingly, the median previous price increases from the median profit to the large profit group. This means that to maximise a profit, instead of focusing on purchasing the cheapest NFT, an investor should purchase a reasonably expensive NFT and aim to sell it at an even higher price in the next sale. Since `median_nft_price_buyer` is also a significant predictor for the return types, an investor can seek such an NFT from a reasonably expensive collection. The reason for recommending a reasonably pricing NFT as an inventory is that a too expensive NFT (e.g., above 5 Ether) may lead to large loss. The interquartile range of the previous prices of large loss is notably above the corresponding ones for the other return types in both periods. The relation between large profit and a reasonably expensive inventory in the NFT market contrasts with the no-frills airline industry, where the main mechanism for profit maximisation is cost minimisation [45].



(a) January 2022 (b) June 2022

Figure 16. Previous price in Ether per return type

Despite an NFT investor's sophisticated strategy formulation observed by Fazli et al.[26], profit generation is not quite common: 38.356% in January and 11.032% in June. When a resale return is calculated based on Equation 5, the proportion explodes to 60.172% for January and 39.050% for June. This triggered the authors to question whether the hidden costs (costs beside a previous price) are still dismissed often by the investors. A previous price is displayed up-front on an NFT's page on the platform. Nevertheless, other costs are somewhat hidden, for instance, finding an NFT's creator royalty rate requires extra navigation - scrolling down and opening Details ribbon. To improve the efficiency of the market, hidden cost information should be made readily available.

Takeaway: Minimising cost via purchasing a cheap NFT is not an effective strategy for profit maximisaiton as the median previous price increases from small profit to large profit. Buying a too-cheap NFT could mean weak selling power the next time. When no hidden cost scenario is simulated, the profit incident proportion surges. To increase the chance of profit-making and thus attract more players to the market, we may need to consider surfacing the hidden cost information up-front.

VI. Discussion

Our examination of the NFT initial and subsequent markets and their comparisons across boom and slump periods yields useful insights for various key stakeholders. Not only the current players but potential unskilled players can gain an applicable understanding of key characteristics in the initial and subsequent sales markets during a boom and slump from this study. As a result of the market type decoupling for every market property assessment, this study unveils the characteristics of the subsequent sales market, which is more accessible to ordinary people. The boom and slump are prominent periods in the business cycle and studying the NFT market during these time periods will provide a comprehensive and possibly unbiased understanding of the NFT market.

This study identifies the marketplace's properties consistent across the boom and slump: higher pricing in the subsequent sales market than the initial sales market, hyper-speed market movement (e.g. most sales on the days of NFT listings), especially in the initial sales market, skewed revenue distribution among sellers and buyers, and the strong explanatory factors to differentiate between various resale return types. The factors are: the number of days a collection made a sale, previous price, median price of a collection, profit-to-loss ratio in a collection, and creator royalty rate. The factors would be especially useful for an investor's strategy formulation in a resale market. The discovery on the markets' intrinsic properties would help provide certainty and thus support the retention of the existing players and attract newcomers, even in an extreme period.

Our study also allow regulators to better understand the dynamics of various NFT market components, including pricing, creator royalty, market activity speed, a player's behaviour, revenue distribution, and resale return. Since this study covers both boom and slump periods, regulators can use the findings for developing a policy working across various economic stages of the NFT market. NFT revenues are very skewed among the sellers and buyers. An NFT policy can be formulated to improve the skewness, implementing an NFT education programme targeting those with extremely low revenue ranks. Since we attempted precisely formulating a resale return, our findings on the return can be useful for formulating a tax system on the NFT market. Our resale return simulation indicates that an NFT seller in the subsequent sales market could be ill-informed of the hidden costs (any cost besides a previous price). Based on this finding, regulators can consider improving the cost information accessibility or/and minimising the costs.

NFT marketplaces will find our results useful for several reasons. By understanding the frequency of investor participation and relative profitability during various market stages, NFT marketplaces can better align their offerings with the prevailing investment trends. For instance, during periods of decreased trading activity, NFT marketplaces may opt to decrease fees as a means of incentivising increased high-volume trading and reducing associated risks. Conversely, during market boom periods, characterised by heightened profitability and volume, NFT platforms may consider increasing fees as a means of maximising revenue potential. Insight into the success of aged collections across various market stages is also beneficial, as it may prompt NFT platforms to prioritise the promotion of, for example, older collections that tend to perform less favorably during market slumps.

Researchers stand to benefit from our findings, as these offer a deeper understanding of the similarities and differences between the initial and subsequent sales markets across boom and slump periods. To the best knowledge of the authors, this is the first study to dissect the NFT market into the initial and subsequent sale types and evaluate various market components in the different types and periods. Our study approach may motivate examining different groups in the NFT market. Furthermore, we have released the dataset for use by researchers to perform additional data-driven analysis or use in teaching case studies.

VII. Conclusion

This study sheds light on understanding different components in the initial and subsequent NFT sales markets. NFT pricing tends to be higher in subsequent sales, suggesting that an investor may consider a target profit in their price formulation. The subsequent sales market has more resilient pricing from a market crash. The median creator royalty rate increased from the boom to the slump. This behaviour could be triggered by an NFT creator's attempt to ensure an adequate profit in a low-sale volume environment. The NFT market movement is extraordinarily speedy, especially for the initial sales. Most sales occur within 24 hours of their listings. Power law is observed in revenues among sellers and buyers in all market types and periods. Nevertheless, it is absent among collections in the boom. Investors in the boom could be more experimental in their collection selection, since the market was flourishing and there could be insufficient information for most of the investors to formulate a strategic selection. Our resale return type prediction by LDA may inspire some possible strategies for both boom and slump periods. One could be buying an NFT from a relatively new collection and selling it quickly before its popularity fades. Another strategy could instead be aiming for purchasing the cheapest NFT for cost minimisation, buying an NFT at a reasonable price from a popular collection, and selling it at an even higher price.

This paper identifies the NFT market's intrinsic properties, which are invariant from the market's economic status. The properties are: more expensive pricing in the subsequent sales market, speedy market movement (more in the initial sales market), skewness in revenues, and statistically strong variables to predict a resale return type, which is the number of days a collection made a sale, previous price, median price of a collection, profit-to-loss ratio in a collection, and creator royalty rate. Our findings have useful implications for the current and potential NFT market participants, policymakers, and marketplaces.

There are several avenues for future work. A resale return estimation can be refined further by using real-time data for gas fees and currency conversion rates. More regressors for predicting a resale return type can be data engineered from our dataset alone or combining it with other dataset, and then their significance can be evaluated. By using our data, returns from NFT initial sales can be also investigated. Such study would be beneficial especially to an NFT creator who uses an NFT market platform for their initial NFT sales. The NFT market movement is extremely fast. For instance, over 50% of initial NFT sales are from less than one-month-old collections. The gap between an NFT's two consecutive sales is for typically three to four days. This triggers a question on the profile of the players participating in this extraordinarily fast market. The profile insight could be useful to define a target audience to advertise the NFT market to. Alternatively, based on the profile information, an NFT marketplace could be redesigned to appeal more to those unlike the profile.

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Footnotes

[1] Wash trading refers to the activity of repeatedly trading assets to feed misleading information to the market [46].

[2] Dataset:

https://jongkyou.com/research_data/3g6A03mUVtDFrZTBNDVE4ip6oVd09oEbyoKdyYS3ihZ8/

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