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Non-Fungible Tokens (NFTs): A Review of Pricing Determinants, Applications and Opportunities

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Non-Fungible Tokens (NFTs):
A Review of Pricing Determinants, Applications and Opportunities*

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This paper provides a review of the development of the non-fungible tokens (NFTs) market, with a particular focus on its pricing determinants, its current applications and future opportunities. We investigate the current state of the NFT markets and highlight the perception and expectations of investors towards these products. We summarize and compare the financial and econometric models that have been used in the literature for the pricing of non-fungible tokens with a special focus on their predictive performance. Our intention is to design a framework that can help understanding the price formation of NFTs. We further aim to shed light on the value creating determinants of NFTs in order to better understand the investors' behavior on the blockchain.

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1. Introduction

During 2021, the popularity of non-fungible tokens (NFT) has grown exponentially. As Figure 1 shows, the NFT market capitalization rose substantially over the period from 2019 to 2021, indicating its peak at 16 billion USD in 2021. Over the last twelve months, the market capitalization of NFT projects increased by 4,440 percent.

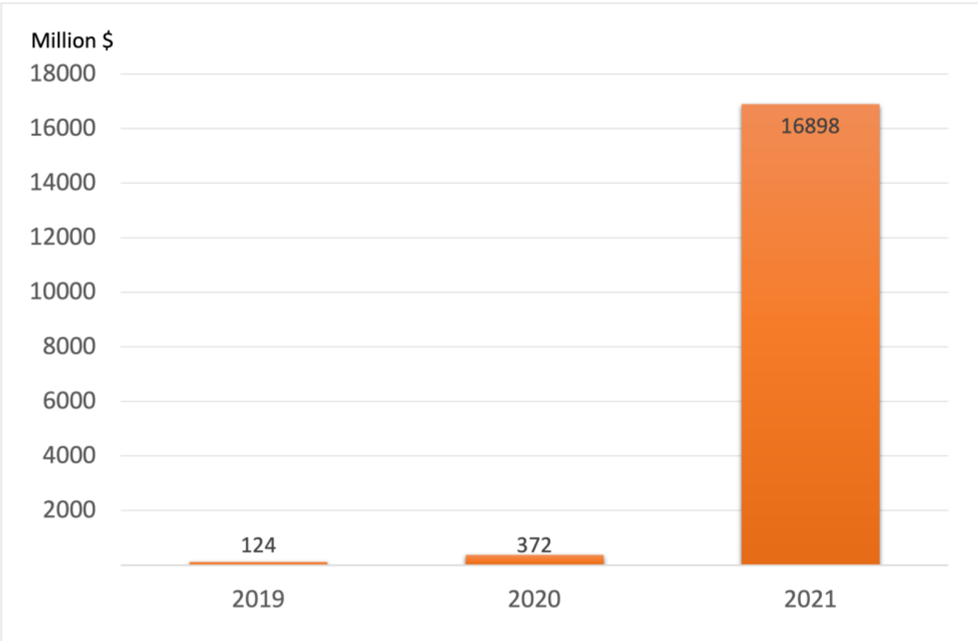

Figure 1. NFT Market Capitalization. This graph depicts the development of the NFT market capitalization, in million of dollars, over the period from 2019 to 2021. The data were retrieved on March 10, 2022, from the *NonFungible* database at nonfungible.com/market-tracker.

It has come a long way since 2012, when the first discussions on the possibility of reducing fungibility on one's Bitcoins were held. Specifically, in the archetypal model of Colored Coins, each Bitcoin (by nature fungible) could be distinguished from all the others by using a specific "mark" assigned through additional lines of code. Those Colored Coins could be used for specific purposes, such as creating digital assets on top of Bitcoin blockchain[1] by using its functionalities beyond a digital currency (Crosby et al., 2016). From that first project, many others have developed, using different structures and protocols. Currently, it is possible to observe NFTs in the most disparate fields, from art to finance. Together with other factors, it is this cross-market presence that has

[1] Blockchains are decentralized protocols for recording transactions and asset ownership (Biais et al., 2019).

contributed to their success and made them of increased interest to individual investors (Wang et al., 2021).

The goal of this paper is threefold. First, we want to neatly trace the history and motivations behind the birth of NFTs. Second, we will discuss the magnitude of their impact on markets and investors, highlighting the popularity that this disruptive technology has gained from its beginning. Third, we will analyze the determinants of NFTs investment choices of practitioners in order to differentiate the systematic from the emotional component in the practices on the blockchain. In fact, only by carefully comparing the regressors in each of the research taken into consideration will it be possible to have a measure of how much the so-called "hype" plays a decisive role in the choices of the players in this market (Wang et al., 2021). Especially this last point will be fundamental to answer the question “why invest in NFTs?”, when there is a well established market based on physical collectibles.

Primarily, NFTs have allowed investors to securitize their digital assets by leveraging the innovation brought by blockchain technology. In fact, through the distributed ledger, all the information concerning the transactions can be publicly consulted and each of the parties involved can verify its veracity, which was not always guaranteed in the world of physical collectibles. Secondly, NFTs are scarce. It has been demonstrated how the scarcity factor plays a fundamental role in the appreciation of a non-fungible object such as works of art or collectibles in general (Burton and Jacobsen, 1999; Mandel, 2009): the fewer specimen exist in circulation, the more that product is perceived as exclusive, and therefore, of value. One prime example for this scarcity feature for the creation of value within the NFT market was the first Tweet by Jack Dorsey, CEO of Twitter, which was sold at auction in March 2021 for USD 2.9 million.

However, as we will demonstrate in the course of the paper, scarcity is not sufficient to preserve the value of these tokens in the long run. More specifically, many investors in the NFT market have based their investment choices on the so called greater fool approach (Harrison and Kreps, 1978; Baker et al., 2012). According to this theory, market agents try to purchase questionably priced securities with the hope of reselling them in the future to a "greater fool" for a higher price. Subsequently, if the theory holds up, the next agent will also be able to resell it, laying the foundations for a real speculative bubble that will burst when there are no more "greater fools" on the market. In the NFT market it is possible to trace a potential dynamic of this greater fool type. After a period of strong enthusiasm due to the introduction of this new digital asset, sales of NFTs dropped dramatically towards the end of 2021. For instance, Jack Dorsey's NFT valued at USD 2.9 million USD in March 2021, was up for resale at auction in April 2022 and the highest bid was just under 10,000 USD, a dramatic loss in its value of over 99 percent in just one year.

Nonetheless, some NFTs continue to attract investors because of their second most important feature: inherent utility. We describe that the NFT market is also made up of so-called utility tokens that offer their owner an intrinsic value given by the different perks that the creator of the NFT wants to deliver to its users. For instance, YellowHeart is a marketplace that creates NFTs for musical artists and issues them as tickets for their concerts and special events in order to strengthen the relationship between fans and musicians. Scarcity remains a key element for the success of NFTs. In order to make this digital asset attractive to investors, we note that scarcity must be supported by an intrinsic utility linked to the token itself.

The remainder of this paper is organized as follows. Section 2 investigates the NFT ecosystem by first deepening their evolution on the Ethereum blockchain and then describing the properties and characteristics of 5 different key categories related to those tokens: gaming, collectibles, utility, art, and metaverse NFTs. Section 3 presents the different approaches used in the literature to price NFTs and compare them based on their predictive power. Specifically, we will examine the hedonic regression (HR), repeat-sales regression, vector autoregressive (VAR), and machine learning (ML) models as well as wavelets analysis (WL). Section 4 discusses the current implementations of NFT pricing models, their applications and their key findings.Section 4 concludes, discusses opportunities within the NFT markets and outlines interesting areas for future research.

2. Non-Fungible Tokens

Non-fungible tokens (NFTs) are digital assets that feature identifying information documented in smart contracts. These, in turn, can be defined as digital contracts allowing terms contingent on decentralized consensus that are tamper-proof and typically self-enforcing through automated execution (Cong and He, 2019), i.e., programs stored on a blockchain that run when predetermined conditions are met. NFTs are cryptographically secured digital assets, usually called digital tokens (Howell et al., 2020), on a blockchain network which provide a representation of a unique item.

In the following we are going to identify a chronology and a differentiation of NFTs based on the blockchain on which they operate as well as the asset they represent. The first NFT prototype was Colored Coins on the Bitcoin blockchain[2] (Rosenfeld, 2012). Colored Coins allowed for further experimentation and created the prerequisites for the birth of NFTs on the Ethereum blockchain. Ethereum was launched in 2016 as an innovation compared to Bitcoin, especially for the possibility of implementing smart contracts. In fact, its flexibility allows users to exploit these contracts for

[2] The Bitcoin blockchain operates as a decentralized, trustless digital currency and payment system (Easley et al., 2019) following the rules explained by Nakamoto (2008).

the creation of different assets (i.e., tokens) by the so-called Ethereum Request for Comments (ERC). These are sets of rules, or standards, which are shared and agreed by the Ethereum community and which summarize the guidelines on how a certain token must be built for it to function correctly.

Then in 2017, Axiom Zen, a Canadian start-up, proposed the ERC-721 standard for writing NFTs on Ethereum. This protocol provides that the two main components of an NFT are kept in two opposite systems: the object of the token (the image, the sound and in general all the graphic characteristics of the NFT) are stored on a private and centralized server of the deployer of the token, while the proof of ownership is stored on the blockchain. The year 2017 also saw the birth of two highly successful NFT collections: CryptoKitties, by Axiom Zen itself, and CryptoPunks, by Larva Labs. Specifically, CryptoKitties is a collection of artistic images representing virtual cats that are used in a game that allows players to purchase, collect, breed, and sell them on Ethereum (Nadini et al., 2021) while CryptoPunks is a collection of 10,000 uniquely generated characters with proof of ownership stored on the Ethereum blockchain (Schaar and Kampakis, 2022).

It is possible to distinguish and summarize the NFT minting process in four steps. In Step 1, the most suitable marketplace (and blockchain) to host a NFT collection has to be chosen: examples can be OpenSea on the Ethereum blockchain or NBA Top Shot marketplace[3] on the Flow blockchain. If Ethereum is chosen, it is possible to use two different ERCs to create an individual NFT. ERC-721 is the standard for creating pure NFTs with full non-fungibility characteristics. Hence, each token created will be unique and will point to a single asset. This implies that each smart contract contains only links pointing to the metadata of the artwork, images or files stored outside the blockchain representing the NFT. Examples of projects using this standard are CryptoKitties and Decentraland[4]. ERC-1155 is the standard of hybrid tokens which possess the characteristics of fungibility and non-fungibility. Through this protocol it is possible to create a single smart contract that points to multiple fungible tokens, non-fungible or both. This standard was created to make the Ethereum network more efficient. In fact, a user who wants to transfer multiple NFTs using the ERC-721 protocol, cannot do this in one transaction, but will have to publish on the blockchain or “mint” multiple unique instances of ERC-721 tokens, with consequent increase of the commissions and slowdown of the blockchain itself, compared to directly using the ERC-1155 protocol. With the ERC-1155 standard, the efficiency of Ethereum is therefore increased, especially for transactions involving the collections of NFTs, and the implementation

[3] NBA Top Shot is a NFT marketplace that facilitates the purchase and (peer-to-peer) trading of sports collectibles.

[4] Decentraland is one of a new generation of virtual worlds, popularly referred to as metaverses, built on the blockchain (Dowling, 2022a).

errors of pre-existing standards are corrected. Examples of projects using ERC-1155 are The Sandbox, which is a blockchain-based virtual sandbox game (Duan et al., 2021), and Enjin, an online gaming community creation platform.

In Step 2, a crypto wallet must be created and connected to the chosen marketplace. The crypto wallet is nothing more than a virtual (or physical) wallet where the public and/or private keys necessary to access the execution of cryptocurrencies transactions are managed. For Ethereum, an example of a digital crypto wallet is Metamask.

In Step 3, the chosen marketplace interface has to be used to enter/upload all the information and characteristics of the NFT to be created (metadata). These information include the file that will become an NFT, the name or title of the work, its description, the collection to which it will be part, its textual characteristics (e.g., the material, the intrinsic features) and possibly its unlockable content, i.e., basically content that can only be viewed by those who own the work.

In Step 4, the NFT for sale has to be listed, after paying the "gas fee". In order to support the energy and computational cost used by the blockchain to process a transaction, each marketplace asks users who decide to mint their NFT to pay a small amount that depends on the demand for cryptocurrencies on the market and the speed with which the user wants to create his own token: the faster the minting process, the higher the fee the user has to pay. In practice, gas fees are used as a pay-back for the resources expended to validate transactions on the blockchain. Thus, transactions that demand more computational power will demand higher fees. In the case of NFTs, their minting can be particularly energy demanding, since it requires converting digital files into digital assets and store them on the blockchain. For that reason, the gas fee required to mint an NFT ranges widely, but basically it depends on the demand on the network and the price of Ether (or, "ETH"), the cryptocurrency used on the Ethereum blockchain.

It is important to note that Ethereum is not the only blockchain capable of hosting NFTs. Although Ethereum is very popular and widely used, starting from 2018, some platforms have decided to create their own blockchain to offer users and investors a different alternative to Ethereum and, above all, to take advantage of a non-congested ledger. Indeed, at the end of 2017, the lack of scalability of the Ethereum was evident at the time of the launch of the Generation 0 (Gen 0) of CryptoKitties when, on the blockchain, there was an increase in pending transactions equal to 6 times[5]. Investors, well-aware of the scarcity and sensing the possibility of very profitable

[5] In fact, by Axiom Zen's own rule, there can only be 50,000 Gen 0 CryptoKitties, which are created directly by the CryptoKitties smart contract and released directly into the blockchain. These were issued every 15 minutes starting from October 2017. Please see for further discussion: https://www.cryptokitties.co/guide/value-of-kitties.

future transactions, have landed in large numbers on Ethereum, causing a general slowdown of the system.

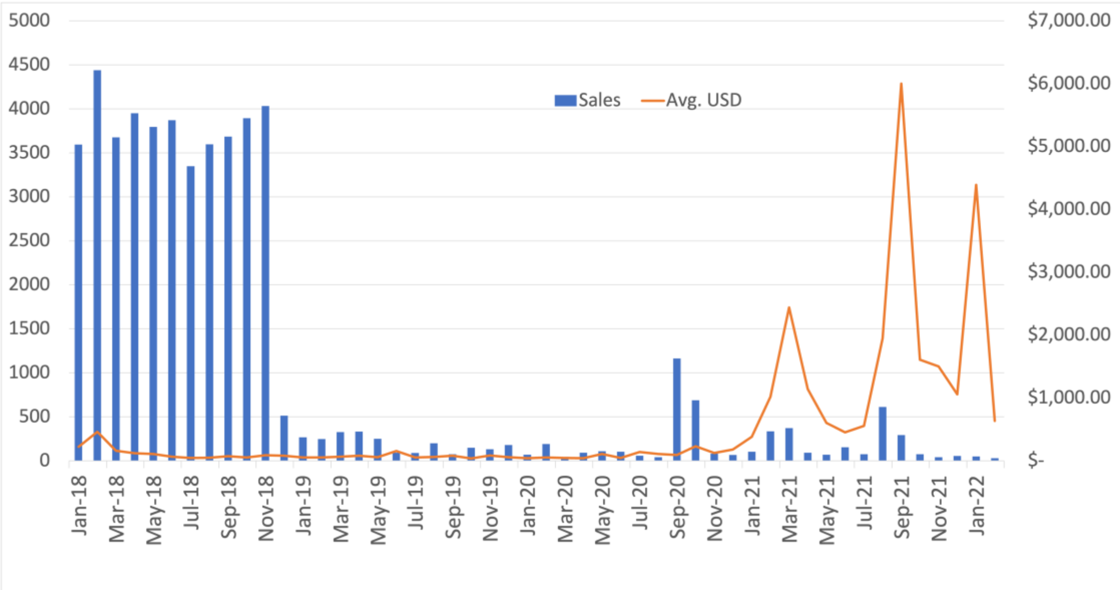

Figure 2. Gen. 0 CryptoKitties Sales. The graph compares the sales quantity with the average amount in USD of the Generation 0 CryptoKitties collection over the period January 2018 to January 2022. Adapted from *Dune Analytics*, dune.com/queries/397282/758734.

Figure 2 shows the number of sales that took place between January 2018 and January 2022 for the Gen 0 of CryptoKitties vs. their average price in USD. We observe that the dynamics of the number of sales and average value in USD of each Gen. 0 CryptoKitties are inverse. More specifically, at the beginning of the observation period, sales reached 4,500, which was an astonishing number for a single NFT collection at that time, but the average price for each of them was very low, barely touching 200 USD per token. We also note a substantial decline in sales after October 2018. At the end of 2018, the algorithm produced about 35,000 Gen 0 CryptoKitties before being stopped once again by the rule established by Axiom. For this reason, transactions involving this generation slowed down as users engaged in pairing their CryptoKitties to create successive generation tokens, which the market then focused on.

After this occurrence, the CryptoKitties developers decided to create a stand-alone company called Dapper Labs, with which they broke away from Axiom Zen and Ethereum to create a new blockchain optimized for applications such as CryptoKitties. As a result, in 2020, the Flow blockchain was launched. It was immediately very successful mainly following the release of the project NBA Top Shot Moments, which are officially licensed NBA or WNBA collectible video highlights. Figure 3 compares the total sales of the two flagship projects of Dapper Labs between July 2020 and February 2022. We note that NBA Top Shot has outclassed Crypokitties on the entire historical series. The cumulative total sales of CryptoKitties since its launch were approximately USD 48 million, compared to approximately USD 944 million for NBA Top Shot almost two years after release.

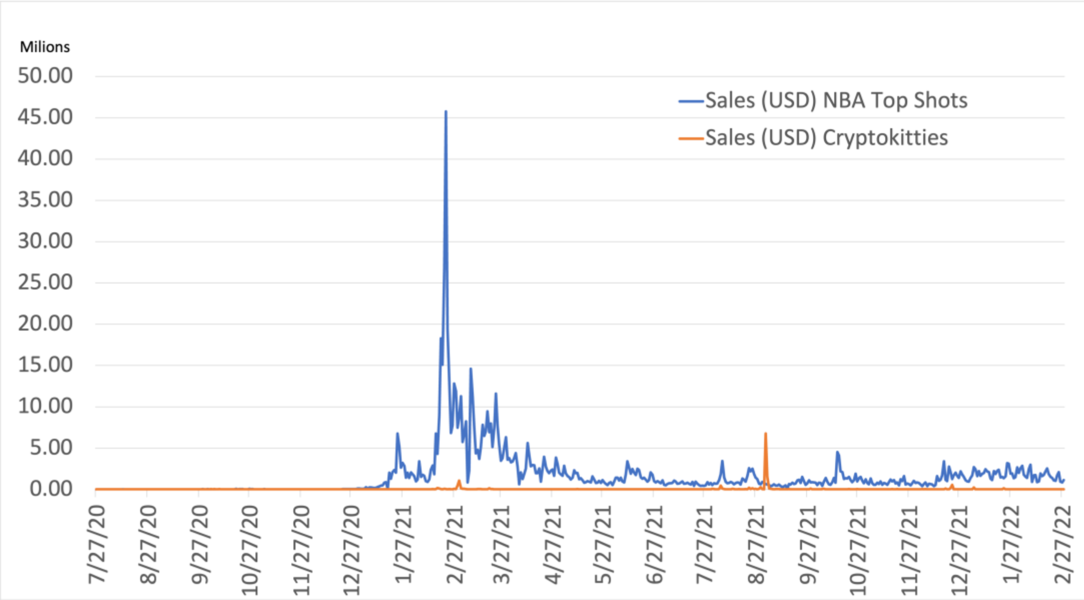

Figure 1. Gen. 0 CryptoKitties vs. NBA Top Shot Sales. The chart shows the USD value (in millions) of sales from all marketplaces of NBA Top Shot and Gen 0 CryptoKitties over the period July 2020 to February 2022. Adapted from *CryptoSlam!* and *Dune Analytics*, cryptoslam.io/nba-top-shot/sales/summary, dune.com/queries/397282/758338

With 2020 and the outbreak of the Covid-19 pandemic, NFTs began to take hold among the general pupulation, attracting investors and stimulating artists to create their own personal series. In general, especially in the short-term, NFTs where capable of absorbing the risk coming from the financial markets due to the outburst of the pandemic (Umar et al., 2022). With the beginning of 2021, NFTs have begun to gain further popularity among the general public, with a substantial increase in their value. In March 2021, Mike Winkelmann's (*aka* Beeple) NFT "*Everydays: The First 5000 Days*" was sold by Christie's for USD 69.3 million. This event made investors understand the profit potential of this new digital asset, thus, allowing the NFT market to grow further. Figure

2 shows a substantial increase in the average value for Gen. 0 CryptoKitties from March 2021 onwards, up to the peak of September when these tokens reached an average of USD 6,000 per NFT. However, Figure 2 also indicates the great volatility that characterizes not only the Gen. 0 of CryptoKitties, but in general the whole NFT market. Indeed, from September 2021 we can see a strong decrease of about 92% of the average value per token. This was mainly caused by the dulling of the excitement and frenzy of these new digital assets. At the time, given that most of the NFTs in circulation were image collections such as CryptoKitties, investors quickly realized that they could not get any use from their possession and rushed to liquidate their positions. Finally, after further market growth towards the end of 2021, the news of the Russian invasion of Ukraine triggered a further market contraction in February 2022.

In recent years NFT marketplaces have gained a lot of success. Following Kireyev and Evans (2021) it is possible to identify two distinct categories depending on the generality of the services offered and the types of tokens dealt with. On one hand, so-called *streamlined* marketplaces are platforms that offer a wide range of NFTs but few additional services. These markets focus mainly on buying and selling through auctions or via direct sales in order to offer increasingly efficient and rapid transactions. Prime examples of this category are OpenSea and Nifty Gateway, a blockchain platform for buying, selling and storing digital art and collectibles. On the other hand, so-called *augmented* marketplaces are specialized markets on particular segments of NFT (gaming, sports, fine arts). These platforms offer their users assistance and services that cover the entire life of the NFT itself: from its creation to its sale through marketing, pricing recommendation and portfolio trackers. Examples of this market are NBA's Top Shot and CryptoKitties. Each of them is characterized by a number formed by 256 bits that identifies the DNA and the different attributes (so-called cattributes within a game). In addition, when two cats mate, they produce a next generation kitten to the newer generation parent. It is important to point out that the augmented markets focused on games NFTs, as in the case of Axie Infinity, which allows the user to purchase tokens and then use them on the platform itself to progress in the game, thus leveraging the need to purchase increasingly rare and powerful items to outperform all other players.

Figure 4 distinguishes the NFT market into the most popular categories. Such a grouping is very useful for analyzing how investors behave within each category, studying the distribution of active crypto wallets and the amount traded. In the following, we distinguish five groups: gaming, collectibles, utilities, art, and metaverse.[6]

[6] We note that these 5 main groups do not represent all types of NFTs. For instance, it is also possible to find tokens in the world of real estate or in the fashion industry.

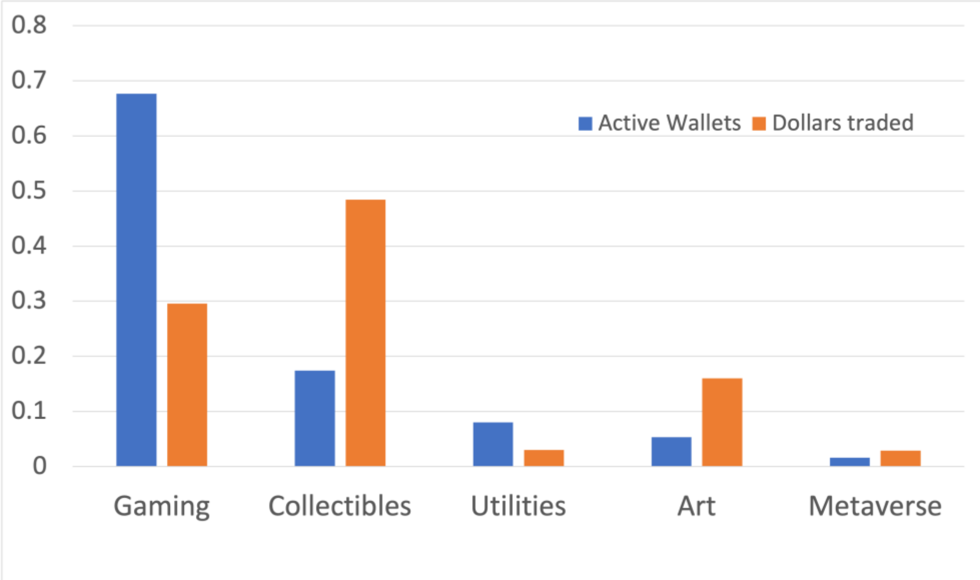

Figure 4. NFT Categories by Active Wallets vs. Volume of Dollars Traded. The graph shows the comparison of active wallets and volumes of USD traded among the five major NFT categories represented as their relative frequency distribution as of December 2021. Adapted from *NonFungible*, nonfungible.com/market-tracker.

In the case of gaming, NFTs represent assets that can be used within a video game whose elements are stored on the blockchain itself. The real novelty compared to a traditional video game is that players, through the sale of NFTs, actually possess real ownership of the assets within the game itself. Analizying the relative frequency distributions in Figure 4, we note that the percentage of active users within the gaming category is with 68 percent the highest relative to the other categories. The continuous exchanges between players make it the second most liquid sector as of December 2021: it was able to attract 30% of the total USD traded on the entire NFT market. Some examples of gaming NFTs are Axie Infinity, NBA Top Shot, and CryptoKitties.

Not much unlike physical collectibles, NFT collectibles are released in collections, or series, which represent variations of the same image, video or other media. The characters in the Cryptopunks project, for instance, differ from each other in certain attributes that also make the price vary: man/woman, human/alien/monkey, and presence or absence of accessories. NFT collectibles record the highest level of transactions though the number of active wallets is much lower than that of gaming NFTs. This is mainly due to two reasons: First, there are far fewer collectible marketplaces than gaming NFTs, so investors will find themselves on a single platform

(OpenSea is currently the largest and most popular) than players who will have to migrate to different platforms for each video game in which they want to trade their assets. The second reason for this concentration of the market lies a few large-value transactions. Nadini et al. (2021) show that the top 10% of buyer–seller pairs contribute 90 percent to the total number of NFT transactions. Examples of NFT collectibles are CryptoPunks, the Bored Ape Yacht Club (BAYC), and Azuki.

NFT utilities, the third main group, are assets that provide utility in the real or digital world through the blockchain. In other words, utility tokens gives its holder consumptive rights to access a product or service (Howell et al., 2020) so that their use is not directly related to the need to collect or play with the token of interest. In particular, because these tokens serve as the means of payment on a platform or offer access to the firm's services, they possess utility features (Gryglewicz et al., 2021). Utility NFTs comprise different categories: finance, health, supply chain, or digital ID. The most popular NFT utility projects are VeeFriends (which grant access to the VeeCon, a multi-day event exclusively for VeeFriends NFT holders), Ethereum Name Service (ENS, where users can purchase and manage domain names for their digital assets), and Nouns.

Art NFTs can be defined by exclusion from the previous sectors. Art NFTs are assets with an artistic function that have not been released in series (as could happen for collectibles) and that cannot be used within any type of video game hosted on the blockchain. This type of tokens has brought many innovations to the art market, especially due to the easing of barriers to entry. Everyone can create and sell their works on different platforms in much shorter time than on the traditional art market, with an average time between purchase and resale in art NFTs of just 33 days versus the average resale period on the traditional art market of 25 to 30 years (McAndrew, 2022). Furthermore, art NFTs have addressed issues that have affected the traditional art market for decades, such as provenance, title, authenticity and a fairer distribution of income. The creation of communities by the artists themselves via social networks such as Twitter gravitating around their NFTs collections, have allowed for a much deeper involvement of buyers. It is the emotional and social values combined with the economic one that make NFTs a different and interesting crypto asset, which reflects pretty much the same motivations of collectors in the traditional art market. Main examples of art NFTs are ArtBlocks, i.e., tokens representing generative art through an algorithm, SuperRare, and The Currency by artist Damien Hirs,t which are 10,000 NFTs corresponding to 10,000 physical artworks stored in a physical vault.

The fifth main group, metaverse, can be defined as an extension and grouping of the previous ones. The metaverse is a virtual universe accessible through a computer screen, laptop, VR, or any other digital system. Users who access this world can create their virtual avatar and interact with the surrounding reality, including other users. They can purchase virtual plots of land within the metaverse to create their own organizations and host events. In many cases, firms have established virtual businesses and created a space where they can offer goods and services, promote their products and organizations, and hold virtual events (Goldberg et al., 2021). Although we are at the dawn of this technology, it is already possible to predict how users will be able to access all the NFTs seen previously in the metaverse that will offer different experiences: gaming, social experiences, economic possibilities, and many more. Some examples are the game developer company Atari in Decentraland, Adidas in The Sandbox, and Cryptovoxels.

Tables 1 summarizes these five most popular NFT categories, their key properties, and there prime examples.

Table 1. The 5 Main NFT Categories. This table provides an overview of the 5 most popular categories, their key properties and prime examples of each NFT category.

NFT Category	Properties	Examples
Gaming	Ownership of in-game assets	Axie Infinity NBA Top Shot CryptoKitties
Collectibles	Multimedia collections. Variation of the same image, video, etc.	CryptoPunks BAYC Azuki
Utilities	Utility of use in the real or digital world through the blockchain	VeeFriends ENS Nouns
Art	Unique depiction with artistic function	ArtBlocks SuperRare The Currency
Metaverse	Expendable assets in a virtual universe, accessible through digital systems	Decentraland The Sandbox Cryptovoxels

Follwoing Wang et al. (2021), we can also group the characteristics of NFTs according to the guarantees they offer to investors. We can identify two families of features. First, there are ownership related features: All the metadata that make up a NFT, as well as its ownership, can always be verified and can never be changed once the transaction has taken place. Furthermore, the system makes sure that these data are up-to-date and user-friendly, which means that the data is verifiable, tamper-resistant, and usable. Second, there are trading related features, implying that every NFT can be arbitrarily traded in one atomic, consistent, isolated and durable (ACID) transaction.

Another interesting phenomenon is the investors' satisfaction and usefulness of their possession of NFTs. Kong and Lin (2021) show that even though NFTs are highly speculative products, investors are ready to bear their high level of risk to take advantage of the "emotional dividends" given by their possession, just like with physical collectibles. An example of this property is shown by Figure 5 which compares the normalized values of volume and active wallets across all NFT markets.

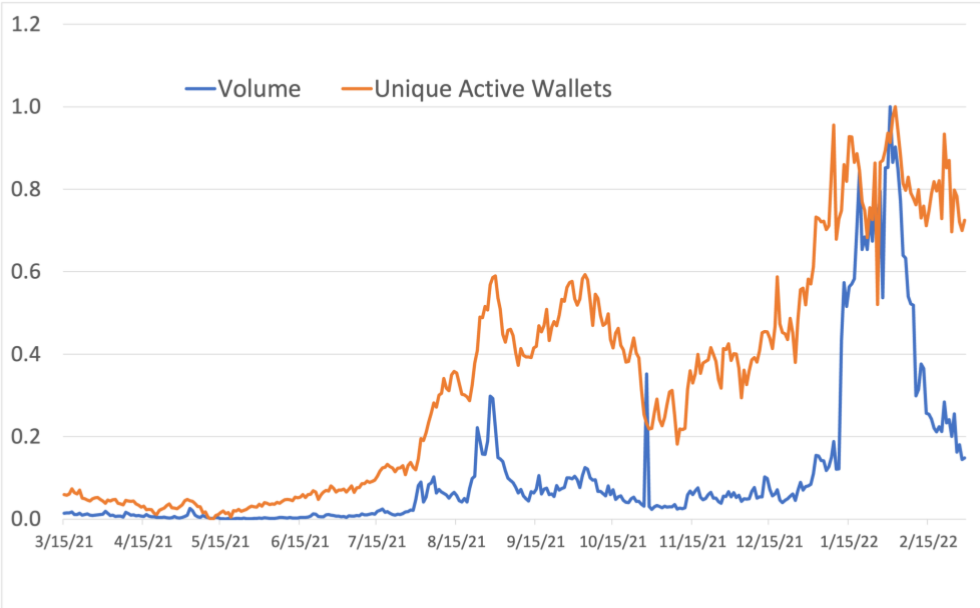

Figure 5. Normalized NFT Volume and Number of Unique Active Wallets. The graph shows the time series related to the total number of NFTs traded on the market and the number of active wallets on the entire NFT ecosystem in the period from March 2021 to March 2022. The two measures have been normalized to the unity. Adapted from *Dune Analytics*, dune.com/rantum/NFT-Sales-Dashboard.

Figure 5 shows that the number of NFTs traded at the end of 2021 underwent a sharp increase until the peak at the end of January 2022. Subsequently, and because of the tensions at the end of February due the war in Ukraine, the bubble burst causing a strong slowdown in trade on all markets. However, this was not the case for active portfolios, which recorded slight growth even at the worst time for the NFT market. This might imply that investors have no intention of leaving

NFT platforms even in times of recession, as the utility they receive from these tokens is not simply linked to a monetary profit factor, but rather to a satisfaction factor in the use of the NFT itself.

3. Pricing Determinants of NFTs

3.1 Models

It is important to note that almost all academic papers on NFT markets have focused on the categories of gaming, collectibles, and metaverse NFTs. Within these key NFT groups only some popular collections have been considered: CryptoPunks, Crypto Kitties, and Axie Infinity. Many categories of NFTs are more complicated to analyze both due to the size of the existing market and due to the lack of a full-fledged market (as in the case of utility NFTs). For these categories and collections of NFTs analyzed in the literature, it is possible to adapt popular econometric models within the physical counterpart of the reference market. For instance, in many cases the determinants of the price of the CryptoPunks collection has been estimated using the models of hedonic and repeated sales regressions (Schaar and Kampakis, 2022), methods already rooted in the literature on the art market (Korteweg et al., 2016) and other collectibles (Scorcu and Zanola, 2011). In the following we will motivate and discuss the five major approaches that have been applied to the determination of pricing NFTs: hedonic regression models, repeat sales regressions, vector autoregressive models, machine learning, and wavelet models.

The hedonic model is used to estimate the impact that intrinsic characteristics and external factors have on the price of a particular product or asset. This model was first introduced by Rosen (1974); recent years have seen numerous applications within the real estate market (Han, 2010; Giglio et al., 2021; and Murfin & Spiegel, 2020) and within the art market (Korteweg et al., 2016; Pénasse et al., 2021; and Goetzmann et al, 2021). In most cases, the marginal contributions of individual characteristics to the product price are estimated using a pure linear ordinary least square (OLS) model:

$$p_i = \beta_0 + \sum_{n=1}^{N} \beta_n x_{ni} + \varepsilon_i \qquad (1)$$

or logarithmic-linear:

$$ln\, p_i = \beta_0 + \sum_{n=1}^{N} \beta_n x_{ni} + \varepsilon_i \qquad (2)$$

where p_i is the price of the product i, $ß_0$ and $ß_n$ are the intercept and the marginal contributions of the variable n, x_n represents the characteristic of the product under study, and ε_i is an error term. The hedonic model is particularly easy to implement, its parameters can be easily estimated, and the results can also be interpreted by non-experts. However, this approach faces numerous issues, mostly related to (i) misspecification of variables, i.e., the inclusion of irrelevant variables within the equation to be estimated which would lead to unbiased and inconsistent results; (ii) market segmentation, i.e., the hedonic model treats the reference market of a product as a single entity when, in reality, it is much more realistic to think of a market that is itself segmented into different markets; and (iii) poor OLS predictive power, i.e., it has been frequently demonstrated how more flexible econometric models have outperformed OLS models in predictive power because they are not linked to a functional form and, therefore, are able to grasp all the non-linear patterns that the market can hide (Mahesh, 2019).

Repeat sales regression (RSR) models have been applied within the real estate market (Bailey et al., 1963) and within the art market (Mei and Moses, 2002), and are commonly used for the construction of price indices on products that have been sold more than once. RSR models assume that the characteristics of a product do not change over time (between the different sales), and that therefore the dynamics of the price formation is simply due to the time between the two transactions. The original model has the following specification:

$$\ln\left(\frac{p_{it'}}{p_{it}}\right) = \sum_{t=0}^{T} \beta_t X_t + \varepsilon_{itt} \qquad (3)$$

where the left-hand side indicates the change in the selling price of the product i in period $t' > t$, X_t is a vector of time dummies equal to 1 in the second transaction period, -1 if it is the time of the first transaction, and 0 otherwise, $ß_t$ indicates the marginal contribution of each year t to the formation of the price index, and ε_{itt} is an error term. The coefficients $ß_t$ can be estimated using the OLS method. The RSR model allows to overcome some of the limitations of the hedonic regression model as it predicts that the characteristics of each product are constant over time, thus avoiding the problem of attribute misspecification (Galbraith and Hodgson, 2018). On the other hand, however, the RSR model is affected by some severe issues: (i) it restricts the amount of data analyzed, as it is simply based on products sold more than once and, thus, disregards all single sales. This could be a source of particular concern when dealing with markets that by their nature are illiquid, such as that of art or collectibles since some unique assets are never resold in markets; (ii) selection bias (Korteweg et al., 2016), which implies that those goods that are traded most frequently on the market are over-represented within the model, which results in a biased price index that does not equally represent all sales for the reference period; and (iii) predictive power, i.e., although the basic assumptions are different from the hedonic regression approach, the RSR remains an OLS model with all its caveats.

The vector autoregressive (VAR) approach (Sims, 1980) is a multivariate linear model in which the dependent variable is explained by its lagged values, plus current and past values of the remaining variables. In the simplest case, where we measure two different time series variables $y_{t,1}$ and $y_{t,2}$, the resulting VAR regression with a single lag is given as follows:

$$\begin{aligned} y_{t,1} &= \alpha_1 + \beta_{11} y_{t-1,1} + \beta_{12} y_{t-1,2} + \varepsilon_{t,1} \\ y_{t,2} &= \alpha_2 + \beta_{21} y_{t-1,1} + \beta_{22} y_{t-1,2} + \varepsilon_{t,2} \end{aligned} \tag{4}$$

where the coefficients $ß_{ij}$ for i = 1, 2 and j = 1, 2 are estimated using OLS, by assuming normality of the error term $\varepsilon_{t,i}$. In general, for a VAR(p) model, the first p lags of each variable would be used as regressors for each variable. This model, in addition to the main advantage of being easy to estimate, has become very popular in financial markets research as it has been shown to be very powerful for studying financial market efficiency, stock return predictability, exchange rate dynamics, and information content of stock trades and market quality (Wu and Zhou, 2015). However, it has also been shown that the VAR fails to incorporate nonlinear and multiplicative relationships between the regressors (Freeman et al., 1989). Furthermore, only by looking at its definition one can one realize that the different $\varepsilon_{t,i}$ will be correlated between the different regressions, making it impossible to study the marginal impact of a single shock on the entire system of equations. Conceptually the VAR model is defined as a-theoretical (Keating, 1990) in the sense that it is not constructed following an economic theory that would impose some kind of restriction on the equations. Each variable influences the other and therefore the interpretation of the coefficient estimates $ß_{ij}$ is complex. A particular decision that must be made is the number of independent variables to include in the system of equations. The so-called Granger Causality (GC) Test (Granger, 1969) is used to solve this problem. This test aims to verify the usefulness of one variable to forecast another, i.e., it measures the variation of the forecasting error when a new variable is added to the system.

Machine Learning is an algorithm approach based on the scientific study of statistical models that computer systems use to perform a specific task without being explicitly programmed. The basic idea is to let the computer learn how to manage data, without human intervention. Once the initial parameters have been set, the algorithm will be able to understand by itself the relationships that binds the data, thus managing to find patterns traditional statistical methods would not be able to identify. Machine learning approaches have been particular successful in recent years due to the vast availability of data that are too complex to analyze for classical econometric methods. Machine learning algorithms can be separated into two broad categories: (i) *supervised* machine learning, where algorithms generate a function that maps inputs to desired outputs (Akinsola, 2017), after the inputs have been labeled by human hand. More specifically, the input is represented by a training data set whose patterns are learned from the model to predict or classify the output variable of the train data set itself. Once this is done, to verify the out-of-sample validity, the identified patterns are applied to a test data set. Examples of such supervised machine learning are algorithms based on decision trees and ensembles of trees (e.g., random forests, bagging, gradient boosting), support vector machine, and naive Bayes models; and (ii) *unsupervised* machine learning, where algorithms are left to their own devices to discover and present the interesting structure in the data (Mahesh, 2019). In particular, the data are not labeled a-priori, therefore, once these models have learned something from the input data, they introduce new data into the analysis whose patterns are identified thanks to the notions learned with the previous data. Examples of these unsupervised machine learning approaches are K-means clustering and principal component analysis.

Wavelets have been widely used in the literature because they represent a useful tool for solving critical issues in time-varying characteristics found in most real-world time series, and thus the assumption of stationarity may be avoided. A wavelet model is a complex mathematical system for analyzing oscillation signals and frequencies with different applications between engineering, mathematics and finance (Addison, 2016). It can be used as a tool for analyzing the interaction between two time series. The cross wavelet transform calculates the cross wavelet power which reveals covariance points between the analyzed time series (Aguiar-Conraria et al., 2014). Therefore, by generalizing the results through the wavelet coherence framework, it is possible to identify areas of co-movement of the two time series and to derive the squared wavelet coherence coefficient that measures the local linear correlation between the two stationary time series (Bouri et al., 2020). The main advantage of this approach is that it provides a clear graphical indication of the results, which can also be understood by non-experts. However, one shortcoming is that this model is particularly complicated to implement due to the underlying required mathematical structure.

3.2 Implementations

This subsection discusses and summarizes the results obtained from the literature examined regarding financial and econometric models adapted to the formation of the pricing of NFTs. We investigate which approaches have been most frequently used and make a comparison between them, in order to better understand which pricing model currently provides the best predictive performance. We also discuss the main determinants of the pricing of NFTs. Table 2 provides an overview of the numerous recent studies and the various NFT pricing methods applied. We see that the most widely used model is the hedonic regression; half of all the studies analyzed specify hedonic modeling in pricing NFTs.

Table 2. NFT Pricing Methods. This table shows the main NFT pricing model that have been used in the literature. HR stands for hedonic regression, RSR for repeat-sales regression, VAR for vector autoregressive regression, ML for machine learning, and WL for wavelet analyses.

Study	HR	RSR	VAR	ML	WL
(Kong & Lin, 2021)	*				
(Schaar & Kampakis, 2022)	*				
(Goldberg et al., 2021)	*				
(Nadini et al., 2021)	*	*		*	
(Kireyev & Lin, 2021)	*			*	
(Ante, 2021a,b)			*		
(Dowling, 2022b)					*
(Umar et al., 2022)					*

Kong and Lin (2021) are the first to analyze the risk-return profile of NFTs using the CryptoPunks collection. Using a sample of 13,712 transactions, including 5,630 unique tokens from June 2017 to May 2021, they analyze the impact of CryptoPunks characteristics, network factors such as the growth of unique wallets, and financial market characteristics such as the average daily closing index value of NASDAQ on the natural logarithm of CryptoPunk token prices in USD. They observe that high returns go hand-in-hand with high volatility. Their results show an adjusted *R2* of over 90% for CryptoPunks' dollar and ETH denominated sales prices. They find that the rarer a CryptoPunk token is, the higher its sales price would be. This is also reflected in the number of market participants: the growth of NFT buyers (sellers) and consequently also the increase (decrease) in the number of transactions, is positively (negatively) correlated with the prices of CryptoPunk tokens. In practice, the situation described is that of a market with a high demand that cannot be satisfied due to the scarcity of sellers: all this makes each CryptoPunk scarce and, consequently, expensive. Regarding the intrinsic characteristics, Kong and Lin (2021) find that investors are willing to pay even many times the initial price for certain accessories (the attribute "beanie", for example, increases the initial price by five times), while tokens with unfavorable characteristics are sold with discounts (e.g., attributes such as "pilot helmet" and "tiara"). The authors also observe that an increase in the attention of the markets on Ethereum seems to cause an increase in the price of the CryptoPunks collection, even if the appreciation of the ETH/USD exchange, causes a reduction in the value of the individual CryptoPunks, suggesting that users prefer to evaluate their NFT investments in USD.

Schaar and Kampakis (2022) obtain similar findings by analyzing the period from June 2018 to May 2021. By explaining the variance of the price of the CryptoPunks collection through the CryptoPunks type (such as “alien” or “zombie”) and the number and kind of attributes, they find a strong explanatory power of over 95%. The authors conclude that rarity plays an important role in the price of the CryptoPunks collection. In particular, 9 of the 10 rarest attributes are also within the top 10 attributes having the highest price impact (such as the “alien” type, which on average is priced three times the average selling price). They show that the number of accessories also plays an important role: for example, pieces with zero attributes are very rare and tend to be priced 329.56% higher than the average selling price. Schaar and Kampakis (2022) compare the average monthly return and standard deviation of the CryptoPunks collection over the period June 2018 – May 2021 with 7 alternative asset classes and find that an investment in CryptoPunks would have outperformed all other asset classes. They note that despite an average volatility of 62%, the average monthly return over the 3 years is around 34%.

Goldberg et al. (2021) also use the hedonic regression model but make the study universe more extensive by focusing on the Decentraland project**.** Decentraland is a virtual world on the Ethereum blockchain that allows users to buy NFTs (called LAND in the ecosystem) that represent the ownership of land parcels, i.e., digital real estate. The authors’ goal is to establish the determinants of the price of virtual plots of land within this metaverse and verify whether these are in line with the rules that determine the price of these assets in the physical world. The underlying idea is to adapt the hedonic model to geographic information. This allows the introduction of regressors which take into account the spatial coordinates of each piece of virtual terrain, a so-called mixed geographically weighted regression (MGWR) model. Their results show an improvement in *R2* from 49.6% of the OLS model to a maximum of 64.2% among the three MGWR models fitted. Goldberg et al. (2021) conclude that the different digital parcels that make up Decentraland are more valuable if they are useful for investors to be recognized by potential customers. They find that parcels cost more based on their location: (i) physical, i.e., parcels that are in close proximity to the city center, plazas, main streets and business districts tend to be valued more; and (ii) virtual, i.e., investors tend to give a higher price to plots containing more easily memorable addresses.

Nadini et al. (2021) perform a comprehensive analysis of the price determinants of the top collections (in terms of number of sales) in each of the 5 key NFT categories over the period from June 2017 to April 2021. In particular, they use CryptoKitties for art, StreetFighter Capcom for collectibles, Alien for games, Decentraland for metaverse, and Unstoppable for utility NFTs. Their goal is to build two models that predict the price of primary and secondary sales for the above collections. For the first model, they try to predict with a hedonic model approach the price of the NFTs using, among other variables, the visual features (and therefore the intrinsic characteristics) of the tokens themselves. For the second model their goal is estimate via a repeat-sales approach the median of the second sale price by restricting the field to all NFTs sold more than once. Nadini et al. (2021) find that generally the prediction of the primary and median secondary sale prices remains accurate even if their calculation is done looking at two years before the time of sale. The latter information is crucial, as it highlights the validity of their model even in periods of extreme price volatility for NFTs. The adjusted *R2* remains almost constant for all types of NFTs, settling at 60% for the hedonic and repeat sales regressions, even if there are improvements in predictive power the closer you get to the time of sale. However, the authors find that the accuracy of the model decreases the more the secondary sales take place into the future with respect to the time of the primary sale. For instance, the adjusted *R2* of the cross-categories for the median of the secondary sale price goes from about 50% for the calculation after one week from the sale to about 35% after 2 years. Nadini et al. (2021) conclude that the price of secondary sales is strongly correlated with the price of its primary sale, especially when short estimation periods are taken into account. Furthermore, they confirm that centrality in combination with visual features (in this case of each parcel) can outperform in several cases other regressors, especially in metaverse NFTs.

Nadini et al. (2021) also use a supervised machine learning classification model in order to understand whether an NFT will be subject to a secondary sale after it has already been sold once.

They find that as the time window considered widens, the number of NFTs that would be subject to a second sale also increases, reaching a percentage of more than 20% after 2 years. In this case, the *F1*-score is used to evaluate the goodness of fit of the model, which measures the percentage of NFTs predicted as second sale items that have actually been sold a second time (sensitivity). They find that in the aggregate case (cross-categories), in line with their previous findings, the statistic increases as the period after the first sale increases, settling at 0.80 after 2 years.

Kireyev and Lin (2021) perform a very different study from those discussed so far as their goal is to demonstrate that traditional pricing methods can cause inaccurate valuations of NFTs. They focus on the CryptoKitties collection during 2019 and compare the *R2* of a hedonic linear regression model and a gradient boosting machine (GBM), a supervised machine learning model based on ensembles of trees. They find that the GBM algorithm significantly outperforms the hedonic regression model (51% vs. 41%). They argue that the hedonic regression approach is not a suitable model for the NFT valuation space due to (i) mispricing bias: The observed sales prices reflect the sub-optimal decisions of the seller in setting the price of the NFT. In fact, the high range of prices that can be found on the market pushes users to wait a long time before completing the purchase. The result is a set of auctions that are successful only when the ending price is substantially low. Given that the hedonic regression is estimated starting from the observed sale prices, the coefficients very likely incorporate this bias; and due to (ii) selection bias: In the case of auction sales, the hedonic regression model focuses only on successful versus unsuccessful ones, resulting in higher valuations for the NFTs sold. In other words, items with a lower selling rate tend to have higher prices, so when they do sell, they sell for a higher price. The hedonic model considers only successful sale prices and gives a higher valuation to these assets (Korteweg et al., 2016). Specifically, it yields higher valuations for items from unsuccessful auctions compared to items from successful auctions. Kireyev and Lin (2021) conclude that, as the ID and generation of each CryptoKitties cat increase, the price of the token itself decreases.

Ante (2021a) studies the cointegration between the 14 projects which reached in the period June 2017 to May 2021 a cumulative trading volume of at least USD 10 million on Ethereum. In particular, the author selects 3 gaming (Axie Infinity, Gods Unchained, Sorare), 4 collectibles (CryptoPunks, CryptoKitties, Hashmasks, Meebits), 3 art (SuperRare, MakersPlace, ArtBlocks), and 4 metaverse (Decentraland, CryptoVoxels, Somnium Space, The Sandbox) NFT projects. The author investigates the relationships existing between NFT sales, volumes and wallets among these 14 projects and finds that significant short-run relationships exist between the different projects. For instance, CryptoPunks have a significant impact on several projects like CryptoKitties or The Sandbox. Furthermore, Decentraland and CrypoKitties Granger-causes the number of CryptoPunks transactions. In particular, while an increase in transactions in Decentraland is responsible for the decrease in the number of CryptoPunks transactions, an increase in the price of CryptoKitties seems to generate a positive effect on the price of Cryptopunks (and vice versa). A key finding is that an increase in the number of sales on younger and not so popular projects result in a decrease in sales on large popular projects. For instance, the NFT transactions of Somnium Space Granger-causes CryptoPunks, Decentraland and Axie Infinity. This may indicate that NFT users are more likely to migrate to Somnium Space than to use the project as an alternative to other NFT projects. Additionally, Ante (2021a) shows that the number of CryptoPunks sold has a positive impact on the number of tokens traded for the CryptoKitties, CryptoVoxels, Somnium Space, The Sandbox and Art Blocks projects. Furthermore, Decentraland has a positive impact on CryptoKitties, CryptoVoxels and The Sandbox projects. Given the result of the Granger-causality tests, the findings of Ante (2021a) reveal that many NFT markets are driven by other NFT markets and, thus, such co-integrations should be included in any NFT pricing models.

In a follow-up study, Ante (2021b) takes into consideration all NFT transactions on Ethereum from January 2018 to May 2021 to investigate the relationship between the sales of NFTs to the price of Bitcoin (BTC) and Ether (ETH). After fitting a vector error correction model (VECM), the author discovers the presence of cointegration between NFT Sales and wallets, BTC and ETH. In particular, he finds that NFT sales are Granger-caused by the BTC price and NFT wallets are Granger-caused by the ETH price. His findings confirm that there is a relationship between NFT sales and the price of BTC and the number of NFT wallets and the price of ETH. To explore the direction and magnitude of this effect, the author relies on impulse response functions. Through the latter, he shows that an increase in BTC and ETH prices also causes an increase in NFT sales by 0.03% and 0.015%, respectively, while an increase in the price of BTC also causes an increase in NFT wallets by 0.012%. Ante (2021b) concludes that, in times of appreciation of cryptocurrencies due to market growth, investors tend to seek for new or alternative investment opportunities.

Dowling (2022b) uses wavelet analysis in order to determine how the price of NFTs co-moves with other markets. The author considers the possible correlation between the NFT market (through CrptoPunks, Axie Infinity, and Decentraland) and ETH during the period March 2019 and March 2021. Dowling (2022b) specifies three bivariate wavelets, ETH-Decentraland, ETH-CryptoPunks, and ETH-Axie, and finds positive short-term correlation for all three NFT markets. In particular, for the binomial ETH-Decentraland wavelet, the author observes a strong correlation during the period January to March 2021, when it seems that ETH almost completely leads the price of Decentraland tokens. The author finds a positive co-movement between LAND and ETH especially for short and medium investment periods (1-4, 8-16 weeks) and a co-movement between ETH and CryptoPunks, especially in the 1-4 weeks investment window.

Umar et al. (2022) investigate the period between June 2017 and October 2021 and also use wavelets in order to analyze the intercorrelation between the NFT market and five alternative asset classes. Their main objective is to understand if, by carrying out wavelet analysis before and after the Covid-19 pandemic, it is possible to observe differences in the co-movements between these markets. In particular, the authors find that in the years leading up to the pandemic, the price of NFTs was driven by BTC and stocks, while it led gold. During the period 2020-2021, the authors observe a stronger co-movement between NFT and the alternative asset classes, especially for short investment horizons (7 days to 2 months). The strongest relationships are those between NFT and BTC, NFT and bonds, and NFT and crude oil. Umar et al. (2022) explain this latest result to the virtuous cycle triggered with the peak of the price of crude oil in October 2020 and subsequent recovery in demand and consumer confidence who have poured this new wealth into even more risky markets such as those of NFTs and cryptocurrencies.

Figure 6 shows the NFT assets that have been analyzed by the nine papers discussed above. We note that most of the papers focus on NFT collectibles or NFT gaming since these markets are much more developed than the other 3 main categories. Due to the ease with which it is possible to extract the intrinsic characteristics of these products and the large availability of historical series of transactions, Decentraland and CryptoPunks lead the ranking.

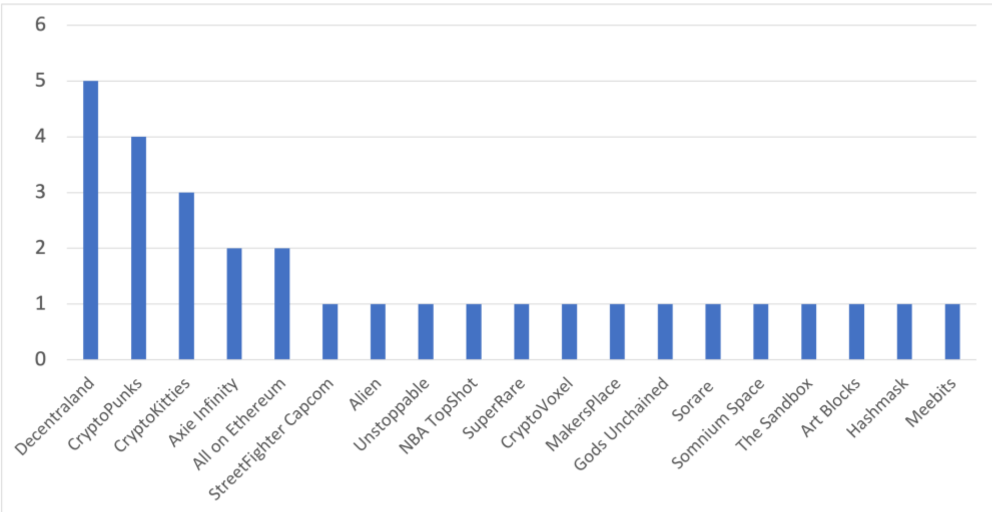

Figure 6. NFT Projects Discussed in the Literature. This figure enumerates the studies which analyze the price dynamics of the NFTs shown on the horizontal axis.

4. Conclusion

This study has analyzed how the NFT market has developed. It also has provided an overview on the different NFT pricing and valuation approaches, discussed the key pricing determinants of NFTs, and highlighted the limitations and opportunities currently existing for potential investors. Our findings show that NFTs share the investment profile of classic collectibles or alternative investments: a high yield with high risk profile.

So what is it that makes NFTs so popular with investors? We argue that there are on and off blockchain reasons. The "on blockchain" reasons concern the existence of the blockchain itself: the novelty and potential introduced by this virtual world have brought many people closer to the NFT world. Furthermore, numerous research papers have shown the existence of co-movements between BTC, ETH and NFTs. It is likely that many users have decided to transform their wealth from cryptocurrencies to an investment in NFTs, some for mere speculative reasons, and some for passion towards a particular creator. Instead, the "off blockchain" reasons encompass all the media coverage that has been given to this new digital world, especially during the year 2021. For instance, Figure 7 compares the number of Google searches "NFT" with the number of unique active wallets.

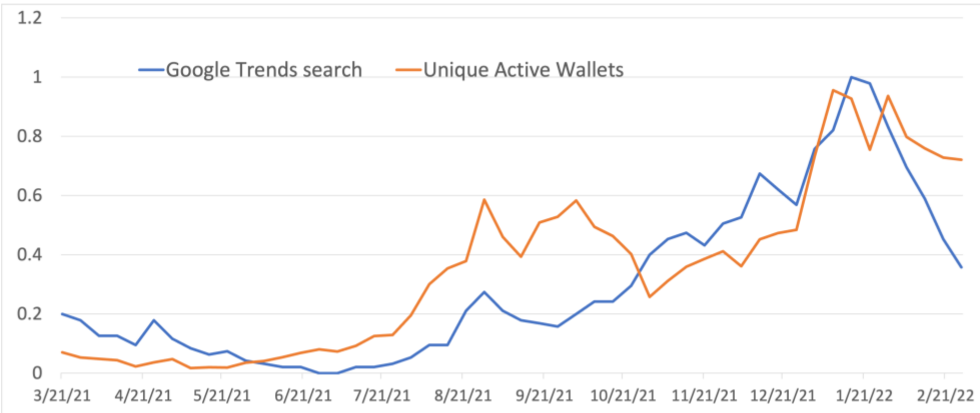

Figure 7. "NFT" Google Searches and Number of Unique Active Wallets. This figure shows the evolution between the number of Google searches for the expression "NFT" and the number of unique active wallets on Ethereum during the period March 2021 and March 2022. The two measures have been normalized to the unity. Adapted from *NonFungible* dune.com/queries/463070/878706 and *Google Trends* rb.gy/wzrql4.

Figure 7 shows that the two time series seem to share the same trend. Furthermore, the presence of the same NFT authors and deployers on social networks (Twitter and Discord above all) has created real virtual communities gravitating around a specific collection. For their part, users can not help but buy a piece of a specific collection to become part of the group and feel even closer to the creators. If we then add to this the media coverage that NFT sales have received in recent times, such as the sale of Beeple's work for USD 69 million, it is possible to see how much attention for this new type of investment has grown in recent years.

On the other hand, it seems to be still very early to draw final conclusions. If we remember that blockchain technology has become popular only in 2008 with the publication of the paper by Satoshi Nakamoto, and that NFTs began to go mainstream only in 2017 with CryptoPunks, we can see just how far this market is still emerging and far from maturity. NFTs share many characteristics with early-stage financial markets: inefficiency because in search of a definitive pricing model.

Another issue affects the NFT world above all: the so-called oracle problem. Zheng et al. (2018) describe this phenomenon as the impossibility, for some blockchains, to import data in a trustworthy and accurate way from the world outside the ledger. Blockchains are very efficient in managing data on-chain but they need oracles to interact with the real world. When it comes to NFTs, there have been few attempts to introduce these tools to these tokens to date. For investors, creators and users, for example, it could be useful to obtain the exchange rate between their NFT and a currency in real time to facilitate payments or create more efficient pricing methods, or to check the delivery status of the physical product purchased through the NFT, to improve buyer protection even within a blockchain.

As a final note, we indicate another limitation that afflicts today's blockchains and the future financial success of NFT markets: the impossibility of interconnection between different ledgers. There is no standard that allows each blockchain to converse with the others and this, if we look at the world of NFTs, results in the impossibility for investors to compare homogeneously markets that run on blockchain different from each other, such as CryptoKitties (Ethereum) and NBA TopShots (Flow).

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