Trading at Round Numbers

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Abstract

Prices of real and private-value assets such as artworks and houses have a strong tendency to cluster at round values. Why? We argue that, first, some investors in these markets operate on coarse valuation grids leading them to use round offers and list prices, and, second, any investor's tendency to round is a function of both their level of informedness and whether they are buying for financial or non-financial reasons. We develop a simple conceptual framework formalizing these hypotheses and find empirical support for the resulting predictions in data from two distinct NFT marketplaces.

Keywords: art valuations; rounding; information; collectors; speculators; list prices; offers; NFTs.

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1 Introduction

Prices of artworks and houses have a tendency to cluster at round values. In markets for such real and private-value assets (Goetzmann et al. 2021), each transaction can be considered the outcome of a different search-and-bargaining process, and agents often use round numbers both when posting prices or when making offers. Why? In this paper, we use detailed data from the market for non-fungible tokens (NFTs) to test two related hypotheses. First, some buyers and sellers operate on a coarser valuation grid than others. Second, the granularity of an agent's grid is a function of both their level of informedness and the extent to which they are investing for non-financial reasons.

To motivate these propositions, let us sketch a simple valuation model that takes into account the dual nature of real and private-value assets as consumption goods and financial investments. Denote by $V_{i,t}$ an agent i's valuation of a unique durable utility-bearing asset at time t. If the agent expects to hold the asset until time t', we can put more structure on this valuation by defining it as the sum of the present value of (common) resale revenues and the present value of the (private) utility stream until resale:

$$V_{i,t} = PV_t(revenues_{t'}) + PV_t(enjoyment_{i,t \to t'}). \tag{1}$$

In the spirit of Grossman and Stiglitz (1980) and Ball et al. (1985), $V_{i,t}$ is an "equilibrium valuation": it only incorporates agent i's information up to point where the marginal cost of information acquisition equates the marginal benefit. Every agent will thus be uncertain about their valuation. Like Ball et al. (1985), we conjecture that this noise, combined with a well-documented human tendency to round in the face of uncertainty, leads agents to "quote" their valuation as follows:

$$V_{i,t}^{*} = V_{i,t} + \rho^{k_{i,t}}(V_{i,t}). \tag{2}$$

$V_{i,t}^{*}$ is now the number that an agent would report if asked for their valuation, and $\rho^{k_{i,t}}(V_{i,t})$ is an adjustment term that rounds $V_{i,t}$ to the nearest k dollars. A casual look at prices in different markets tells us that the degree of valuation "resolution" k—the extent of rounding—is very context-specific. While it might be 100 (dollars) for many used car market participants, maybe it is 1 million for owners of Picasso paintings.

So what can we say about the drivers of k, i.e., of the granularity of the relevant valuation grid, for any combination of asset, agent, and time period? The above model naturally generates a role for two different factors. First, all else equal, investors that are less certain about the revenues from resale will have more noisy valuations and hence a higher k. Prior literature focusing on financial assets has indeed argued that the level of informedness about market conditions may matter (e.g., Kuo et al. (2015)). To quote Ball et al. (1985), "one can only quote prices as precisely as one can estimate them". Yet, this hypothesis has been hard to test outside of the lab. In many empirical settings, we only observe price realizations and not which actions (e.g., listings, bids) by which agents have led to these outcomes. Moreover, we typically cannot track market participants' behavior over different assets, making it impossible to study persistence in the use of round numbers or to link it to investor characteristics. Therefore, one goal of this paper is to leverage the uniqueness and comprehensiveness of our NFT data to re-examine the old question of whether the clustering of prices at round values is at least partially driven by the behavior of lesser-informed market participants.

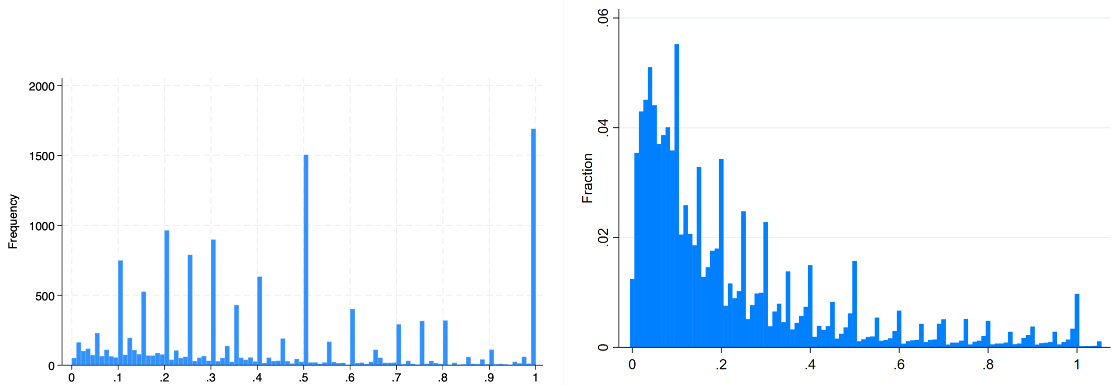
Second, both the relative importance of the future enjoyment dividends in Eq. (1) and average holding periods $t' - t$ will be higher for "collectors" than for "flippers" (Lovo and Spaenjers 2018). Naturally, there can be more noise about $V_{i,t}$ if t' is further in the future. It also seems natural to assume that individuals have imprecise preferences over their future real asset consumption (Butler and Loomes 2007; Pope et al. 2015), implying that future enjoyment dividends are harder to estimate than resale values. Hence, we can hypothesize that agents who derive a relatively high enjoyment of ownership will be more likely to round than financially-motivated agents who buy with the intention of reselling quickly.

The testing ground for our analysis is the market for NFTs, which are blockchain-based digital assets most commonly associated with digital artwork or collectibles. They are traded in online peer-to-peer marketplaces that provide multiple ways to transact. In particular, sales can result both from a buyer agreeing to pay the listed price or from an owner accepting an offer on their NFT. Many platforms also allow for auctions, but such trades constitute a small share of total volume and we will ignore them here. Our main analysis uses data from SuperRare, a marketplace for single-edition NFTs. Our data set contains all events (listings, offers, transactions) on the platform between its launch in April 2018 and October 2021. We also consider transaction-level data captured on the Ethereum blockchain for a set of roughly 700 NFT collections (e.g., Bored Ape Yacht Club) launched between March 2021 and September 2021. Relative to SuperRare, these data only include realized transactions but in terms of empirical analysis they provide the benefits of a larger sample size of trades and cross-section of groups of related tokens. We will refer to this data set as "OpenSea" given that nearly all of the transactions occurred on that platform.

In both data sets, we classify a list price or offer as "round" if it is a a multiple of 0.01 for amounts up to 0.50 ETH, a multiple of 0.05 for amounts from 0.50 to 1 ETH, a multiple of 0.10 or 0.25 for amounts from 1 to 5 ETH, a multiple of 1 for amounts from 5 to 20 ETH, and a multiple of 5 for amounts higher than 20 ETH. Figure 1 shows histograms of prices in the interval between

0 and 1 ETH for our two data sets. In both cases, the jumps at round numbers are striking. The majority of prices shown here are round according to the definition above.

Figure 1. Transaction Prices Up to 1 ETH by Platform



Panel A. SuperRare

Panel B. OpenSea

Clustering of transactions at round price levels such as documented in Figure 1 does not imply that these trades are "special"; they might simply emerge from a human tendency to round shared by all market participants. Instead, we are interested in testing that there exists heterogeneity in the resolution of market participants' valuation grids—and thus in their propensity to trade at round numbers—that is both systematic and predictable. As such, our empirical analysis is composed of two main parts.

In the first part, we want to test the hypothesis that the clustering of prices at round numbers reflects the fact that some buyers and sellers operate on a coarser price grid than others. Because this hypothesis is impossible to test directly, we need to focus on a number of implications. To structure our empirical analysis in this respect, we develop a simple conceptual framework of NFT trading illustrating how systematic differences in valuation grids can be expected to affect investment decision-making and outcomes. In our set-up, some investors always have precise valuations, while the valuations of other investors move on a coarse grid of round numbers. The game starts with a listing by one agent; another agent then either buys at the list price or makes a (counter)offer, depending on their own valuation. We assume that offers are always truthful; we thus abstract away from any forms of strategic behavior.

Our stylized framework delivers a variety of empirical predictions. First, the use of round numbers should be relatively persistent. Second, our model predicts lower returns on resales at round list prices but higher returns on transactions where a round offer is being accepted. Third, round list prices are associated with lower counteroffers. Fourth, round offers are more likely to be accepted if the list price is round as well. Fifth, round list prices are adjusted more slowly but more substantially—and to other round levels. We find empirical support for all these predictions in our NFT data.

In the second part of our empirical analysis, we study whether the use of round numbers is a function of agents' level of informedness and of the extent to which they are investing for non-financial reasons. We find evidence in support of these conjectures. We show that more experienced NFT market participants are less likely to make round offers or use round list prices. We also document that sophisticated, profit-motivated NFT wash traders are less likely use round numbers while bidding, while the opposite is true for NFT artists that are collecting their colleagues' work. Finally, we show that those who act like collectors (as opposed to speculators) on OpenSea are more likely to transact at round prices.

1.1 Related literature

Our paper contributes to different strands of the literature. First, there is a long literature, going back to at least Niederhoffer (1965), documenting clustering of asset prices at round numbers. A number of papers relate this clustering to the use of round numbers as cognitive short cuts or reference points when information acquisition is costly (Ball et al. 1985; Bhattacharya et al. 2012; Kuo et al. 2015). A larger literature in economics and psychology studies the relation between uncertainty and rounding (see, for example, Binder (2017) and the references therein). We propose a new framework based on valuation grids to analyze investor behavior in markets for real and private-value assets. We link to existing studies focusing on the use of round numbers as a function of investor informedness by testing whether experienced investors are less likely to use round numbers. However, we also propose and empirically test the hypothesis that buyers that are less financially motivated may be more likely to use round numbers.

Second, a number of papers have studied the effects of the use of round vs. non-round list prices or offers on outcomes in bargaining settings. A number of papers have argued that use of round numbers is associated with unfavorable outcomes, for example in the context of M&A negotiations (Hukkanen and Keloharju 2019) or real estate transactions (Mateen et al. 2023). Such findings are in line with a literature in psychology arguing that precise numbers are more powerful anchors (Janiszewski and Uy 2008), and that negotiators making precise offers are perceived to have more knowledge of the value of the underlying good (Mason et al. 2013). By contrast, Backus et al. (2019) develop a model in which round list prices can be used by a seller to credibly signal their impatience; using data from eBay, they show that round initial list prices are associated with lower (counter)offers but faster sales. In developing our empirical predictions, we will abstract from such strategic-competitive interactions between market participants. Our goal is to study how far we can get in explaining empirical patterns associated with round numbers with a very simple framework focused on heterogeneity in investors' valuation grids.

Finally, we contribute to the nascent literature on the markets for NFTs. Nadini et al. (2021) and Borri et al. (2022) describe the market structure and recent price history for the NFT market. A longer-run art historical and cultural perspective is offered by Whitaker and Burnett Abrams (2023). Oh et al. (2023) model NFT collections as digital Veblen goods. Sun (2023) highlights the importance of personal experience effects for NFT trading, while Huang and Goetzmann (2023) study the interaction of selection neglect with extrapolative beliefs. A number of papers have analyzed the price determinants of NFTs (see Kräussl and Tugnetti (2022) for a review), connecting to a literature that uses hedonic models and machine learning to understand art pricing (e.g., Renneboog and Spaenjers 2013; Aubry et al. 2020).

2 Data

We study two marketplaces within the Ethereum-based NFT market: SuperRare and OpenSea. While each one is comprised of NFTs associated with digital artwork, their institutional details differ and, as a result, their data provide distinct advantages for our empirical analysis. For example, we observe bids and offers in addition to the realized transactions within SuperRare. Hence we consider data from both in each step of our empirical analysis.

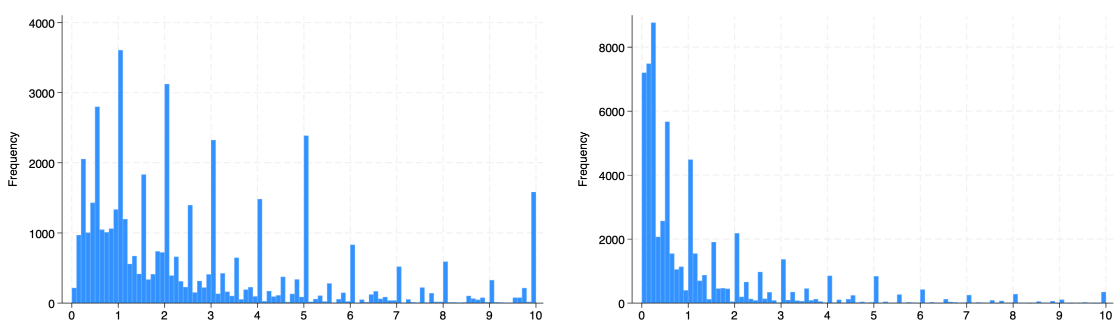
2.1 SuperRare

SuperRare is a peer-to-peer marketplace for "unique, single-edition digital artworks". Different from most of its competitors, it vets NFT artists through an application process. After an artist has minted an NFT on the SuperRare platform, three types of transactions can take place. First, collectors can always make offers on any artwork. Owners can choose to accept offers, in which case a transaction takes place, or ignore them entirely. Second, owners can set a list price on the artwork. Collectors can still make offers if there is a list price, but the list price is also available if the collector wants to quickly make a purchase without needing the seller to accept it. Third, since December 2020, SuperRare also allows owners to launch auctions.

SuperRare provided us with a data set containing all events on their platform between their launch in early April 2018 and mid-October 2021. We here focus on all instances where the owner (potentially the creator) listed an item for sale. (We remove instances where the list price equals zero.) We have data on 56,703 listings—where every listing or list price adjustment by an owner is considered a separate event—representing 15,958 different NFTs and 2,599 different owners (or, to be more precise, wallet addresses). We keep track of all offers after a listing. For 15.6% of listings we observe at least one offer. In terms of final observed outcome, 11.8% of listings result in a transaction at the list price and 8.1% in an offer being accepted by the owner. For the other listings we do not observe a transaction (at the list price or following an offer) before a list price adjustment, a transfer of ownership, or the end of our sample period.

The median list price is 2.5 ETH and the median offer (conditional on an item being listed) is 0.35 ETH. Panel (a) of Figure 2 shows a histogram of list prices, while panel (b) shows the distribution of offers (both truncated at 10 ETH). Given the clustering of transaction prices at round numbers that we documented in Figure 1, it is not a surprise that we see spikes in both panels at round values. The distribution of offers clearly is tilted more to the left than the distribution of list prices.

Figure 2. List Prices and Offers on SuperRare



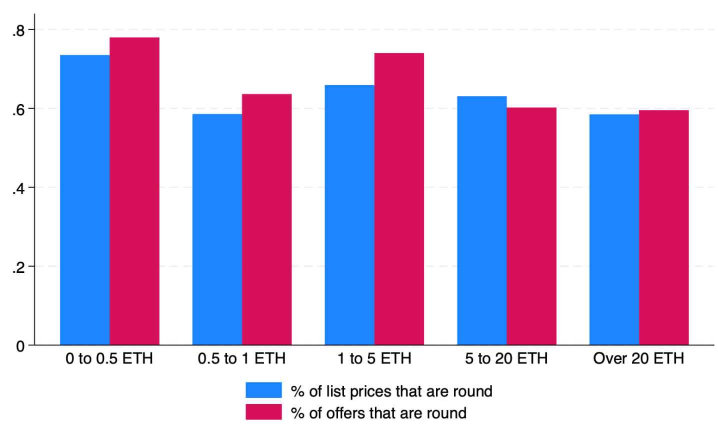
Panel A. List prices between 0 and 10 ETH

Panel B. Offers between 0 and 1 ETH

For our empirical analysis below, we classify a list price or offer as being "round" if it is: a multiple of 0.01 for amounts up to 0.50 ETH, a multiple of 0.05 for amounts from 0.50 to 1 ETH, a multiple of 0.10 or 0.25 for amounts from 1 to 5 ETH, a multiple of 1 for amounts from 5 to 20 ETH, and a multiple of 5 for amounts higher than 20 ETH.

64% of listings, 74% of offers, and 77% of transactions are associated with a round value. The correlation between transaction prices and our newly-created round number dummy is virtually zero, indicating that there is no mechanical relation between the two. Figure 3 shows the proportion of list prices and offers classified as round for each of the value bands introduced above.

Figure 3. Proportion of Round List Prices and Offers on SuperRare



2.2 *OpenSea*

Like SuperRare, OpenSea is a peer-to-peer marketplace for NFTs. However, OpenSea is open to listing all types of NFT collections from any blockchain. We gather data for and focus on Ethereum-based "generative" NFT collections (GCs) launched between March 2021 and September 2021. GCs are collections of NFTs for which the associated digital artwork features a common theme and each individual NFT represents a unique variation on that theme. Sometimes referred to as "profile picture collections" or "PFPs," GCs represented the majority of the NFT market during the period of our analysis and shaped the public perception of NFTs. For example, the Bored Ape Yacht Club, a well-known NFT collection that launched in April 2021, is a GC. Accordingly given their prominence, NFT-focused papers such as Oh et al. (2023) and Sun (2023) focus their analysis exclusively on GCs.

Our data include all secondary market transactions for our sample of GCs in the period March 2021 through March 2022. Unlike SuperRare, OpenSea data only include realized transactions. Therefore we cannot explore the presence of round prices in sequential bargaining as we can do with our SuperRare data. However, the OpenSea data offer two key advantages from the perspective of our empirical analysis. The first advantage of OpenSea data is sample size. We have a large cross-section of collections (692), corresponding set of secondary market transactions (3 million), and participating wallets (more than 0.5 million). Therefore we can control for aggregate and collection-level factors in our regression analysis using a multitude of fixed effects. The second key advantage of OpenSea data is the fact that the underlying NFTs are grouped by collection. Oh et al. (2023) show that the prices of individual NFTs within a collection are highly correlated. This fact means that, by controlling for collection, we control for an important source of variation in prices. It also affects the nature of price discovery because investors can infer an individual NFT's price from others in the same collection. We will leverage this aspect of the market when studying returns in the OpenSea data and interpreting the corresponding results.

We follow the same definition for a round price in the OpenSea data as described for SuperRare in the previous section. Approximately half of the transactions on OpenSea were done at a round price. One can also see in Figure 1 that the average price on OpenSea is lower than SuperRare and that the majority of prices were below 0.25 ETH.

3 Investors with Coarse vs. Fine Valuations

We want to start our empirical analysis by studying whether some investors move on a coarser valuation grid than others. This hypothesis is impossible to test directly, as we cannot observe investors' valuation grids. Therefore, we will focus on a number of implications that we can test using the actions and outcomes—list prices, offers, and transaction prices—that we observe.

3.1 Conceptual framework

To develop our empirical predictions on what patterns we can expect to see in the presence of systematic heterogeneity in valuation grids, we can build on the simple valuation framework presented at the start of this paper.

Consider a market in which one agent j lists an item at $t = 0$, and another agent i then either buys at the list or makes a (counter)offer at $t = 1$. Let us conjecture that there exist only two types of market participants: f has a fine valuation grid (i.e., $k_{f,t} = 0$ for any t) and c has a course valuation grid (i.e., $k_{c,t} > 0$ for any t). This means that the former would quote their valuation—the summed present value of resale revenues and enjoyment until resale—at time t as $V^*_{f,t} = V_{f,t}$, while the latter would quote it as $V^*_{c,t} = V_{c,t} + \rho^{k_{c,t}}(V_{c,t})$, which includes an adjustment term that rounds $V_{c,t}$ to the nearest k dollars.

Consider any asset that has been listed for sale by agent j at time $t = 0$ for a price equal to $L_{j,0}$. We assume that bidding is truthful. If the first agent to see the listing is of type f, they make a precise offer $B_{f,1} = V_{f,1}$, unless $B_{f,1} \geq L_{j,0}$ in which case f buys at the list.[1] If the first agent to see the listing is of type c, they make a round offer $B_{c,1} = V^*_{c,1}$, unless $B_{c,1} \geq L_{j,0}$ in which case c buys at the list.

Agents will always list at a price that exceeds what they would offer for the same item, i.e., $L_{j,t} > B_{j,t}$. Moreover, we will assume that the same kind of price resolution adjustment as before becomes relevant, as any uncertainty in terms of valuations will also spill over into uncertainty about appropriate list prices. Consider a function $l(.)$ that reflects agents' list price strategy. While $L_{f,t} = l(V_{f,t})$ represents a precise listing price, $L_{c,t} = l(V_{c,t}) + \rho^{k_{c,t}}(l(V_{c,t}))$ is a round number.

[1]There thus exists some frictions in investor behavior (e.g., limited attention) that creates a wedge between an owner's contemporaneous valuation on the one hand and their outstanding list price (which reflects a lagged valuation) on the other hand.

In case of an offer by an agent i on the item at time $t = 1$, selling agent j decides whether to accept the offer based on their time-1 valuation. They accept the offer if the bid is at least equal to their valuation, i.e., if and only if $B_{i,1} \geq V^*_{j,1}$.[2] If they do not accept the offer, they update their list price to $L_{j,1}$, and the game continues as before.

We want to explicitly acknowledge that, as a guide to our empirical predictions, the above framework abstracts from different types of strategic behavior. First, we assume that there is no strategic (lack of) rounding to influence other parties in the game. Second, agents do not infer—or act on their knowledge of—counterparties' valuation grids. Third, there is no competition between potential buyers, in the sense that only a single offer is made in every period. We do not want to claim that the NFT market is really this stylized or that agents in the market are this unsophisticated. Instead, the goal here is to see how far we can get in explaining empirical patterns with a simple framework that ignores strategic and competitive interactions and that does not depend on additional assumptions (e.g., distributional assumptions about investor types or assumptions about the time-series dynamics of investors' valuations).

3.2 *Persistence in use of round numbers*

In our simple model, a round price occurs either because an owner of type c successfully sold at their list price or because a bidder of type c had their offer accepted. If the clustering of NFT prices is indeed driven by the presence of market participants that move on a coarse valuation grid, then the use of round numbers should be relatively persistent. We can consider a number of simple correlations. We start by looking at either successive listings or successive offers by the same market participant. In our SuperRare data set, the correlation of the round list price indicator for a listing with the same indicator for the same wallet's previous listing is 0.40. When

[2] We thus assume that there is some value to trading, and that listing agent j is happy to sell as soon as there is a bid equal to their valuation.

we repeat the analysis for offers, the correlation is 0.22. Table I shows that both of these relations are also highly significant in a regression set-up where we control for year-month and NFT creator fixed effects.

Table I
SuperRare: Persistence of Round Price Usage

This table shows the results of OLS regressions where the dependent variable is a dummy variable indicating whether the list price is round or an offer is round. We run the regressions separately for listings and offers.

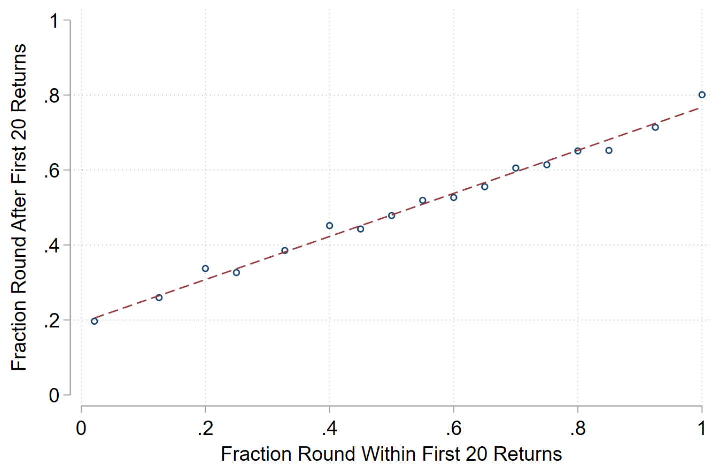
	(1) Round list price?	(2) Round offer?
Previous list was round	0.303***	
	(0.005)	
Previous offer was round		0.207***
		(0.004)
Year-month FE?	Yes	Yes
NFT creator FE?	Yes	Yes
Observations	35,008	56,613
R-squared	0.237	0.085

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We can also consider those market participants for whom we observe both listings and offers. As expected, we find a positive correlation between the use of round list prices and the use of round offers. When pooling data over the full sample period and limiting the analysis to the approximately 600 wallets with at least five listings and five offers, the correlation between the proportion of round listings and that of round offers amounts to a highly significant 0.24.

We also find a strong persistence in the rate of round price usage within the same investor in the OpenSea data. Here, we focus on a subset of wallets that realized at least 20 returns from a mint through a listing (i.e., not based on a bid). We do so to focus on high-volume wallets and also transactions in which the seller chose the price. We report our findings visually through the binned scatter plot in Figure 4, which compares the fraction of returns realized at a round price within and after the first 20 observed. The usage of round prices is clearly very persistent within a given wallet.

Figure 4. OpenSea: Persistence of Round Price Usage at the Wallet-Level



3.3 *Returns on resales*

Our simple model implies different relative price levels—and thus investment returns—associated with round-price transactions depending on whether the round outcome comes from a round list price or a round offer. First, we consider how relative investment performance correlates with transaction price roundness for transactions that take place at the list price. Let us compare an owner c to an owner f who is otherwise identical. If $\rho^{k_{c,0}}(l(V_{c,0})) < 0$, then a sale at the list price becomes more likely. The transaction price will be round and relatively low. If $\rho^{k_{c,0}}(l(V_{c,0})) > 0$, then a purchase at the (round) list price becomes less likely. Compared to transactions at a non-round list, resales at a round list should thus be associated with relatively low returns on average.

We test this prediction using our SuperRare data in columns 1–2 of Table II. We regress log total returns (in ETH) for items that we observe trading twice against a dummy that equals one if the resale price is round, limiting the analysis to resales at the list price. We control for both purchase and sale year-month fixed effects and transaction price category dummies (following the price bands introduced when defining roundness in the data section). In model 2, we also control for NFT creator fixed effects, as there might be systematic artist-level heterogeneity in both investment performance and the use of round numbers by collectors. Standard errors are clustered at the resale year-month level. The results show that resales at round list prices are associated with substantially lower capital gains between purchase and sale. In other words, if an item sells at a round list price, it may have been priced too cheaply by the owner.

Table II
SuperRare: Returns on Resales

This table shows the results of OLS regressions where the dependent variable is the log return on an NFT resale. We run the regressions separately for resales at the list price and resales that are generated by accepted offers. Standard errors are clustered at the resale year-month level.

	(1) Transactions at list	(2) Transactions at list	(3) Accepted offers	(4) Accepted offers
Round resale price	-0.365***	-0.366***	0.306**	0.298*
	(0.067)	(0.057)	(0.139)	(0.167)
Purchase and sale year-month FE?	Yes	Yes	Yes	Yes
Price band FE?	Yes	Yes	Yes	Yes
NFT creator FE?	No	Yes	No	Yes
R^2	0.331	0.539	0.305	0.496
N	2,966	2,812	1,466	1,317

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second, how can we expect price roundness to correlate with investment performance for transactions where a bidder's offer is accepted by the owner? Let us compare a potential buyer i of type f versus one of type c in their counteroffers in case of no purchase at the list price. A potential buyer of type c will make an offer $B_{c,1} = V^*_{c,1}$, compared to $B_{f,1} = V_{f,1}$ for a potential buyer of type f. If $\rho^{k_{c,1}}(V_{c,1}) > 0$, this makes the offer more likely to succeed; the offered price will be round and relatively high. By contrast, if $\rho^{k_{c,1}}(V_{c,1}) < 0$, this makes the offer less likely to succeed. Conditional on an offer being accepted, a round offer should thus imply a higher return for sellers on average. The results of this test can be found in columns 3–4 of Table II. As predicted, we find that resales at round offers are associated with substantially higher capital gains between purchase and sale. In other words, if an item sells after a round offer, this signals that the buyer may have overestimated its value.

We test a related hypothesis using returns in the OpenSea data. If a round purchase price signals that an investor paid too much for an NFT, the subsequent return from reselling it should be lower, all else equal.[3] We test this hypothesis by regressing returns on a round purchase price dummy and a multitude of fixed effects. Specifically, we control for the combination of transaction dates, NFT collection, and whether the purchase and sale legs of the return were achieved through a bid by the buyer.[4] Taken together, these fixed effects capture much of the variation that might otherwise explain an individual return. We also focus on returns from secondary market purchases given that purchase prices during mints are almost always round. We present our findings in Table III. Overall, we confirm that round purchase prices are associated with lower returns.

Table III
OpenSea: Returns on Resales

This table shows the results of OLS regressions where the dependent variable is the log return on an NFT resale. "IsBid" refers to whether the sale leg of the transaction was achieved through an offer by the ultimate buyer. "WasBid" refers to whether the purchase leg of the transaction was achieved through an offer by the initial buyer, which is investor who earns the return captured in the dependent variable. Standard errors are clustered at the resale date-collection level

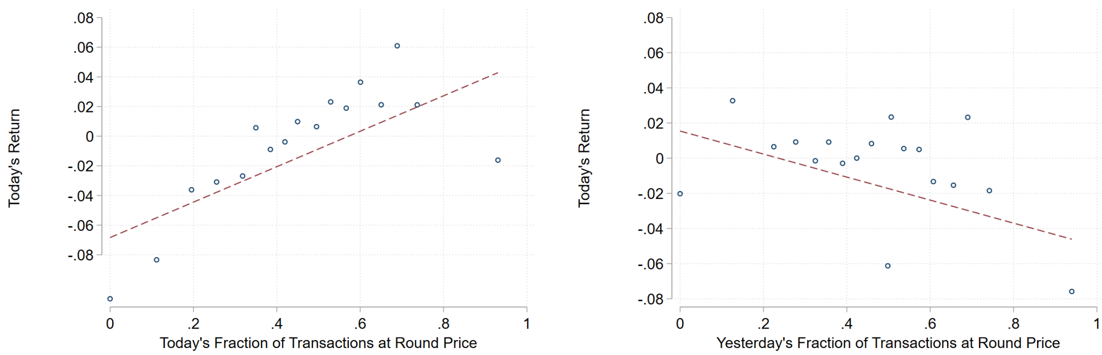
	(1)	(2)	(3)
Round purchase price	-0.048***	-0.047***	-0.037***
	(0.007)	(0.007)	(0.008)
SellDate-BuyDate-Collection FE?	Yes	No	No
SellDate-BuyDate-Collection-IsBid FE?	No	Yes	No
SellDate-BuyDate-Collection-IsBid-WasBid FE?	No	No	Yes
R^2	0.784	0.788	0.790
N	748,959	728,140	712,518

An additional benefit of the OpenSea data is that we can explore the connection between round price usage and returns at the collection-level. Given that the prices of NFTs within a

[3] Given the microstructure of the GC market, where every collection has a "floor", we are less likely to see listings or accepted offers at round prices that are relatively low. Our conceptual framework thus maps less directly into this market, and any round price is indicative of a relatively high valuation.

[4] In the OpenSea market, a transaction can be realized after a seller accepts a "bid" offer from a buyer. Such bids can be sent in response to an existing listing or unsolicited to the owner of the NFT. In the data, we only observe the final outcome, not the sequential bargaining process if there was one.

Figure 5. OpenSea: Round Price Usage and Collection-level Returns



collection are highly correlated (Oh et al. 2023), this allows us to consider how round price usage and NFT valuations are related. We measure collection-level price indexes on a daily basis using the median observed price if there were at least 5 transactions. A collection-level daily return is simply the percent change in the price index from the previous date provided both values are not missing (i.e., there were sufficient trades on each date).

In Figure 5, we observe that the fraction of round price transactions for a given collection are positively associated with the collection's relative price level on the same date, as measured by the daily estimated return. More interestingly, the round price fraction from the previous date is associated with lower collection-level returns on the following day. Taken together, these figures are consistent with the notion that round prices are too high.

3.4 *Relative size of counteroffers*

In the previous subsection, we looked at heterogeneity in the relative price levels associated with successful transactions at round vs. non-round numbers. In this and the next subsection, we dig deeper into listing-counteroffer dynamics. For this part of our analysis, we focus entirely on the SuperRare data in which we observe each step of the sequential bargaining process.

Let us again start by comparing an owner c to an owner f who is otherwise identical. It follows from the reasoning in the previous subsection that an item is more likely to remain unsold at the list price if $\rho^{k_{c,0}}(l(V_{c,0})) > 0$, meaning a round and relatively high list price. Given that counteroffers are truthful bids, this implies that these offers will be relatively low on average compared to the list price for round listings.

We take this prediction to the data in Table IV. In columns 1–2, the dependent variable is the ratio of the first offer to the list price. We control for year-month fixed effects and list price band fixed effects. Model 2 also controls for owner fixed effects, which means that we are exploiting within-seller heterogeneity in the use of round numbers across items. This mitigates worries that we are simply picking up some other investor characteristic that makes certain owners choose list prices that are both high and round. Standard errors are clustered at the owner level.

Table IV
SuperRare: Round List Prices and Counteroffers

This table shows the results of OLS regressions where the dependent variable is either the ratio of the first offer after a listing to the list price (columns 1–2) or the ratio of the accepted offer to the list price (columns 3–4). Standard errors are clustered at the owner level.

	(1) First offer	(2) First offer	(3) Accepted offer	(4) Accepted offer
Round list price	-0.030***	-0.031***	-0.042**	-0.049***
	(0.008)	(0.006)	(0.021)	(0.014)
Year-month FE?	Yes	Yes	Yes	Yes
List price band FE?	Yes	Yes	Yes	Yes
Owner FE?	No	Yes	No	Yes
R^2	0.173	0.371	0.204	0.572
N	8,769	8,265	1,716	1,493

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results in columns 1–2 are in line with our hypothesis: the first offer received by the owner is lower by about 3% of the list price if the owner sets a round list price. In columns 3–4 of Table IV, we repeat the analysis but now using the ratio of *accepted* offer price to list price. We find similar results.

3.5 *Probability of accepting counteroffers*

In the previous subsection, we studied the average magnitude of the counteroffers as a function of the roundness of the list price. We now want to look at the likelihood of a counteroffer being accepted by the owner. It is theoretically unclear whether a round offer has a higher unconditional probability of success; some round offers will be relatively high and others will be relatively low. However, a prediction of our model is that round offers should be more likely to be accepted if the list price itself is round. To see why, consider that a round list price signals that the seller is of type c. This means that they will accept an offer if and only if $B_{i,1} \geq V^*_{c,1}$. Now, compare the possible bids of a potential buyer of type c to an otherwise identical potential buyer of type f. The latter makes a precise offer of $B_{f,1} = V_{f,1}$. The potential buyer of type c will make a round offer $V^*_{c,t} = V_{c,t} + \rho^{k_{c,t}}(V_{c,t})$. If $V_{c,t} = V_{f,t}$, that means that type f's offer will be rounded upwards or downwards. Given that the seller is operating on a coarse valuation grid themselves, rounding downwards does not change the probability of a successful offer, while rounding upwards would increase the probability that the offer gets accepted.

We test this hypothesis in Table V. We regress a dummy variable indicating whether an offer is accepted by the owner against a dummy that equals one if the list price is round, a dummy that equals one if the offer is round, and—as our main variable of interest—a dummy variable interacting the previous two variables. We control for year-month fixed effects and list price band fixed effects as before, and in columns 2 and 3 we also control for NFT creator and owner fixed effects, respectively. As predicted, a round offer is more likely to be successful in case of a round list price.

Table V
SuperRare: Round List Prices and Round Counteroffers

This table shows the results of OLS regressions where the dependent variable is a dummy variable that equals one if an offer is accepted by the owner. Standard errors are clustered at the owner level.

	(1)	(2)	(3)
Round list price	-0.014	-0.003	-0.011
	(0.015)	(0.016)	(0.016)
Round offer	0.017	0.038**	0.035**
	(0.015)	(0.015)	(0.015)
Round list price x round offer	0.038**	0.029*	0.030*
	(0.018)	(0.018)	(0.018)
Year-month FE?	Yes	Yes	Yes
List price band FE?	Yes	Yes	Yes
NFT creator FE?	No	Yes	No
Owner FE?	No	No	Yes
Observations	14,771	14,653	14,412
R-squared	0.071	0.178	0.225

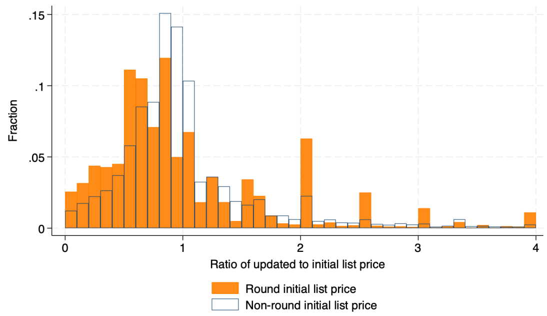
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6 *List price adjustments*

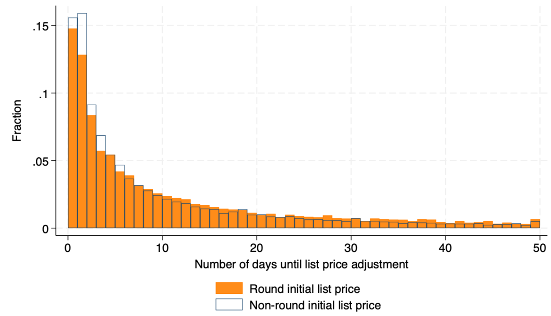
Our model implies that if an item is listed at a round price $L_{c,0}$ but does not sell, the owner will either not change the listing price or make a large adjustment—from one round value to a much lower or higher round value. The reason is that not every change in $V_{c,t}$ implies a change in list price, given that $L_{c,t} = l(V_{c,t}) + \rho^{k_{c,t}}(l(V_{c,t}))$. By contrast, if an item is listed at a non-round price $L_{f,0}$ but does not sell, the owner will likely make a small upwards or downwards list price adjustment, because every change in $V_{f,t}$ implies a change in list price.

Are list price adjustments indeed larger—but less frequent—for items listed at a round value? We consider all observations of list price adjustments. In Panel A of Figure 6, we show the distribution of new to old list prices separately for round and non-round (initial) list prices. Two patterns stand out. First, as expected, we find that downwards price adjustments tend to be larger for round list prices. Second, we see that upwards price adjustments cluster at round multiples (e.g., 0.5; 1.5; 2; etc.) for round (initial) list prices. In Panel B of Figure 6, we plot histograms of the

Figure 6. SuperRare: Size and Timing of List Price Adjustments



Panel A. Size of list price adjustments



Panel B. Timing of list price adjustments

number of days it took for the list price to be adjusted. In line with our stylized model, non-round list prices are adjusted faster.

4 Drivers of Investors' Valuation Grids

In the first part of our empirical analysis, we have established that the patterns associated with the use of round numbers in the data line up with the predictions of a simple model of heterogeneity in market participants' valuation grids. In this second part of our empirical analysis, we want to go a step further and examine what drives this heterogeneity.

4.1 Conceptual framework

Following Eq. (1), we can think of an agent i's valuation (before rounding) $V_{i,t}$ of an NFT as the sum of the present values of future resale revenues and of the stream of "emotional dividends" (Lovo and Spaenjers 2018) until resale. The more uncertain about this valuation an agent i is, the higher the degree of valuation resolution k will be, so that $V_{i,t}^*$ is more likely to be defined as a round number by the econometrician.

So what will drive this uncertainty—and thus the granularity of any agent's valuation grid? In the next subsections, we will test two hypotheses. First, all else equal, investors that are less informed about the market will have more noisy valuations, and thus be more likely to round. We will use past investment experience as a proxy for investors' market knowledge. Second, both the relative importance of the future enjoyment dividends in Eq. (1) and average holding periods $t' - t$ will be higher for "collectors" than for "flippers" (Lovo and Spaenjers 2018). Naturally, there can be more noise about $V_{i,t}$ if t' is further in the future. It also seems natural to assume that individuals have imprecise preferences over their future real asset consumption (Butler and Loomes 2007; Pope et al. 2015), implying that future enjoyment dividends are harder to estimate than resale values. Hence, we can hypothesize that agents who derive a relatively high enjoyment of ownership will be more likely to round than financially-motivated agents who buy with the intention of reselling quickly.

4.2 *Role of investment experience*

If worse-informed market participants are more prone to rounding behavior, we can expect a negative correlation between their NFT investment experience and the use of round list prices. We test this prediction using our SuperRare data in Table VI. We use OLS to estimate linear probability models where the dependent variable is a dummy variable that equals one for round list prices. The independent variables measure the cumulative number of sales, purchases, or bids until the month prior to the listing of interest. We control for year-month and NFT creator fixed effects throughout. For each independent variable we run a specification without and with owner fixed effects. Standard errors are clustered at the level of the owner. The results show that the use of round list prices is negatively correlated to the NFT owner's market experience. The coefficient remains strongly significant for seller experience once exploiting within-owner variation in experience and rounding behavior only.

We observe the same pattern in the OpenSea data: the fraction of returns realized at a round

Table VI
SuperRare: Experience and Use of Round List Prices

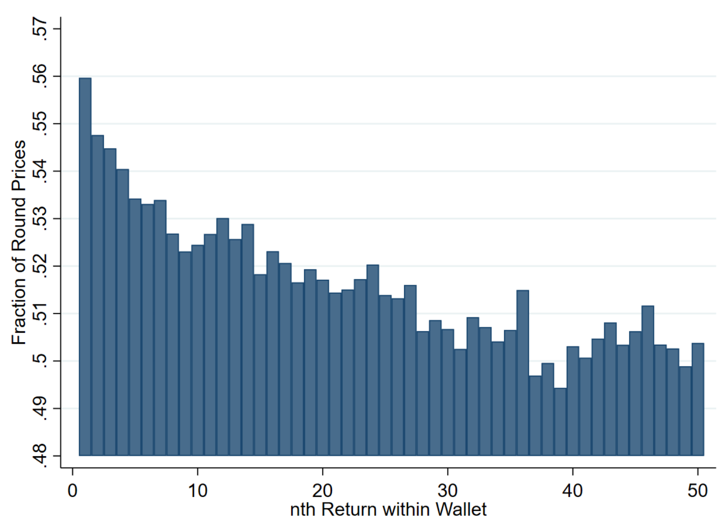
This table shows the results of OLS regressions where the dependent variable is a dummy that equals one if a list price is round. The numbers of sales, purchases, and bids are measured at the wallet level, and take into account all observable events in the SuperRare marketplace until the month prior to the listing. Standard errors are clustered at the owner level.

	(1)	(2)	(3)	(4)	(5)	(6)
Ln(no. of sales)	-0.024**	-0.038***				
	(0.010)	(0.014)				
Ln(no. of purchases)			-0.034***	-0.001		
			(0.011)	(0.013)		
Ln(no. of bids)					-0.025***	-0.002
					(0.009)	(0.010)
Year-month FE?	Yes	Yes	Yes	Yes	Yes	Yes
NFT creator FE?	Yes	Yes	Yes	Yes	Yes	Yes
Owner FE?	No	Yes	No	Yes	No	Yes
R^2	0.145	0.310	0.143	0.311	0.139	0.303
N	53,198	52,977	47,312	46,747	50,283	49,833

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

price decline as investors gain more experience. In Figure 7, we depict this fraction based on the nth return obtained through a listing (i.e., not through a counteroffer).

Figure 7. OpenSea: Round Price Usage and Experience



4.3 *Speculators vs. collectors*

Are financially-motivated market participants, whose valuations mainly stem from expected revenues from resales in the near future, less likely to use round numbers? To address this question, we categorize investors based on their observable behavior on the blockchain.

When analyzing our SuperRare data, we focus on two proxies that align with investor motives. First, we use data from blockchain analytics platform Nansen to identify wallets that have engaged in "wash trading" (anywhere in the NFT market). Wash trading is artificial trading between different wallets owned by the same individual with the intention to boost volume or reported prices for a collection. Arguably, such a strategy will only be used by quite sophisticated profit-seeking market participants. Not surprisingly, in our data less than 1% of offers are done by bidders labeled as wash traders. Second, some of the bidders and buyers on the SuperRare platform are artists themselves, collecting works by their colleagues. This is the case for almost 9% of the offers in our data set. Arguably, these market participants are less likely to be buying with the expectation of making a quick profit.

Table VII
SuperRare: Bidder Characteristics and Use of Round Offers

This table shows the results of OLS regressions where the dependent variable is a dummy that equals one if an offer is round. Standard errors are clustered at the bidder level.

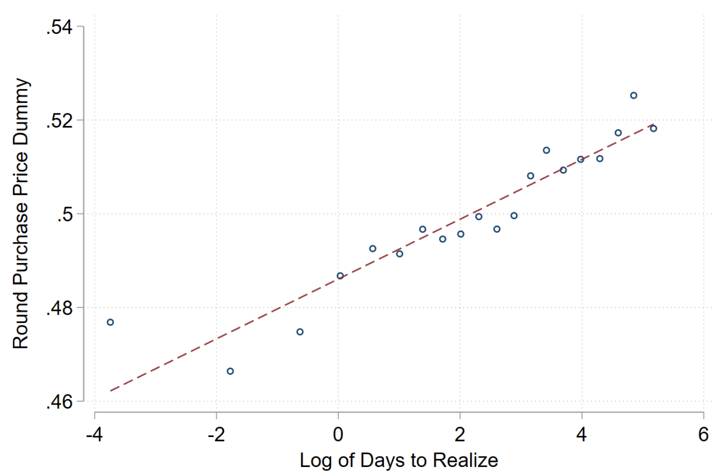
	(1)
Bidder is wash trader	-0.105**
	(0.050)
Bidder is artist	0.076***
	(0.017)
Year-month FE?	Yes
NFT creator FE?	Yes
Observations	52,725
R-squared	0.052

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We the regress a round offer indicator variable against these newly-constructed bidder-level variables and similar controls as before. The results are shown in Table VII. We find statistically and economically significant evidence in support of our predictions. Bidders labeled as wash traders are about 10 percentage points less likely to put in a round offer, while artists are almost 8 percentage points more likely to use a round number when bidding.

Within our OpenSea data, we ask whether investors who purchased NFTs in the secondary market at round prices subsequently hold their purchases for longer. Such behavior would be consistent with an NFT collector as opposed to a flipper. We find and depict this positive correlation in Figure 8, which is a binned scatter plot comparing round purchase price usage and the log of the subsequent holding period. Overall, this figure supports the notion that those who act like collectors (as opposed to speculators) on OpenSea are more likely to transact at round prices.

Figure 8. OpenSea: Round Price Usage and Holding Period



5 Conclusion

Prices of real and private-value assets such as artworks and houses have a strong tendency to cluster at round values. Why? We argue that, first, some investors in these markets operate on coarse valuation grids leading them to use round offers and list prices, and, second, any investor's tendency to round is a function of both their level of informedness and whether they are buying for financial or non-financial reasons. We develop a simple conceptual framework formalizing these hypotheses and find empirical support for the resulting predictions in data from two distinct NFT marketplaces.

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