Non-Fungible Tokens as Investment[*]

William N. Goetzmann, *Yale School of Management*

Dong Huang, *Yale School of Management*

Milad Nozari, *Travelers Insurance*

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Abstract: NFTs provided an extraordinary real-time laboratory for bubble economics: returns were exceptionally right-skewed, illiquidity pervaded even the most active platforms, and a handful of trades drove aggregate performance. Investors extrapolating from realized returns without recognizing selection bias and survivorship faced a substantial risk of disappointment. As our data and simulations confirm, successful NFT investing during the bubble required an almost perfect confluence of timing, liquidity, and luck.

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1. Introduction

Non-fungible tokens (NFTs) emerged as a new technological medium for digital artists. Built on decentralized, immutable blockchain infrastructure, NFTs offer artists the potential to disintermediate the gallery system and create a permanent public certificate of ownership and authenticity. They also enable artists to share their work, express creativity, connect with others about a shared virtual aesthetic experience, ask for and receive help, and develop and share technological expertise. For buyers, NFTs offered not only artistic value but also a sense of community belonging and social identity.

At the same time, NFTs also attracted considerable speculative interest, especially following the sale of a work of digital art by artist Mike Winkelmann (aka Beeple) at Christie's on March 11th, 2021 for $69 million.[1] Popular investment sites like the Motley Fool and mainstream financial media like Forbes soon began to treat NFTs as a new financial opportunity.[2] Importantly, expectations of financial gains do not undermine community bonds and social signaling embedded in NFTs. Instead, profit motives often serve as a catalyst for initial purchases among many new investors, who may later become active community members through self-reinforcing community engagement (Brahmstaedt, 2025; Griffiths et al., 2024).

The challenge for NFT investors is a lack of statistical information to assess the potential returns and risks of this new asset class. Analysts accustomed to working with historical data faced the limitation of a relatively short time horizon and a paucity of realized returns to study. For example, in the SuperRare database we study in this paper, most purchased NFTs had not been resold, despite many being listed for sale. We show that the absence of transactions due to seller reserves in the NFT market was highly relevant to the assessment of investment risk and return, and successful NFT investing during the bubble required an almost perfect confluence of timing, liquidity, and luck.

In this paper, we use data from the curated marketplace SuperRare (April 2018-December 2024) to study NFTs as an investment asset, and later extend the analysis to a broader marketplace, OpenSea. We exploit the fact that NFT records provide much richer information than is available in most markets in which bubbles have formed. Buyers, sellers, creators, and owners are identified by wallets, and can be classified by type of activity. At any given time, a fraction of NFT owners post asking prices for works they own. Using this information, we document a number of things potentially relevant to NFT investment during the bubble.

[1] https://www.theverge.com/2021/3/11/22325054/beeple-christies-nft-sale-cost-everydays-69-million
[2] https://www.fool.com/investing/stock-market/market-sectors/financials/non-fungible-tokens/how-to-buy-nft/ https://www.forbes.com/advisor/investing/nft-non-fungible-token/

In our analysis of the SuperRare database, we first observe considerable variation in return performance across tokens and agents as well as over time. The realized returns are right-skewed: a small tail of extremely profitable trades drove overall positive mean returns. At the investor level, active participants averaged 94% return on the works they both bought and sold, yet nearly two-thirds incurred losses. This dispersion reflects variation in market liquidity, measured by resale probability. Only about 6.2% of works resold during our sample, and nearly 20% of primary market purchases remained unsold through 2024. We show that this illiquidity was related to a behavioral preference for realizing gains over losses, rather than a preference for permanent ownership. Correction for the bias caused by conditioning on realized returns substantially lowers measures of NFT market returns.

More importantly, we simulate the experience of actual NFT investors in our sample. While the NFT bubble was a short-lived phenomenon, asset market dynamics characterized by rapid price appreciation are of great practical interest to market participants. The questions of how profits from these episodes are distributed among agents and across assets have implications for investors in future high-growth asset markets.

In the analysis, we simulate NFT investment rules that plausibly correspond to realistic NFT investment strategies and report results that explicitly take illiquidity into account. A back-test that simulated a reasonable strategy of buying the work of "liquid" NFT artists reveals the extent to which expected returns depended crucially on assumptions about liquidity, market timing, and terminal value.

Although the simulated strategy we study generates a considerably high IRR of 14% per month (nearly 400% per annum), or 12% after accounting for transaction fees and royalties in SuperRare, it is quite sensitive to the size, composition, market timing, and liquidity of the portfolio. First, there is substantial underdiversification risk: the strategy cannot guarantee a positive IRR return with 90% confidence unless more than 400 NFTs are in the portfolio. Also, realized NFT returns were highly concentrated: less than the top 1% of resales were responsible for the positive return of a portfolio.

In addition, we calculate the return multiple for vintage portfolios, i.e., portfolios that are formed at a specific date and held over time, liquidating the assets as the market permits. The results show that, while high returns over 800% are not uncommon for vintage portfolios constructed prior to the summer of 2019, the returns decline significantly for later portfolios, which are also associated with a higher fraction of unsold NFTs in the inventory as of the end of our sample period. Our findings provide implications for portfolio construction in bubble markets, especially regarding illiquidity, selection bias, and time-varying market conditions.

As an extension, we apply our analytical framework to OpenSea art NFTs from 2018 to 2024. Although OpenSea is generally more liquid than SuperRare, OpenSea investors are also reluctant to realize losses

due to behavioral factors, as suggested by a jump in the sale probability when the holding return for an NFT becomes positive. We show that an observed NFT price index is overestimated due to this conditioning bias. An investment strategy that purchases the most-traded art NFTs on OpenSea each month turns out to be profitable, but, as in SuperRare, the performance is highly sensitive to portfolio size, timing, and tail outcomes. Also, wash trading on OpenSea can create false liquidity signals and harm investment performance. To conclude, we discuss the cultural and community values underlying NFTs that support their liquidity.

Preliminary to our empirical analysis, we provide institutional background, discuss related research, and explain the source and nature of our data.

2. Institutional background

NFTs are electronic files—digital assets—that are tokenized on the blockchain, a distributed ledger system that secures ownership through verification of file transfers from one agent to another. The past decade has seen an explosion of creative applications of the blockchain – one of these is the emergence of a novel medium and marketplace for visual art. The first NFT was created in 2014.[3] NFTs trade in a number of online marketplaces that have opened since 2017. Some are selective (i.e., curated); some are not. Currently, the largest is OpenSea, an uncurated venue. Other major marketplaces include Rarible—also open-access to artists —and SuperRare, a curated marketplace that screens for quality (Nadini et al., 2021). According to most marketplace arrangements, NFT owners list their works for sale or set up auctions for which potential buyers place bids. For the major marketplaces, bids, asks, and transactions are denominated and executed in the cryptocurrency Ethereum. Ownership of an NFT file is transferred from the digital wallet of the seller to that of the buyer, and the transaction is recorded on the blockchain.

Several NFT investment funds have been launched, including an NFT index tracker product.[4] These funds provide a way for investors to financially participate in a curated, diversified portfolio of digital art. Natural questions arise from the treatment of NFTs as financial investments as opposed to collectibles bought solely for aesthetic enjoyment. What are the expected risk, return, and covariance characteristics of NFT investing? What factors influence NFT returns? How do the limitations of the data affect inference about risk and return?

[3] https://www.altpress.com/meta/history-of-nfts-non-funfible-tokens/
[4] https://www.bloomberg.com/news/articles/2022-01-05/cashing-in-on-crypto-hype-finance-pros-lure-investors-wanting-to-buy-nfts

3. Related Literature

NFTs – at least the subset created as works of art – share many characteristics of other heterogeneous goods. Indeed, the term non-fungible applies equally well to individual works of physical art. As such, the considerable literature on art as an investment is potentially applicable to the study of NFTs.[5] Stein (1977) is one of the earliest econometric analyses of art auction transactions to use a repeat-sale regression to construct an art index. He estimated a 10% annual compound US dollar return to investment in paintings in the 1940's through the 1960's, and a stock market beta of .82. Subsequent research has generated roughly similar -- although somewhat more moderate -- estimates about the risk and return of art investment over different time periods and different kinds of art. One useful question from the investor perspective is whether this prior evidence about art as an investment applies to this new virtual collectibles genre.

Several articles study the market dynamics and trends, the pricing of NFTs based on their financial and visual characteristics, and their relationship with other asset classes, such as Borri et al. (2022), Nadini et al. (2021), Wang et al. (2021), Schaar and Kampakis (2022), Dowling (2022), and von Wachter et al. (2022). Alternatively, Franceschet et al. (2021) characterize cryptoart as a cultural movement. Sharma et al. (2022) document the technology and community motives among NFT creators, while Brahmstaedt (2025), Cao et al. (2025), and Griffiths et al. (2024) find that a confluence of financial gains, socio-cultural motivations, and community identity contributes to the purchase and sustained engagement in the NFT market. A few papers also document behavioral biases in the NFT market. Oh, Rosen, and Zhang (2025) analyze buyer herding behavior in primary sales. Huang and Goetzmann (2024) emphasize how the interaction between selection-neglect bias and extrapolative beliefs can create or sustain a bubble. Rosen and Spaenjers (2024) focus on round-number sales prices in the market. In related work using data from the SuperRare platform, Franceschet (2020) finds evidence of prestige influencing NFT pricing. Estorick, Waters, and Diamond (2021) examine transaction networks and other characteristics. Fridgen et al. (2025) find many of the empirical effects related to liquidity and the superstar phenomenon documented in Huang and Goetzmann (2024).

4. SuperRare Data

SuperRare selects and invites digital artists to create their work on the platform and provides a digital contract that facilitates future royalties from resale. For the first sale of the work, SuperRare takes a 15%

[5] The literature on estimating the returns to art investment is voluminous, but key references include Ashenfelter and Graddy (2003), Baumol (1986), Beggs and Graddy (2008), Campbell (2008), Frey and Eichenberger (1995), Goetzmann (1992, 1993), Goetzmann and Spiegel (1995), Peng (2002), Korteweg, Kraussl, and Verwijmeren (2016), Mei and Moses (2002, 2005), Pesando (1993), Buelens and Ginsburgh (1993), Renneboog and Spaenjers (2013), Worthington and Higgs (2004), and Zanola (2007).

commission.[6] Resales of works created on SuperRare are not restricted to the platform, so we may lack a complete record of creation and off-platform resales. However, the data shared with us contains all the events on the SuperRare platform beginning in April 2018 through December 2024. These events include NFT creation, sales, bids, listings, and transfers. Events record the unique identifier for the NFT, as well as prices (in Ethereum), time-stamp, name of the NFT, unique identifiers for the parties to the event, and, in many cases, a JPEG file of the NFT.[7]

Transactions on SuperRare occur through different processes: owners can list NFTs for sale, and buyers can acquire them by paying the asking price in Ethereum [ETH]. Alternatively, bidders can offer the seller a bid below the asking price, and the owner can accept. Finally, a seller can set up an auction with a time limit and accept bids, with a transaction at the highest bid. The SuperRare platform engages participants in a variety of ways. They feature certain works, trending artists, and top collectors. They also sponsor a blog, provide links to "spaces" of interest, and have "tokenized" curation through a distributed autonomous organization [DAO].

SuperRare charges fees at uniform rates for all secondary sales. Specifically, the seller receives 90% of the sale amount, and the remaining 10% goes to the original creator as a royalty. The buyer must also pay a 3% marketplace fee on top of the sale price, which adds to the SuperRare DAO Community Treasury.[8]

Summary statistics and overall market dynamics

Table 1 reports counts for the number of events, the number of NFTs, and the number of agents in the data. NFT counts are grouped by the number of times sold or resold. Agent counts are grouped by the nature of their participation in the market. Creators are those agents who produced NFTs but did not buy them. Collectors are those who only bought NFTs but did not sell or create them. Intermediaries are those who bought and sold NFTs, but did not create NFTs.

Around 40% of NFTs created on SuperRare sold at least once. This may not be representative of the wider NFT market since SuperRare is a curated marketplace: artists are screened and selected. Presumably, a factor in the selection is their marketability. Table 2 reports the distributions of ask, sale, and bid prices in US dollars and ETH. Over this period, the exchange rate between US dollars and ETH was in flux, so these summary distributions depend significantly on when the prices were established. The median asking price over the time period was about $1,110.5 and 1.0 ETH. The median US dollar sale price was about 80% of

[6] https://decrypt.co/resources/what-is-superrare-3-minute-guide-explained-art-collectibleether
[7] Starting from August 2021, the SuperRare platform also allows its NFTs to be denominated in $RARE, a cryptocurrency issued by the platform. For simplicity, all event prices are converted to either ETH or US dollars according to the end-of-day exchange rates.
[8] https://help.superrare.com/en/articles/10629742-offers-auctions-and-pricing.

the asking price, and the median bid was about 60% of the asking price. Notice that the distribution of sale prices is highly right-skewed; the mean is much higher than the median.

Table 3 reports summary statistics for the sub-sample of NFTs that sold more than once. On average, purchase prices are higher than in the full sample. The returns are reported in ETH and in USD. There are two notable things in this table. First, the median realized return in ETH is 60% (sale price/purchase price – 1). The median realized USD return for the repeat-sale subset is even higher: 170%. Transaction fees moderately shrink the median return to 140%. The annualized return in ETH is also around 170%.[9] The top 10% of realized returns amount to an order-of-magnitude increase in investment.

Figure 1 presents the NFT price indexes, denominated in US dollars and Ethereum, based on the realized returns of the repeat-sales sub-sample, following the standard repeat-sales regression (RSR) method from Bailey et al. (1963). The US dollar-denominated price index grows much faster than other asset classes, including ETH, Bitcoin [BTC], and S&P500 common stocks, in the first half of the sample period. It reached its peak in October 2021 with slightly more than 490 times its initial level. The rise of NFT prices is associated with a surge in trading volume, especially in the secondary market, as shown in Figure 2. Following the peak, the observed sales prices declined, accompanied by increasing volatility and a decrease in transaction volume. Unlike most financial asset classes, which have recovered to their 2021 peak levels by the end of 2024, the NFT market remains well below that peak.

Another interesting observation from Figure 1 is the comovement between the US dollar-denominated NFT prices and the ETH prices, especially in the first half of the sample. ETH-denominated NFT prices display a different, flatter path. Table 4 formally tests this observation by regressing monthly NFT index returns in US dollars onto ETH returns. The NFT price index in US dollars moves almost one-to-one with ETH prices but also has a significantly positive alpha. By splitting the sample period in half, the last four columns confirm that the comovement mainly comes from the first half. Table 5 replicates the results by replacing US dollar-denominated NFT returns with ETH-denominated returns and finds no significant comovement.

The realized returns of repeat-sales pairs are, of course, subject to the occurrence of a second sale, which in turn is conditional on the expectations of the owner. Both observation of returns and formation of expectations may be endogenous. For example, if a naive investor investing US dollars were to extrapolate their expectations about risk and return from this realized return sample of price pairs, he or she might expect a five-fold increase in investment.

[9] Since returns are generated entirely by capital appreciation, if this were representative of expected price growth, the NFT market would overtake the US stock market in capitalization within a decade.

There is some evidence that participants in the NFT market indeed had high expectations of resale value compared to the purchase price they paid. Figure 3 plots a monthly time series of median prices in both ETH and US dollars for NFTs listed for secondary sales, as multiples of the most recent sale prices. The average asking price was typically about six times the purchase price in the first half of the sample. It varied considerably through time. It was higher from inception through the end of 2019, below six until roughly the Beeple sale, and then varied between six and ten afterwards. Listing prices declined after 2021 but were still two to five times the purchase price. By definition, the rate of resale and hence the liquidity of NFTs posted for resale has been a function of a dynamic process of expectations that likely constrained turnover in the market to a relatively low rate. Figure 4 shows Kaplan-Meier survival curves for the three types of sales intervals, adjusted for right-censoring due to the short sample period. The first figure is the survival probability as a function of the time between creation and the first sale for those NFTs that sold at least once. The half-life of this interval is roughly one year. The half-life of a resale or second resale is substantially longer than our six-year sample period. Taken together, Figures 3 and 4 clearly suggest that NFTs did not turn over much after their first sale, and that this may be due to high seller expectations as indicated by asking prices. Any index constructed from transaction prices, and particularly an index constructed from repeated sales, must adjust for the unobserved value of NFTs in order to construct an index indicative of the transaction prices that might have been observed if they were offered without reserve. Put differently, if sellers were unwilling to transact except at a price six times their asking price, this would skew repeat-sale data heavily towards returns that generated profits that were multiples of the original purchase price.

5. Conditioning bias in non-fungible markets

Bias caused by conditioning observations on price thresholds is a well-known problem in many markets. It is particularly relevant for markets in which agents have non-pecuniary preferences, for example, housing and art markets. In the housing market, homeowners may be reluctant to sell at a price below their outstanding mortgage balance due to liquidity constraints. When prices decline, fewer sales occur. Those that do sell are likely to be those whose prices exceed outstanding mortgage levels. Similarly, in the NFT market, the owner may not sell an artwork unless the offer price is sufficiently higher than the cultural or community-driven value of the NFT, or unless hit by an adverse liquidity shock.

Conditioning seller willingness based on a reference point may also be due to human nature. Aversion to selling at a loss is well-documented in the stock market. Shefrin and Statman (1985) coin the term disposition effect to describe a behavioral tendency to realize gains but not losses. Empirical evidence of

this tendency and its economic effects are legion.[10] In short, loss aversion can bias a sample of realized returns towards positive gains.

Goetzmann and Peng (2006) and Lin and Vandell (2007) show that reference-dependent behavior can mask both booms and crashes in housing prices when they are measured by repeat-sales indexes.[11] There is no reason to expect that participants in the NFT market are not similarly prone to reference-dependent behavior. An approach to this problem is to use a Bayesian method to estimate the unconditional prices under the assumption that NFTs did not sell because bids failed to exceed seller reserves. In this paper, we construct a cumulative return index using a Markov-Chain Monte-Carlo [MCMC] Bayesian algorithm developed by Korteweg, Kraussl, and Verwijmeren (2016) [KKV].

KKV develop a method to estimate unconditional indexes that mitigates the effect of reference-dependent decisions to sell in an art market and apply it to the estimation of an art index.[12] Specifically, KKV model the probability of a sale as a function of the log difference between the artwork's latent price if sold and its purchase price. This decision rule of sales acts as the sample selection equation in the two-step Heckman selection model (Heckman, 1976, 1979) and can be used to estimate the sample selection probability in the realized returns.

We adopt a variant of the KKV methodology proposed by Huang and Goetzmann (2024), who improve the original method for the NFT market in two ways.[13] First, instead of imposing a quadratic sale-probability function with a discontinuity, they estimate this relationship nonparametrically: the log return since purchase is partitioned into equally spaced bins, and the average sale probability is computed within each bin. This provides a more flexible representation of the trading decision rule. Second, since investors may evaluate performance in ETH, the currency of denomination, Huang and Goetzmann (2024) first estimate the model in ETH and then convert the resulting ETH-denominated index into U.S. dollars using the end-of-month exchange rate.

Figure 5 reports the MCMC selection-corrected NFT price indexes, which show a different dynamic than the standard RSR index due to selection bias. First, the selection-corrected index in US dollars reached a

[10] Later work has suggested the disposition effect is prevalent in behavior and may influence asset prices. Odean (1998) documents loss-aversion in individual investor behavior. Grinblatt and Han (2005) show how unrealized gains due to loss-averse behavior could explain the momentum effect in stock returns. Goetzmann and Massa (2008) show how disposition behavior could explain differences in individual and aggregate stock price dynamics.
[11] Goetzmann and Peng (2006) introduced reference-conditioned sales choice in the housing market and showed that it induced a systematic bias in estimated house price indexes.
[12] Goetzmann and Peng (2006) identified reference-conditioned sales choice as a source of systematic bias in house price indexes, and introduced a Bayesian correction procedure to correct for it. The procedure is essentially a reduced form of KKV, estimated via iterated maximum likelihood. Although the estimation procedures differ, they are both Bayesian methods that estimate unconditional return indexes that correct for non-randomly sampled data.
[13] We refer the reader to that paper for details on the estimation methodology.

lower peak at an earlier time: 6,207 points in March 2021, only slightly more than one-tenth of the unadjusted peak in October 2021. Second, in the latter half of the sample, despite the relatively resilient unadjusted prices, the selection-corrected index suggests that the NFTs lost most of their value by the end of 2024. Moreover, the selection-corrected index appears to be more volatile than the unadjusted index.

One useful feature of KKV's MCMC method is that it also provides an estimation of the latent prices of the NFTs when they are not traded. Using these latent prices, Figure 6 presents a binned-scatter plot of the probability of a sale as a function of the log returns since purchase. When the returns are unrealized, the latent prices are used as the as-if sales prices. Consistent with a disposition effect, the probability of a sale is uniformly higher in the positive region than in the negative region, with a significant jump at the origin. The probability also spikes at the log return bins of -0.7, 0.4, 0.65, and 0.9, corresponding to arithmetic returns of -0.5, 0.5, 1, and 1.5, consistent with the round-number effect, which suggests non-financial motives for trading and is associated with longer holding periods before resale (Rosen and Spaenjers, 2024).

6. Investment portfolios

Active intermediaries

In this section, we report the results of actual investment portfolios by SuperRare market participants. We focus on a subset of 199 intermediaries who bought more than thirty NFTs in the sample period. We make two different assumptions about the values of unsold NFTs at the end of the sample period. One conservative assumption is that NFTs that were unsold at the end of the sample period in December 2024 had no residual value. Another assumption is that the unrealized returns of unsold NFTs follow the MCMC selection-corrected index returns or the standard RSR index returns we estimate above.[14] Table 6 reports the distribution of various performance metrics of active intermediaries. We define return as $\frac{cash\ out}{cash\ in} - 1$.

Note that the median number of NFTs purchased was 57, and the median number sold was 5. Consequently, the return estimates are highly dependent on the assumptions about future resale values. The median active intermediary had a negative return, and the maximum had a return of 73. Transaction fees reduce the maximum return to 64 and offset the gains of active intermediaries even for the top 25%. The mean investment return was 94%, i.e., a 1.94 multiple. A cash flow multiple is commonly used as a metric for private equity portfolios. The benefit is its simplicity; the drawback is that it ignores the timing of cash

[14] These measurements resemble the performance metrics commonly used in private equity and venture capital: the Distributed to Paid-In Capital ratio (DPI), in which only realized returns are included, and the Total Value to Paid-In Capital ratio (TVPI), in which the projects' residual values are also included.

flows and the time value of money. It also penalizes investors who purchased late in the sample and have not had time to sell. In practice, a 1.94 multiple might be a reasonable multiple for a private capital limited partnership, but perhaps a bit low for a successful venture LP multiple. Of course, this ignores the residual value of unsold NFTs by the end of 2024.

If we assume positive residual values proxied by the standard RSR index returns (MCMC selection-corrected index returns), the average multiples would significantly (albeit slightly) increase by 2.48 (0.03). The future value of unsold NFTs is a fundamental question in considering an investment strategy. An unconditional repeat-sale index suggests that the future value will likely be highly volatile and often prone to overestimation from sample selection bias, and the survival curves suggest realizing re-sales could take years. However, the MCMC valuation takes these conditioning factors into account and provides an estimate at the end of the sample period that includes both realized and unrealized values.

We next examine the performance of active intermediaries using an augmented RSR, following Mei and Moses (2002). Specifically, in addition to the month dummies in the standard RSR, we add an interaction between the duration of the repeat-sales pairs and an indicator for active intermediaries as defined above. The coefficient of the interaction term, therefore, captures the average monthly performance difference of an active intermediary. For brevity, we report only the coefficients on the interaction terms.

Table 7 reports the regression results. The first two columns use only realized returns, while the last two columns also incorporate unrealized returns of unsold NFTs estimated with the MCMC selection-corrected algorithm.[15] Columns 1 & 3 show that active intermediaries modestly underperformed other investors in both specifications. The underperformance, however, is concentrated in purchases made during the boom period, as shown in columns 2 and 4. Moreover, NFTs purchased by active intermediaries in the later period generated realized returns similar to those of other NFTs, but substantially higher returns once unrealized positions are included. This suggests that active intermediaries are more willing to realize losses than other investors – a result aligned with the behavior of speculators as modeled in Lovo and Spaenjers (2018). Overall, the results are consistent with active intermediaries pursuing a defensive trading strategy that captures less of the upside in the boom but shows greater resilience in the bust.

Liquid artist investment strategy simulation

In this section, we simulate a reasonable strategy that could have been implemented by an investor who values liquidity and purchases works by artists with the most liquidity over the prior three months.

[15] Specifically, to incorporate unrealized returns, we construct a pseudo repeat-sales pair for each NFT that remains unsold at the end of the sample. The pseudo pair "purchases" the NFT at its last observed transaction price and "sells" it at the end of the sample period (December 2024) at the MCMC-estimated latent price.

In the strategy, we use the entire SuperRare database of transactions, not just realized returns. We thus remove the effects of conditioning on resale to measure returns. Each month of the sample beginning in July, 2018, we identify the liquid creators who were in the top 5% in the prior three months. The proxy for liquidity is based on the number of NFTs created and also the number of successful sales. We do not consider those artists who created or sold fewer than 3 NFTs in the prior three months. In any month, we buy the NFTs from the most liquid creators that we identified in the previous step and whose prices are below $10,000 in our baseline strategy. The investment in the identified NFTs occurs only if there is a sale price. Then, we assume that the NFTs are sold at the next known transaction. We further assume that unsold NFTs are kept until the end of our sample period and have zero terminal value.[16]

Figure 7 reports the number of NFTs purchased and sold in the strategy each month, as well as the cumulative net cash flows generated by the strategy on the right axis. The strategy continues positive net investment during the boom and realizes most of the gains in late 2021, just a couple of months prior to the collapse of the NFT bubble. We measure performance with a monthly internal rate of return [IRR]. The analysis is based on simulating purchases of NFTs that met the liquidity criteria. The IRR of our baseline strategy using the entire sample is 14.05% per month, which is approximately equal to a 384% compounded annual return. As mentioned above, at that rate, a $1,000 investment in NFTs would be worth more than the total capitalization of the US stock market within a decade. After accounting for transaction fees and royalties, the IRR of our simulated strategy reduces moderately to 12.01% per month, which is still considerably high.

In the simulated strategy, we refrain from purchasing expensive NFTs above $10,000, roughly the 90th percentile of the asking price distribution. More conservative strategies perform even better in this highly volatile episode. Figure 8 reports the cumulative net cash flows and the IRR from strategies with different purchase price caps. Even purchasing only NFTs from liquid creators below $100 generates eight million US dollars of cumulative net gains with little net investment, corresponding to a 16.6% IRR. Increasing the price caps actually lowers the gains, since we are more likely to purchase overpriced NFTs.

Another aspect of the strategy we may need to consider is market timing. It is unreasonable to continue purchasing new NFTs when a salient market downturn is observed. An *ex ante* feasible stopping time could be May 2021, when the number of sales dropped sharply from the peak of more than 3,000 to roughly 500, an 18-month low. The dashed line in Figure 7 shows the cumulative net gains from the strategy that stops

[16] Because NFTs depreciated heavily in the bust, the MCMC-estimated latent prices produce performance results close to simply assuming zero terminal value in the following simulated strategies.

purchasing new NFTs after May 2021 and just liquidates existing inventory. It provides lasting gains in the later months, generating a 15.37% IRR per month, or 456% per annum.

While commonly used in the evaluation of investment performance, the main limitation of IRR is that it assumes that intermediate cash flows can be reinvested at the IRR. In the case of non-fungible assets, this assumption is particularly suspect since only a small fraction of NFTs had extreme positive returns.

We performed three additional experiments based on simulation. First, in order to understand the risk of underdiversification, we examine how varying the number of NFTs would affect the IRR estimate in Figure 9. Specifically, we randomly sampled smaller groups of qualifying NFTs and calculated the range of realized IRRs. The simulated strategies in Figure 9a stop purchasing new NFTs after May 2021. The strategy cannot guarantee a positive IRR with 90% confidence until about 400 NFTs are purchased, even if the investor stops before the bust. The left-tailed risks are even more severe when the purchase of new NFTs is allowed in the whole period, as shown in Figure 9b. We saw above that more than 75% of the active investors had substantially fewer purchases than 400. In short, they were likely insufficiently diversified, given the characteristics of the NFT market.

In the second experiment, we test the sensitivity of the IRR to the exclusion of the most profitable NFT purchases. We simulate purchases only up to 12/31/2023, which gives the hypothetical investor a year in which to liquidate unsold inventory. Figure 10 shows the IRR for the strategy as a function of the number of NFTs dropped. We sequentially exclude the most profitable NFT purchases, where profitable is defined as sales price minus purchase price in US dollars. Note that, in the strategy that stops purchasing NFTs after May 2021, the IRR becomes non-positive after dropping the top 75 NFTs out of 13,019 purchased NFTs, so only 0.6% of purchased NFTs make the IRR positive. The performance of the simulated strategy deteriorates more rapidly if purchases after May 2021 are allowed. IRR could become negative, but that is not reported in the figure.

The third experiment is equivalent to calculating the return multiple for vintage portfolios, i.e., portfolios that are formed at a specific date and held over time, liquidating the assets as the market permits. This is a well-known approach for private capital investment, where capital is raised in a certain year and then subsequently invested, with the goal of returning capital to investors over a limited time horizon.

As before, the simulations construct 200 portfolios by drawing with replacement from the NFTs of liquid artists that sold in a particular month. For each month, the size of the simulated portfolios is the same as the number of NFTs bought by our simulated investment strategy described above. Returns are calculated as the sum of sales divided by the sum of purchases minus 1, all in Ethereum. We assume that the NFTs that remain unsold at the end of the sample period have zero residual value. Figure 11 presents the performance

of our simulated portfolios in a heatmap. The horizontal axis indicates the vintage month of the portfolios, i.e., when the portfolios are constructed. In each month, we group the simulated portfolios by the fraction of unsold inventory at the end of the sample period. The fractions are measured by their ETH-denominated purchase prices and indicated on the vertical axis.

First note that returns over 1,000 percent are not uncommon for purchases in 2018. There are also profitable portfolios built in the summer of 2019, but the returns decrease in the later periods. Similarly, portfolios constructed in the early years have higher fractions of liquidation, while more than 80% of NFTs bought after 2020 remain unsold at the end of 2024. These two patterns result in returns being highly dependent on timing. Investors who entered early benefited much more from the growing prices and a liquid market during the booming episode.

To evaluate the assumptions about the residual value of unliquidated NFTs, we perform an additional experiment based on the simulated vintage portfolios constructed above. Different from above, we pool all portfolios together and calculate their average performance based on different assumptions about the residual value. Specifically, we assume that the residual value of unsold NFTs varies from 0 to 100% of their purchase price in ETH. Figure 12 reports the performance of portfolios under different assumptions. The horizontal axis still indicates the vintage date, but the vertical axis now indicates the assumptions about the residual value. As before, returns rely heavily on the vintage date, and early portfolios generally perform better. However, returns are not quite sensitive to the assumptions about residual values. This is consistent with our observation in the second experiment that good performance was mainly driven by the most profitable NFT purchases, which compensate for the failed investments.

7. OpenSea Marketplace

In this section, we apply our analytical framework to the OpenSea marketplace. Unlike SuperRare, which is a curated platform specializing in digital artworks, OpenSea is a broad marketplace that facilitates trading across many NFT categories, including digital art, profile pictures (PFPs), gaming assets, photography, music, sports collectibles, memberships, domain names, and virtual land. Here, we focus on NFTs in OpenSea collections labeled “Art” by collection creators, which generated more than 9 million sales between 2017 and 2024 (This classification is creator-defined and may be noisy.). In unreported results, we

also examine the most-traded PFP collections of all time, including well-known collections such as Cryptopunks, Bored Ape Yacht Club, and Pudgy Penguins, and find similar results.[17]

To implement our MCMC selection-bias adjustment algorithm at a feasible scale, we further restrict the sample to a random 5% subset of NFTs on the Ethereum chain. This yields a sample of 452,636 transactions covering 231,828 art NFTs, including 62,743 repeat-sale pairs. Given the sample size, we expect the results to be generalizable.

Figure 13 plots the price dynamics of art NFTs on OpenSea. The OpenSea repeat-sale index exhibits a trend similar to SuperRare's: both peak in late 2021 and decline through the end of the sample period. In levels, however, the peak of OpenSea's index is lower than SuperRare's, and falls more sharply during the subsequent collapse.

As with SuperRare, our MCMC selection-correction algorithm indicates substantial sample selection bias in OpenSea's repeat-sale index. Figure 14 presents the estimated probability of a sale as a function of the MCMC-implied log return since purchase in OpenSea. The probability rises with holding-period returns, especially in the loss domain, and exhibits a pronounced discontinuity at the origin, as previously observed. In other words, although OpenSea is more liquid than SuperRare, OpenSea investors also appear reluctant to realize extreme losses and have a greater tendency to sell at break-even, consistent with non-financial trading motives and prospect theory preferences.

Next, we simulate a liquidity-oriented trading strategy to evaluate the factors that affect the performance of investing in OpenSea art NFTs. We follow the approach used in SuperRare but adjust the baseline strategy in the following aspects to reflect OpenSea's market structure and governance. First, because OpenSea is primarily organized at the collection level (with collections often containing thousands of NFTs), we target the 1% most liquid NFTs, defined by the number of transactions over the past month, rather than the most liquid creators or collections. We count transactions in only the past month, given the high turnover of these NFTs. Second, in addition to excluding NFTs priced above 10,000 USD, we exclude NFTs priced below 100 USD. Third, we exclude the first month of each collection since our liquidity metric may be distorted by the minting of the collection and the following hype.

In addition, several studies find wash trading activities in the NFT market (Wang et al., 2025; Oh, 2025; Jayant, 2023; Liu et al., 2023; Serneels, 2023), in which an NFT returns to the same wallet after a few

[17] PFP and art NFTs dominate the OpenSea marketplace, accounting for 42.2% and 12.7% of total sales transactions, respectively. Gaming NFTs represent 20.2% of sales by count, but only 7.6% of total sales volume in USD. Memberships, virtual land, photography, music, domain names, and sports collectible NFTs combined make up roughly 10% of sales, while uncategorized collections account for the remaining 15% of total transactions.

transactions (a loop trade) to manipulate prices and boost volume. Therefore, each month, we refrain from purchasing NFTs that have experienced any loop trade before. These suspicious NFTs account for about 5% of transactions (i.e., potential trading opportunities for our strategy), consistent with findings in existing literature. To be conservative, we also avoid NFTs sold by sellers who previously participated in more than five wash trades. This filter excludes another 15% of transactions. Under this baseline strategy, we make about 800 purchases a month on average over the sample period, with some NFTs purchased multiple times.[18] Given OpenSea's higher liquidity and our focus on the most actively traded items, about 96% of the positions built each month can be unwound within the same month.

Table 8 reports the return of the baseline strategy and a set of variations that echo earlier analysis. Since most positions can be settled within the same month, we calculate the ratio of cash inflows to outflows minus 1 in each month as the return and use the investment-value-weighted average return across months to measure strategy performance. The baseline strategy yields a monthly return of 5.04%, corresponding to 60% per annum. A lower return than that in SuperRare may reflect lower liquidity risk in OpenSea. The return declines to 2.73% after accounting for a 2.5% fee per sale prior to February 2023 and a 0.5% fee thereafter.[19]

The second row also considers NFTs and sellers involved in wash trading. Doing so doubles the number of NFTs that our strategy purchases, since wash trading generates false signals of trading volume. As wash trading also manipulates prices and is often associated with insider trading, purchasing washed NFTs reduces strategy performance. This finding emphasizes the importance of identifying and avoiding wash trading in NFT investments.

In rows 3-4, including cheaper NFTs significantly increases the number of transactions each month but only modestly increases returns. The effect of excluding expensive NFTs on returns is nonlinear. Lowering the upper bound (row 5) reduces returns by forfeiting potential gains from high-valuation NFTs. Raising the upper bound, as in rows 6-7, also hurts the simulated returns because losses from purchasing potentially overpriced NFTs now outweigh potential gains. Rows 8 to 10 repeat the portfolio-size exercise in Figure 9. Smaller portfolios tend to have lower returns and greater volatility, suggesting high idiosyncratic risk in underdiversified portfolios. Even a portfolio comprising 20% liquid NFTs does not guarantee a positive return with 95% confidence. Also, consistent with Figure 10, the last two rows indicate that investment performance is highly sensitive to tail outcomes: omitting only the 100 most profitable trades results in a

[18] When an NFT is traded multiple times, our simulated strategy purchases the NFT in the first transaction, sells it in the next transaction opportunity before purchasing it again in the third trade, and so on.
[19] The investors may also need to pay a royalty fee for the secondary sales of some collections to their creators. For collections that charge royalty, the royalty rates are commonly 5% to 10% (Tunc et al., 2025; Elad, 2025).

negative average monthly return. Finally, as in SuperRare, our simulated strategy derives most of its gains from the NFT market's boom while incurring modest losses during the bust. A closer look at the strategy's cash flows shows that the largest loss occurred in early 2023, when trading volume surged following a decline in OpenSea's transaction fees from 2.5% to 0.5%. Such replenishment of liquidity, however, did not lead to a long-run full recovery of the market.

8. Cultural and Community Values of NFTs

Although this paper focuses on NFTs as a financial investment, we also recognize that they originated as a non-pecuniary good among a community of creators and collectors that coalesced around the emerging potential of the blockchain, crypto, and new technologies for creating and distributing art. The NFT collector community inevitably changed with financial-oriented entrants, but this transformation may have itself engendered new, sustainable NFT clienteles. In fact, expectations of financial gain may drive initial purchases, while social identity formation and strong community bonds are factors that can sustain continued market engagement (Brahmstaedt, 2025). These two forces may have helped catalyze the broader NFT market and sustained participation after the collapse of the bubble. Notably, a large share of the liquid NFTs selected by our simulated strategy comes from collections with strong community identities and cultural messages. In short, some market participants may have come for the money but stayed for the art.

The most-traded art collection in our sample between 2023 and 2024 is "The Memes by 6529," a collection of 441 unique NFT memes curated by the prominent thought leader and Web3 builder @punk6529. The collection centers on memes that advocate for a Web3 open metaverse, emphasizing decentralization, community, and self-sovereignty. Purchasing these NFTs can be interpreted not only as an investment decision but also as an expression of support for the project's mission to build "a decentralized open metaverse, bridging virtual and physical spaces, that people use in their day-to-day lives."

Another popular art collection is "DAMAGE CONTROL" by XCOPY, one of the most recognized digital artists. His work fuses "death, disorder, and crypto themes in chaotic visual loops," often depicting glitchy figures in neon colors against dark backgrounds. XCOPY's adoption of the Creative Commons Zero (CC0) license, which allows for the free use of his work in the public domain, also signals a commitment to a more open, collaborative creative ecosystem aligned with Web3 values.

Other liquid art collections in our sample similarly foreground distinct themes. Jack Butcher's "Opepen Edition" and "Checks VV" function as experiments in openness and collective participation of the Web3

community. Also in this community, Des Lucréce's uses street-art graphics that belie his sly references to Roland Barthes, Jacques Lacan, and post-modern literary theory.

Beyond communities organized around a single collection, we also examine communities of art collectors connected by their shared preferences across multiple art collections. We construct a network of art collectors based on portfolio similarity, shown in Figure 15. As before, collectors are defined as NFT buyers who never sell at the wallet level. Two collectors are connected if their portfolios overlap in at least two collections and their overall portfolio similarity exceeds a specified threshold.[20] The Leiden algorithm is then applied for community detection (Traag et al., 2019). Figure 15 visualizes the ten largest communities, and Table 9 reports the three most-purchased collections within each community. Our analysis focuses on the period from January 2023 through December 2024.

The largest community (1) comprises 456 collectors. In addition to holding "The Memes by 6529" collection, these collectors appear to share a preference for XCOPY's work, particularly through MAX PAIN AND FRENS and DAMAGE CONTROL. As discussed above, XCOPY's artworks exhibit a distinctive personal signature in style, color, and theme. Community 1 overlaps in preference with communities 6, 8, and 10 – all of which share anti-establishment and decentralization themes and an interest in Pepe the Frog, the de facto mascot of the crypto community. Additionally, Communities 3, 4, and 7 form a relatively cohesive group around innovative graphic design and the novel potential of the NFT medium through collections by Jack Butcher. Butcher is the thought leader of this community. Trained in graphic design, he offers instructional products for NFT artists.

While many communities are interconnected, Communities 5 and 9 are comparatively isolated. The three most-purchased collections in Community 5 are all on the Base blockchain – a new Ethereum Layer-2 Web3 blockchain launched in August 2023 that is designed to support faster, cheaper, and more creator-friendly decentralized applications. Although we cannot rule out the possibility that some buyers use separate wallets for the Base blockchain, the resulting clustering of the wallets is nonetheless consistent with a community organized around the adoption of this newer technological environment. The technology allows for generative, interactive artwork that, for example, reacts to the viewer's mouse movements and clicks. The other isolated community (9) centers on "Crypto Dragon King Club" and its successor "Pi DAO Club," both of which are mainly about dragons, often associated with strength or luck in several Asian cultural contexts. It trades on a Chinese blockchain that restricts access to Ethereum and thus to most other

[20] Specifically, we first construct a portfolio vector for each collector. Each element represents an art collection in our sample, and the value of the element is the frequency of the collection in the portfolio, scaled by the logarithm of the total purchases of the collection to downweight commonly held collections and upweight unique ones (i.e. a TF-IDF transformation). Two collectors are connected if their portfolios' cosine similarity is larger than 0.6 and have at least two common collections.

major collections. Additional communities appear to reflect shared aesthetic preferences, such as poster-oriented collections (e.g., Community 10) or algorithmically generated pattern-based works (e.g., Communities 3, 6, and 7). Overall, the network analysis identifies communities of art NFT collectors structured around common affinities—whether for an emerging technology, a specific artist, a recognizable aesthetic style, or a cultural motif. What remains in the aftermath of the NFT bubble is a community that values NFTs for a constellation of apparent non-pecuniary motives: group identity and alliance with crypto culture, fascination with experiments in a new graphic medium, cultural criticism, and humor. Whether these clienteles will become a foundation for a renewed interest by investors remains to be seen.

9. Conclusion

Few episodes in financial history feature such rapid increases in prices and realized returns as the COVID-era NFT bubble. By our measure, the NFT bubble, even corrected for selection bias, likely surpassing Dutch tulipomania, the South Sea & Mississippi bubbles of 1720, Britain's railway mania in the 1840s, the Florida land bubble of the 1920's, the Wall Street boom in stock prices before 1929, the Dot-com bubble of the 1990's and the U.S. housing bubble of the 2000's. What is remarkable about the NFT bubble is that it left a blockchain record of extraordinary detail and completeness. This rich, agent-specific, and transaction-level information allows us to document and decompose realized returns by actual market participants, and track the timing and magnitude of the bubble's rise and fall in a way almost no other bubble has been studied. The NFT market provides a rare episode for economists to test theories about bubbles.

In this paper, we consider the perspective of an investor in the NFT market. We analyze the SuperRare marketplace with rich data on bids, asks, transactions, and agents, and we extend the analysis to OpenSea. This allows us to evaluate portfolio risk and return and to highlight the perils of conditioning on realized returns. We document a few basic facts about investment in NFTs over the period of study.

First, basing estimates of future investment returns by relying on measures of realized returns is tricky. Returns are highly right-skewed. Removing a relatively small number of highly profitable returns from the data dramatically reduces the IRR and other metrics of success. Because a few large gains drive portfolio returns, the IRR is highly sensitive to the number of NFTs in the portfolio.

Second, relying on realized returns biases time-series estimates of NFT returns. An index corrected for conditioning sales based on a reference point shows an underestimate of growth over our sample period, especially during the market downturn.

Simulations of an implementable strategy of investing in the most liquid artists, defined each month retrospectively, showed that returns were reasonable compared to norms in the private equity industry, but unremarkable if investors expected multiples of 2, 4, 6, or more.

Third, market timing mattered. The largest gains accrued to portfolios established well before the surge in attention in early 2021, so even conservative early entrants realized comparatively high returns. On exits, halting new purchases once liquidity declined after May 2021 materially improved performance relative to strategies that kept buying into the bust.

Fourth, we found that the NFT resale market was not particularly liquid. A standard survival analysis showed that it took a long time for the market to absorb an inventory of once-sold NFTs. This illiquidity was, of course, based upon reservation prices set by sellers, whose expectations about very high multiples may have been set by high asking prices.

Finally, assumptions about the residual value of unsold NFTs remain the most consequential and uncertain. There are many choices. One could forecast their value by extrapolating index trends over the long or short term. One could assume they could be sold for their purchase price. One could use a factor model based upon covariates like ETH.

The equilibrium effects of these various assumptions are of interest to the study of asset bubbles. One particularly fertile area for future economic analysis is in the domain of behavioral finance. Barberis et al. (2018) show how extrapolative beliefs can support a bubble. In related work, we test this and other theories about the psychological factors influencing the NFT bubble – for example, if a significant number of investors extrapolated price trends of NFTs – particularly trends conditioned on realized returns – this has the potential to create or sustain a bubble. A blockchain record of one of the biggest bubbles in history will likely become a testing ground for economists interested in speculative behavior for many years to come.

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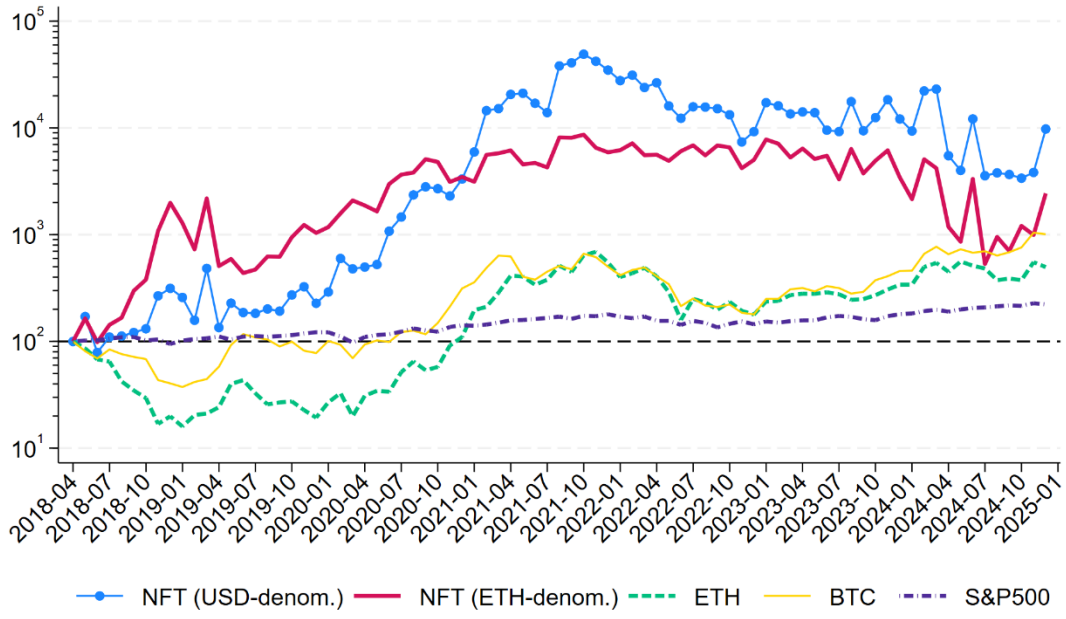


Figure 1. Market price indexes. SuperRare NFT price indexes are from standard repeat-sale regressions with US dollar- and Ethereum-denominated NFT sale prices. ETH is the price index of Ethereum, BTC is the price index of Bitcoin. Index levels in April 2018 are normalized to 100.

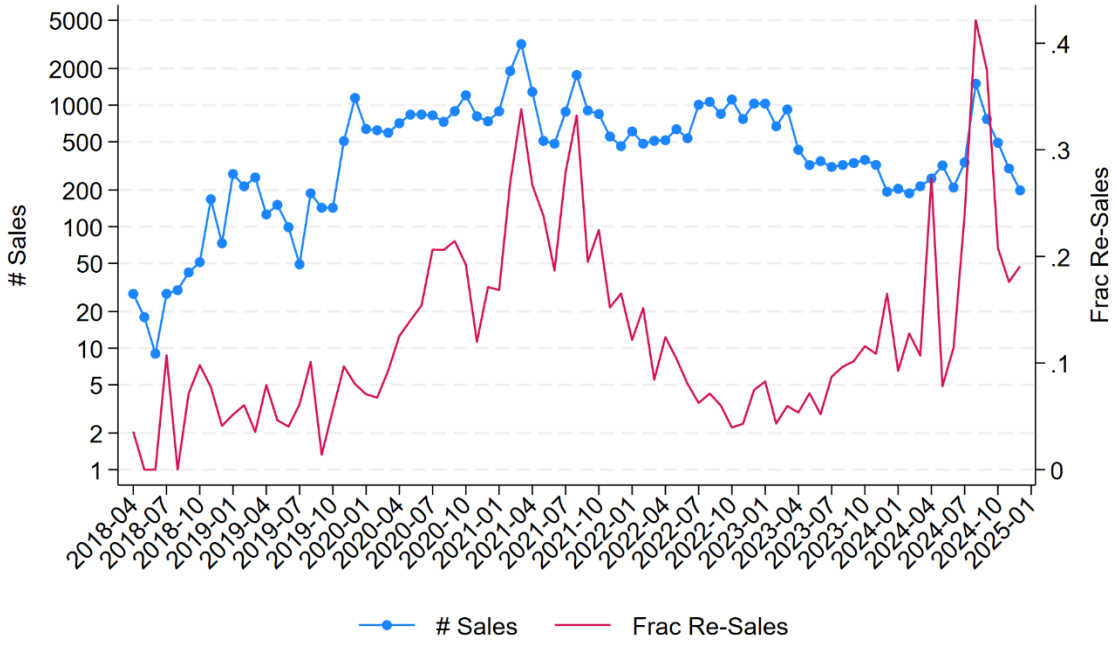


Figure 2. Trading volume and the fraction of re-sales in SuperRare.

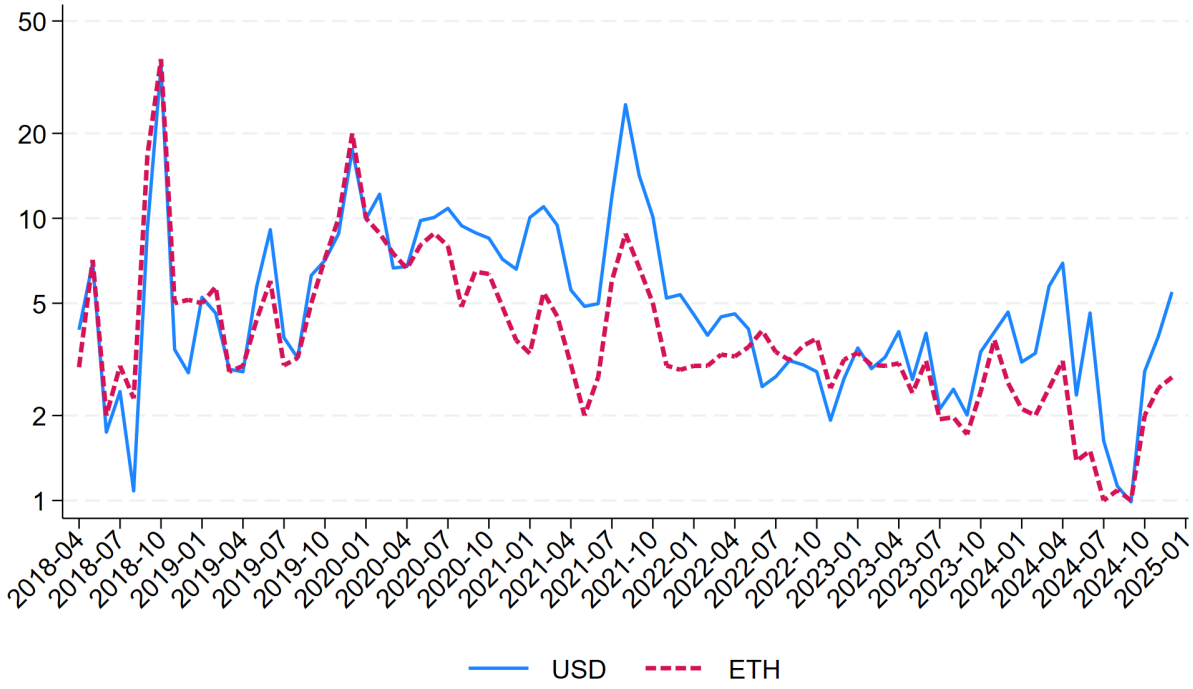
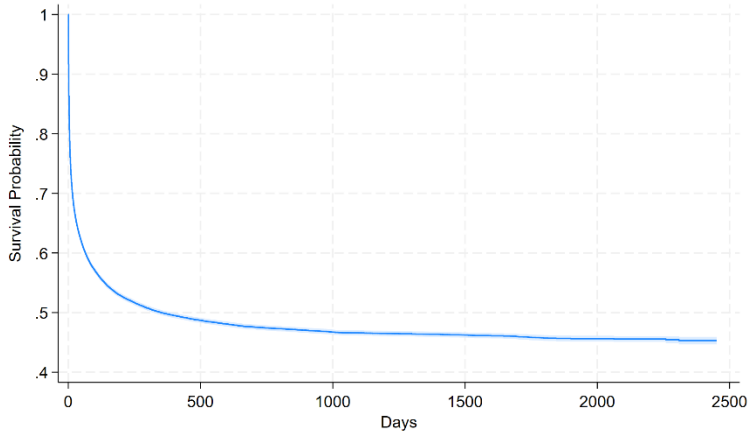
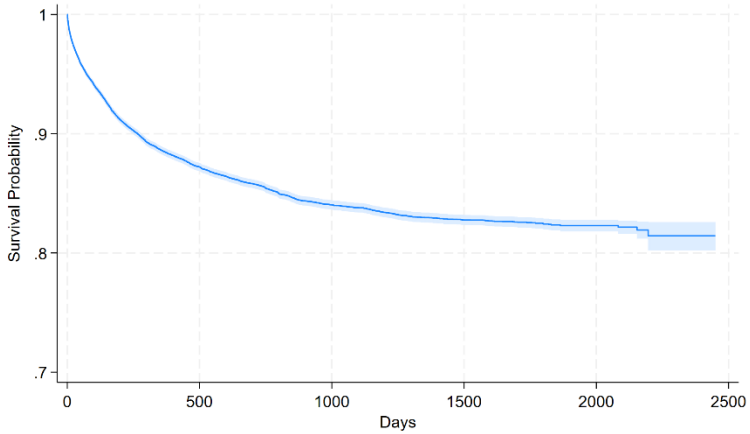


Figure 3. Median of the asking price multiples in SuperRare, US dollar- and Ethereum-denominated. The asking price multiple is defined as the ratio of the asking price to the most recent sale price.

(a) First sale.



(b) Second sale.



(c) Third sale.

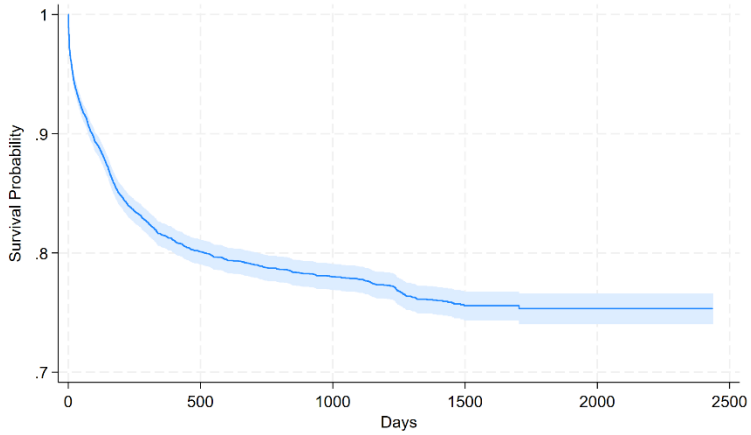


Figure 4. Kaplan-Meier survival curves estimating the probability of sale (one minus the survival probability) by holding period (the horizontal axis). 4a is the first sale, 4b is the first resale, and 4c is the second resale. Kaplan-Meier curves are corrected for right-censoring.

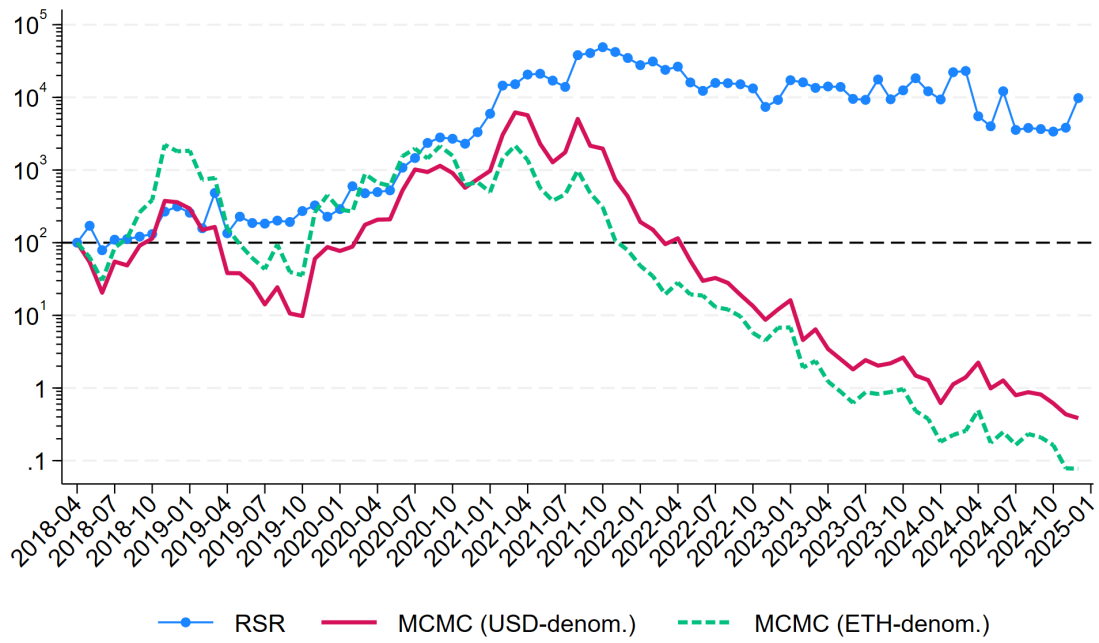


Figure 5. SuperRare Selection-corrected NFT price indexes, US dollar- and Ethereum-denominated. RSR is from the standard repeat-sale regression. MCMC indexes are selection-bias-corrected indexes estimated using the Monte Carlo Markov Chain algorithm by Huang and Goetzmann (2024).

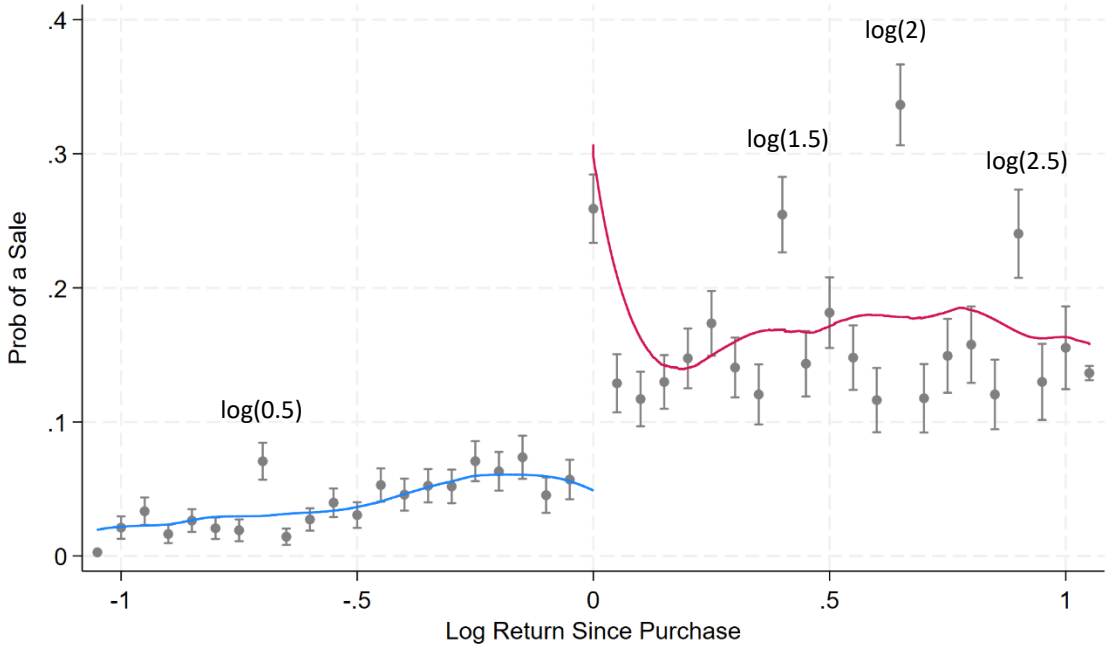


Figure 6. Probability of a sale as a function of the log return since purchase. Sale prices used in the return calculation are either the actual sale price if a transaction occurred or the MCMC-simulated latent price otherwise. The segments show the 95% confidence intervals of the bin averages (dots), and the curves are the locally weighted average of the sale probabilities.

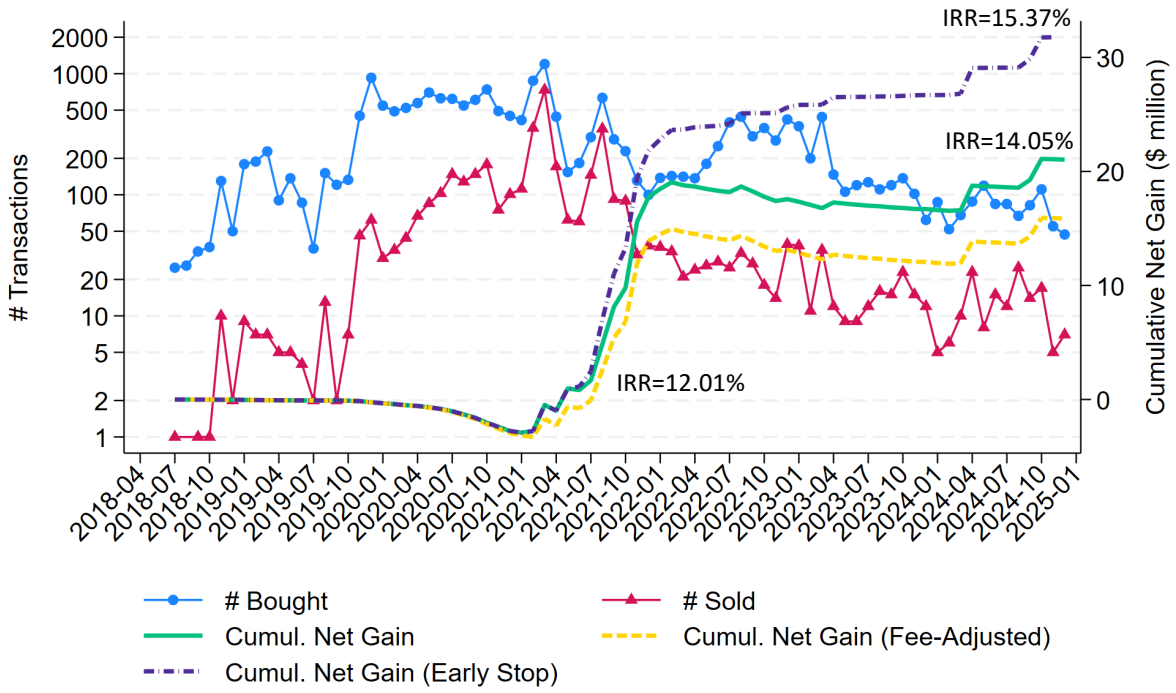


Figure 7. Simulated investment strategy outcomes in SuperRare. The graph shows how many NFTs are identified and traded based on a simulated investment strategy of purchasing NFTs of the most liquid artists each month. "Cumul.Net Gain" is the cumulative net cash flow of the simulated strategies, in which the investor follows the strategy for the whole period (solid line) or stops purchasing new NFTs after May 2021. Monthly IRRs are reported.

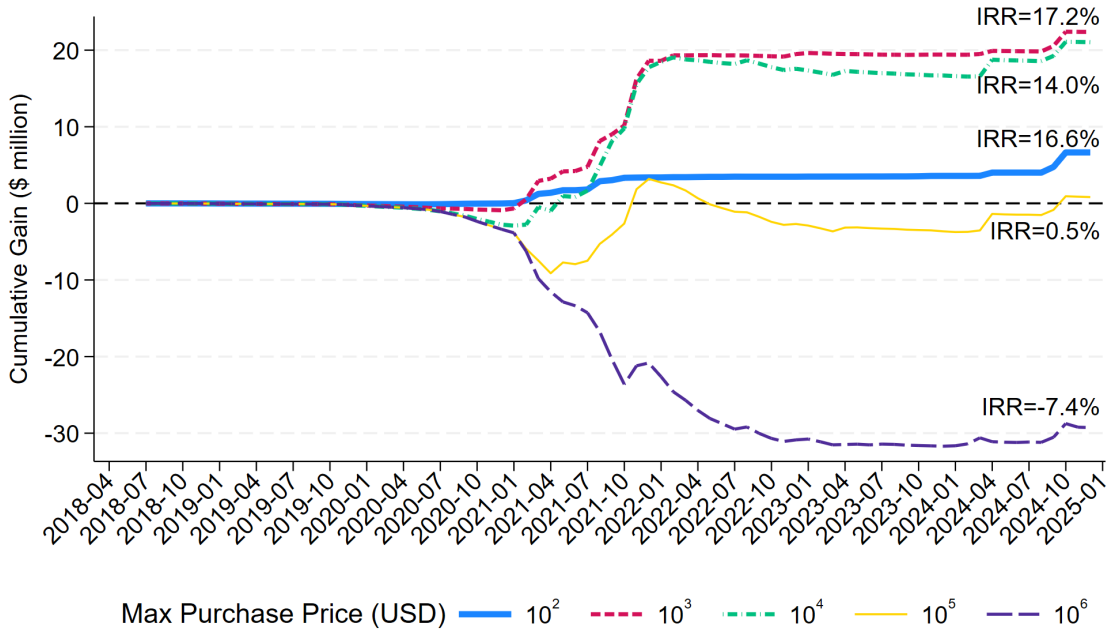
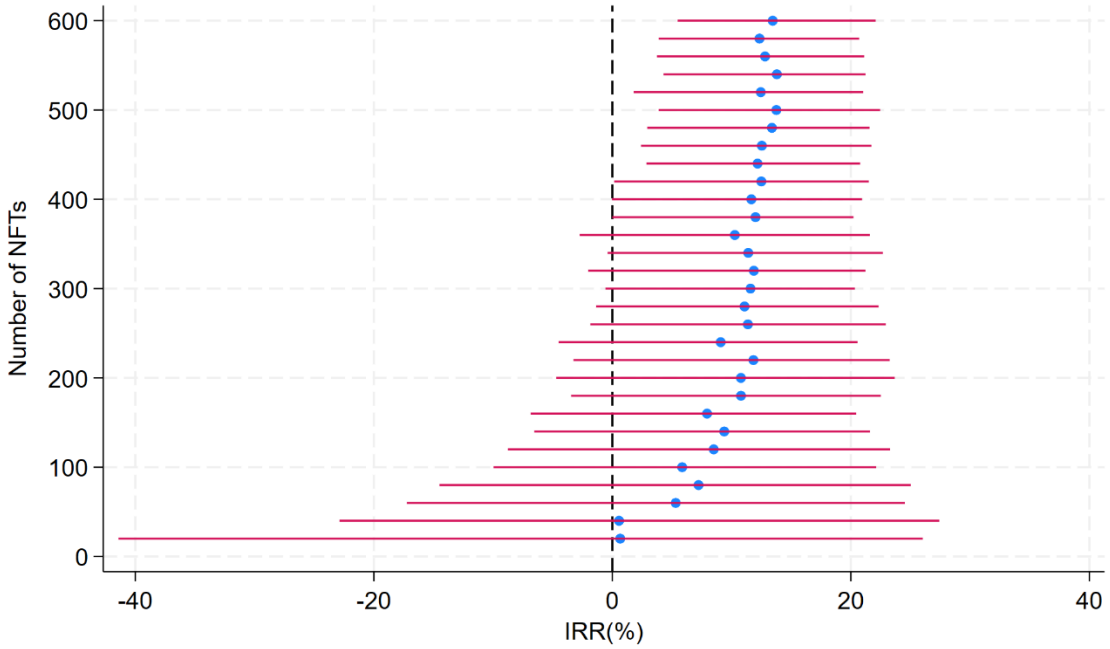


Figure 8. Cumulative net cash flows of variations of the simulated strategies, in which expensive NFTs above different thresholds are excluded from purchasing. Monthly IRRs are reported.

(a) Stop purchasing new NFTs after May 2021.



(b) Full period.

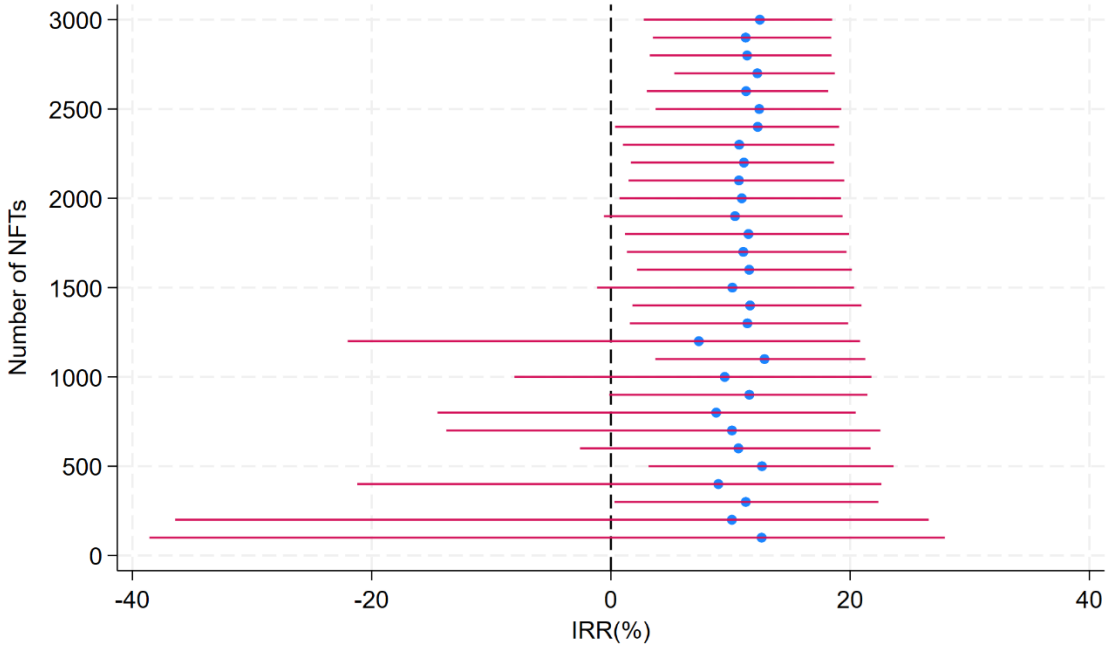


Figure 9. Returns of underdiversified portfolios. The blue dots show the average monthly IRR for a random portfolio of y NFTs purchased based on the strategy of purchasing the work of liquid artists. The red lines show the 5th and 95th percentiles for the IRR distribution of 100 random portfolios of y NFTs.

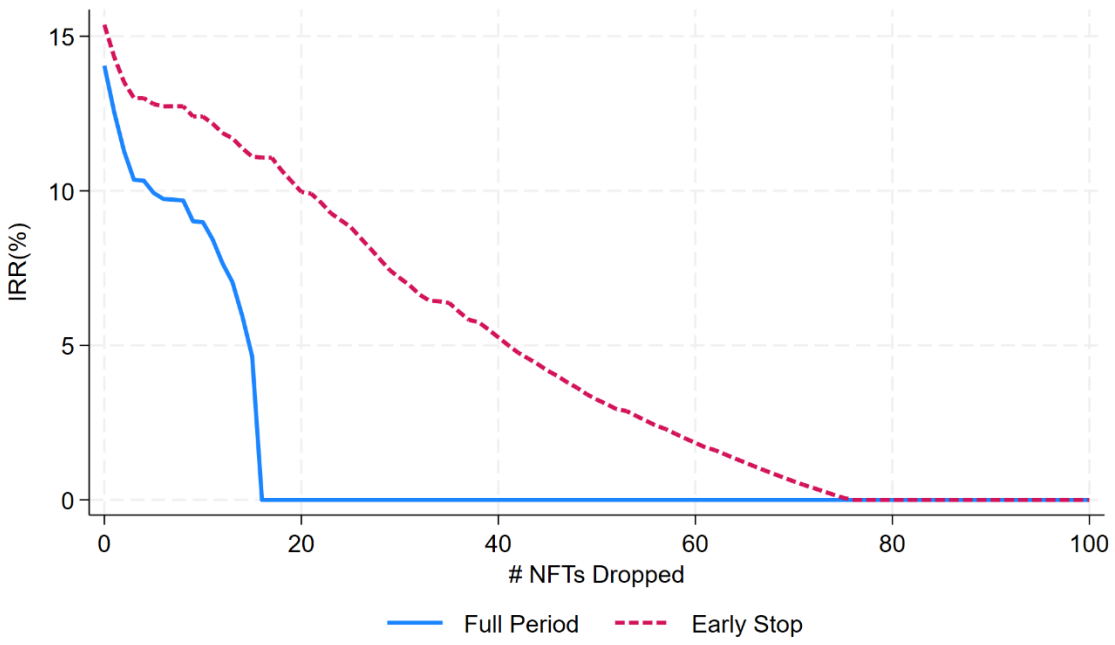


Figure 10. Monthly IRR as a function of dropping the most profitable NFT sales in the simulated strategy. Profits are defined as the sales price minus the purchase price, in US dollars. The "Early Stop" strategy stops the purchase of new NFTs after May 2021. Negative IRRs are censored at zero.

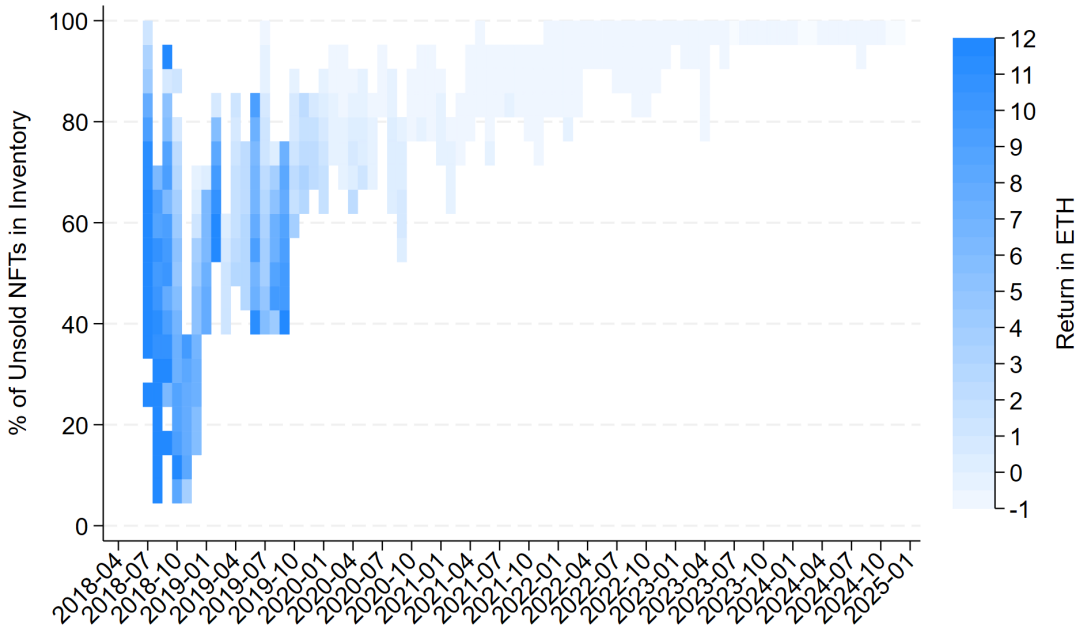


Figure 11. Heatmap of return multiples for simulated vintage portfolios, by the fraction of unsold NFTs in the inventory as of December 2024. The horizontal axis indicates the vintage month of the portfolios. The fractions are measured by their ETH-denominated purchase prices.

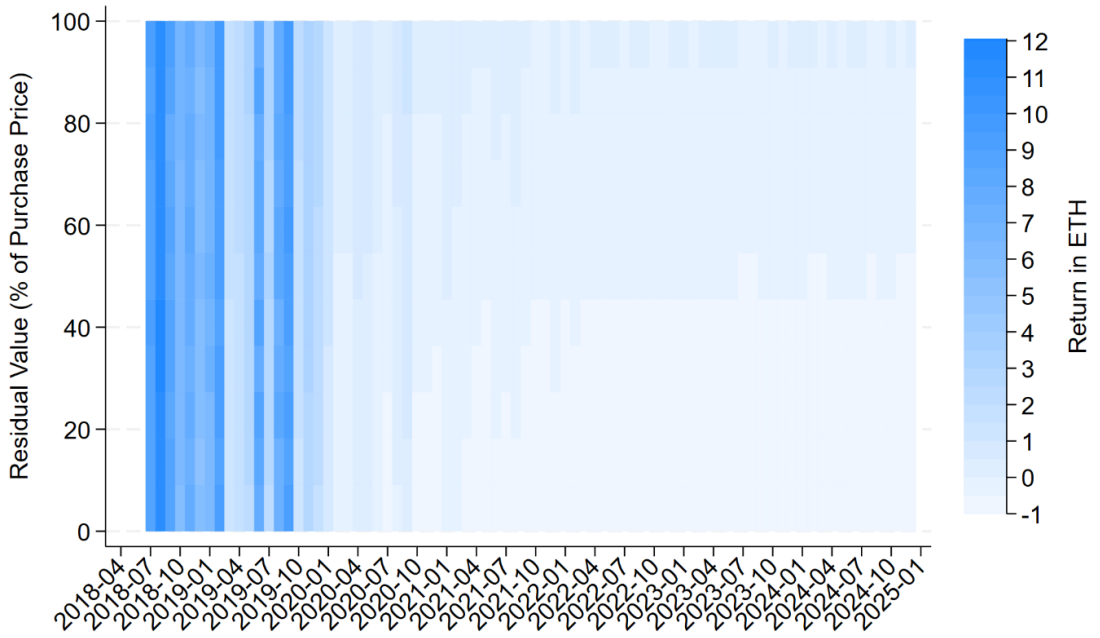


Figure 12. Heatmap of return multiples for simulated vintage portfolios, based on the assumption of the residual values of unsold NFTs in the inventory as of December 2024. The horizontal axis indicates the vintage month of the portfolios, i.e., when the portfolios are constructed.

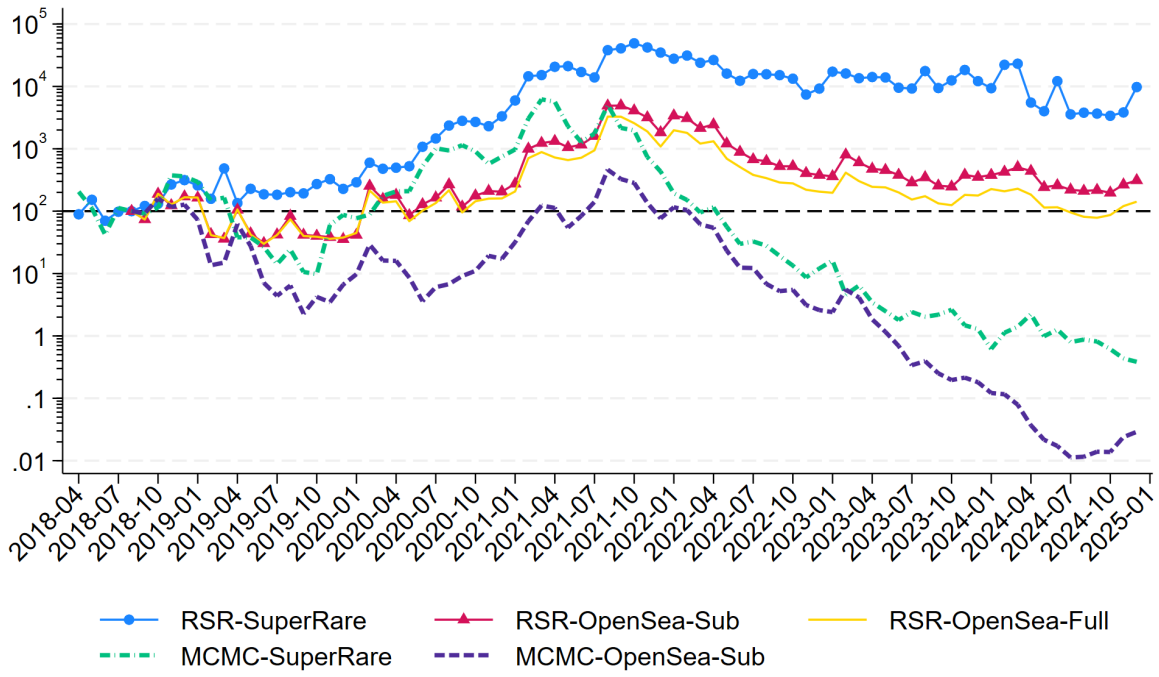


Figure 13. Repeat-sale and selection-corrected NFT price indexes in SuperRare and OpenSea. "Full" refers to the whole art NFT sample, while "Sub" refers to a random 5% subset of art NFTs on the ETH chain in OpenSea. The index levels in August 2018 are set to 100.

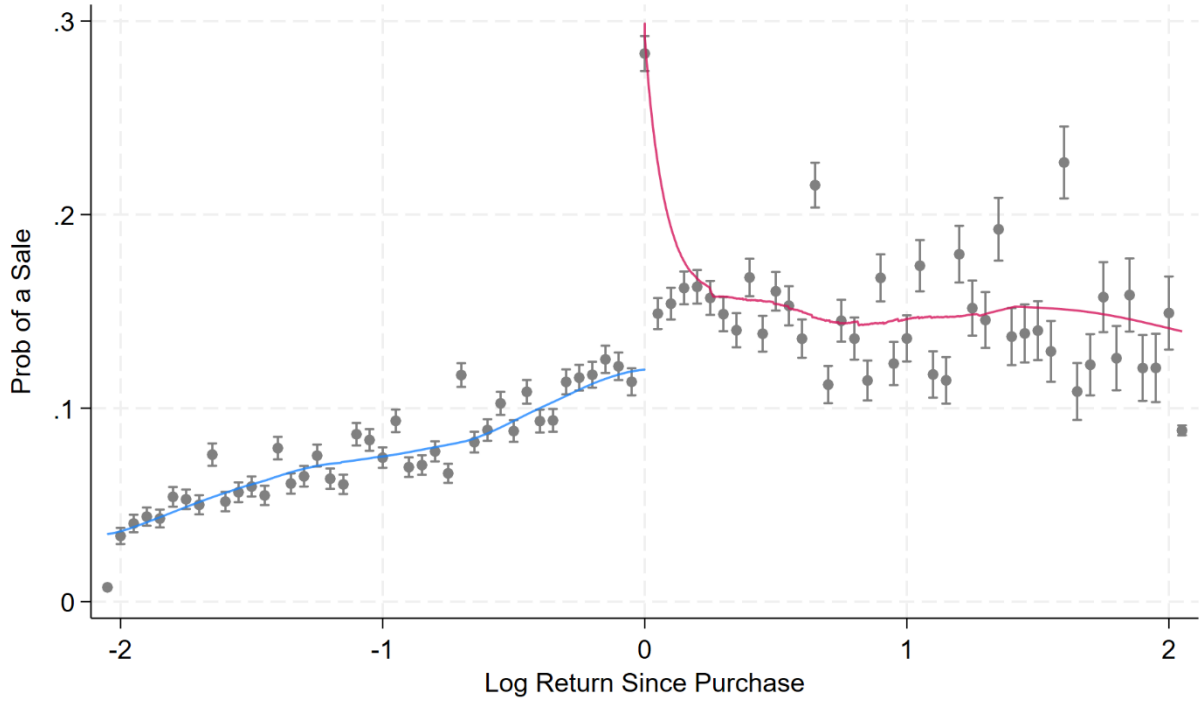


Figure 14. Probability of a sale as a function of the log return since purchase in OpenSea. The segments show the 95% confidence intervals of the bin averages (dots), and the curves are the locally weighted average of the sale probabilities.



Figure 15. Art collectors and their community network in OpenSea. Each node represents a collector (a buyer who never sells). Two collectors are connected if their purchases have at least two collections in common and their collection portfolios are sufficiently similar. The sample period is from January 2023 to December 2024. The ten largest communities are reported.

Table 1

Descriptive statistics for the SuperRare database over the period April, 2018 through December, 2024. Panel A reports the total number of unique events in the SuperRare data, including creations, transactions, and bids in auctions, the number of NFTs in the sample, with a breakdown of the subset of those that sold at least once. Panel B reports the number of agents in the sample, with a breakdown into categories according to the nature of their activity.

Events	**Number**	**Percentage**
Number of events	410,086	-
NTFs	**Frequency**	**Percentage**
Number of unique NFTs	96,688	100%
NFTs sold at least once	38,610	39.9%
NFTs sold at least twice	5,990	6.2%
NFTs sold at least three times	1,356	1.4%
NFTs sold more than three times	345	.36%
Total number of repeat-sale pairs	7,704	
Agent	**Frequency**	**Definition**
Total	11,748	
Creator	3,056	*Artists who create NFTs*
Collector	6,763	*Those who only buy*
Intermediary	1,929	*Those who buy and sell*

Table 2

Quantiles of the distribution of the ask, bid, and sale prices of the SuperRare sample in Ethereum (ETH) and US dollars (converted at the end-of-day prices from ETH). The ask price refers to the list price (or the transaction price if the list price is not available) immediately after creation. List prices do not exist for all the NFTs.

	10%	25%	50%	75%	90%	Mean	Std dev	Max	N
Ask (USD)	79.4	245.7	1,110.5	3,994.3	10,956.4	15,440.7	483,780.3	60,817,836.3	52,230
Ask (ETH)	0.1	0.3	1.0	2.9	6.5	14.8	679.9	88,888.9	52,230
Sale (USD)	35.5	155.4	804.5	3,248.7	9,556.2	6,899.3	74,741.7	6,591,705.3	46,482
Sale (ETH)	0.1	0.2	0.7	2.0	5.0	3.1	22.0	1,630.0	46,482
Bid (USD)	29.1	129.9	635.7	2,832.1	8,838.7	5,824.0	56,543.1	6,591,705.3	116,645
Bid (ETH)	0.1	0.2	0.6	2.0	5.0	2.8	16.6	1,630.0	116,645

Table 3

Summary statistics for the sub-sample of 7,704 NFTs in the SuperRare data that were sold more than once. The distributions of the prices are reported in both Ethereum (ETH) and US dollars (converted using end-of-day ETH prices). Sale and Buy months are the number of months with April 2018 as the zero month. Ann. Ret. is the annualized compound growth rate in ETH. Due to rounding, the reported minimum values are not meaningful. For example, the lowest sale price in the sample is 0.000001 ETH for an NFT that was purchased for 0.1 ETH. Maximum annualized returns can explode for very short holding periods, and medians are more informative.

	Min	**10%**	**25%**	**50%**	**75%**	**90%**	**Max**	**Mean**	**Std dev**
Sale (ETH)	0.0	0.0	0.2	0.7	2.0	6.8	1630.0	5.8	44.6
Sale (USD)	0.0	28.9	177.6	956.9	3,810.9	13,428.5	6,591,705.3	14,306.0	152,707.1
Buy (ETH)	0.0	0.0	0.1	0.4	1.2	3.5	1,000.0	2.2	15.6
Buy (USD)	0.0	19.0	34.0	177.1	1,288.1	5,271.1	2,925,565.6	4,278.4	45,737.9
Sale Month	0	27	34	37	52	76	80	43.6	17.2
Buy Month	0	16	24	33	39	76	79	35.0	18.5
Return (ETH)	-1.0	-0.5	0.0	0.6	2.3	7.6	1,499,999.0	397.0	22,381.9
Return (USD)	-1.0	-0.4	0.2	1.7	8.9	39.9	1,835,033.3	549.5	29,054.7
Return (USD, fee-adjusted)	-1.0	-0.4	0.0	1.4	7.9	35.8	1,651,629.9	494.5	26,149.2
Ann. Ret. (ETH)	-1.0	-0.7	0.0	1.7	16.9	1,304.1	2.4×10^{20}	7.5×10^{16}	4.3×10^{18}

Table 4

Results for the regressions of the US dollar-denominated monthly repeat-sale return series for NFTs on monthly returns of cryptocurrencies (ETH and BTC) and the total return of the S&P 500 index. Newey-West autocorrelation-adjusted *t*-statistics in parentheses.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: NFT return ($)					
	Full sample	Full sample	Before Sept. 2021	Before Sept. 2021	On and after Sept. 2021	On and after Sept. 2021
ETH	0.942***	1.143**	1.059***	1.155**	0.775	0.769
	(2.74)	(2.54)	(2.85)	(2.54)	(1.20)	(0.60)
BTC		-0.243		0.047		-0.640
		(-0.40)		(0.07)		(-0.40)
S&P 500		-0.696		-2.903		3.187
		(-0.34)		(-1.65)		(0.71)
Alpha	0.301***	0.310***	0.251***	0.283***	0.345*	0.341
	(2.77)	(2.73)	(2.96)	(2.97)	(1.72)	(1.63)
N	80	80	40	40	40	40
R^2	0.046	0.047	0.174	0.209	0.014	0.022

Table 5

Results for the regressions of the Ethereum-denominated monthly repeat-sale return series for NFTs on monthly returns of cryptocurrencies (ETH and BTC) and the total return of the S&P 500 index. Note that the ETH, BTC, and S&P series are not denominated in ETH. Newey-West autocorrelation-adjusted *t*-statistics in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: NFT return (Ξ)					
	Full sample	Full sample	Before Sept. 2021	Before Sept. 2021	On and after Sept. 2021	On and after Sept. 2021
ETH	-0.348	-0.241	-0.428	-0.322	-0.224	-0.192
	(-1.19)	(-0.59)	(-1.14)	(-0.71)	(-0.51)	(-0.21)
BTC		-0.184		-0.097		-0.390
		(-0.36)		(-0.17)		(-0.34)
S&P 500		0.046		-1.332		1.703
		(0.03)		(-1.32)		(0.54)
Alpha	0.252***	0.255***	0.279***	0.296***	0.229	0.228
	(2.90)	(2.86)	(2.71)	(2.78)	(1.66)	(1.58)
N	80	80	40	40	40	40
R^2	0.011	0.012	0.038	0.049	0.002	0.007

Table 6

Distribution of returns to active intermediaries. We assume all unsold NFTs have no residual value or are evaluated at the price levels implied by the RSR or MCMC selection-corrected indexes at the end of the sample period. Active intermediaries are those who have purchased more than 30 NFTs in the sample period.

	Mean	SD	Min	p25	p50	p75	Max	Count
Return (zero residual value)	0.94	6.69	-1.00	-1.00	-0.85	0.04	73.39	199
Fee-adjusted	0.69	5.85	-1.00	-1.00	-0.87	-0.10	64.00	199
Return (MCMC residual value)	0.97	6.69	-1.00	-0.97	-0.76	0.04	73.40	199
Fee-adjusted	0.72	5.84	-1.00	-0.97	-0.79	-0.09	64.01	199
Return (RSR residual value)	3.42	10.75	-0.78	-0.36	0.05	2.04	99.93	199
Fee-adjusted	2.86	9.40	-0.81	-0.44	-0.08	1.65	87.19	199
# NFTs bought	92.98	108.99	30	39	57	95	951	199
# NFTs sold	17.47	38.14	0	0	5	17	310	199
Investment ($1000)	673.26	1,961.76	1.83	63.55	197.34	503.57	21,708.68	199
Entry date	0.40	0.16	0.01	0.29	0.4	0.49	0.97	199

Table 7

Results for the repeat-sales regressions augmented by investor and NFT characteristics. An interaction term between the duration of the repeat-sales pairs and a dummy variable for NFTs purchased by active intermediaries is added to the standard repeat-sales regressions. For conciseness, only the coefficients of the interaction terms are reported. Active intermediaries are those who have purchased more than 30 NFTs in the sample period. Even columns further split the NFT purchases by whether they are purchased in the early or the latter half of the sample period (cut-off at September 2021). Estimated repeat-sales returns are not reported for conciseness. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
	Realized Returns Only		Unrealized Returns Included	
HoldTime × Active Intermediary Dummy	-0.67***		-0.45***	
	(-3.12)		(-3.80)	
HoldTime × Active Intermediary Dummy (Early Purchase)		-0.73***		-1.29***
		(-3.39)		(-10.53)
HoldTime × Active Intermediary Dummy (Late Purchase)		0.82		5.42***
		(1.41)		(19.07)
N	6,549	6,549	11,877	11,877
R^2	0.767	0.767	0.915	0.919

Table 8

Investment-value-weighted average monthly return of simulated trading strategies on the most liquid art NFTs in OpenSea. The strategies are restricted to the NFTs priced between the "Min Price" and the "Max Price." The mean and standard deviation (s.d.) of the returns in each of rows 8-10 are based on 200 simulation samples of randomly selected liquid art NFTs identified by the baseline strategy. Fee-adjusted returns are reported in brackets, assuming a 2.5% fee per sale before February 2023 and a 0.5% fee thereafter through 2024.

	Min Price	Max Price	Additional Modification	Average Monthly Return [Fee-adjusted]	Transactions per Month
(1)	100	10,000	None, Baseline	5.04% [2.73%]	807
(2)	100	10,000	Include wash-traded NFTs	4.70% [2.54%]	1,648
(3)	10	10,000	None	5.19% [2.89%]	1,226
(4)	1	10,000	None	5.38% [3.08%]	1,457
(5)	100	1,000	None	3.11% [1.11%]	627
(6)	100	100,000	None	1.80% [-0.53%]	825
(7)	100	1,000,000	None	-0.47% [-2.74%]	826
(8)	100	10,000	Random 5% NFTs	2.95% ± 12.18% (2 s.d.)	
(9)	100	10,000	Random 10% NFTs	4.23% ± 10.92% (2 s.d.)	
(10)	100	10,000	Random 20% NFTs	5.01% ± 8.07% (2 s.d.)	
(11)	100	10,000	Drop the 10 most profitable purchases	3.85% [1.56%]	
(12)	100	10,000	Drop the 100 most profitable purchases	-0.57% [-2.74%]	
(13)	100	10,000	Year 2021 and before	14.33% [11.47%]	534
(14)	100	10,000	Year 2022 and later	-1.26% [-3.20%]	898

Table 9

Top 10 collector communities in OpenSea identified based on portfolio similarity between collectors, along with the top 3 most-purchased collections in each community. Collectors are defined as buyers (wallets) who never sell. Collections are ranked by purchase frequency, scaled by the log of overall purchases in the sample. The sample window is from January 2023 to December 2024.

Community	# Collectors	Top Collection Name	Rank	# Purchases	Scaled Freq.
1	456	The Memes by 6529	1	1250	0.227
		MAX PAIN AND FRENS	2	338	0.187
		DAMAGE CONTROL	3	201	0.110
2	410	Memeditions by Yonvisuals	1	666	0.304
		NessGraphics Open Editions	2	293	0.136
		Proceed w/ Caution	3	422	0.134
3	409	MERGE VV	1	1592	0.525
		Opepen Edition	2	409	0.140
		Checks - VV Edition	3	261	0.107
4	363	Checks - VV Originals	1	745	0.296
		Trademark by Jack Butcher	2	825	0.292
		Opepen Edition	3	814	0.280
5	360	if you're here, you're based and early	1	1192	0.449
		swatches by jvmi	2	594	0.220
		follow the white rabbit	3	339	0.195
6	330	Crowd	1	486	0.268
		Notable Pepes	2	241	0.130
		AIORBIT	3	104	0.083
7	323	UNITS	1	994	0.211
		Crowd	2	301	0.179
		This Artwork Is Subject To Change	3	729	0.178
8	283	Opepen Edition	1	416	0.348
		Checks - VV Edition	2	320	0.304
		The Memes by 6529	3	153	0.079
9	262	Pi DAO Club	1	928	0.726
		Crypto Dragon King Club	2	841	0.646
		Voice NFT for Vcity	3	97	0.040
10	257	Notable Pepes	1	377	0.257
		The Memes by 6529	2	422	0.213
		STM!	3	498	0.212