Valuation Precision and Economic Outcomes

Samuel Rosen and Christophe Spaenjers*

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Abstract

Markets aggregate agents' valuations through prices and trades, yet agents may differ in how precisely they form and express those valuations. We study persistent heterogeneity in valuation precision and its implications for bargaining behavior and economic outcomes. Using transaction-level data from decentralized non-fungible token markets without mechanical pricing constraints, we show that round pricing reveals stable, agent-level differences in valuation precision. Rounding behavior predicts systematic variation in listing choices, counteroffers, price adjustments, and realized returns. Decomposition analyses show that investor heterogeneity explains a substantial share of rounding behavior beyond price-level focal points and asset-specific conditions.

Keywords: valuation precision; price clustering; round numbers; investor heterogeneity.

JEL Codes: G14, D83, D91

*Rosen (sir@temple.edu) is at the Fox School of Business, Temple University. Spaenjers (christophe.spaenjers@colorado.edu) is at the Leeds School of Business, University of Colorado Boulder. We thank the SuperRare team for sharing data, and Will Goetzmann, Brian Waters, Amy Whitaker, Anthony Zhang, and participants at the CFDM Brown Bag at CU Boulder, the Interdisciplinary Brown Bag at Temple University, the 2024 Paris December Finance Meeting, and the 2025 Eastern Finance Association Annual Meeting for valuable comments and feedback.

1 Introduction

Markets aggregate agents' valuations through prices and trades. While most economic models focus on heterogeneity in the level of willingness to pay, they typically abstract from differences in how precisely agents form and express those valuations. Yet in many decentralized markets, prices cluster disproportionately at round values, even when pricing is unconstrained by tick sizes or quoting rules. We interpret this clustering as evidence of heterogeneity in valuation precision and study whether such heterogeneity is persistent, economically meaningful, and consequential for bargaining behavior and market outcomes.

A large literature documents price clustering at round values across financial and real-asset markets (e.g., Niederhoffer 1965; Harris 1991; Ball et al. 1985; Ikenberry and Weston 2008; Bhattacharya et al. 2012; Pope et al. 2015). Existing explanations emphasize several mechanisms, including focal price levels, asset-specific conditions, strategic considerations in bargaining, and limits to information processing and numerical precision (e.g., Binder 2017; Han et al. 2025; Janiszewski and Uy 2008; Kandel et al. 2001; Kuo et al. 2015; Lin and Pursiainen 2021; Mason et al. 2013; Mateen et al. 2023; Thomas et al. 2010). In traditional markets, several institutional features obscure inference. Tick sizes and quoting conventions mechanically generate price clustering even when underlying valuations are continuous. Researchers typically observe only final transaction prices rather than the full sequence of listings, offers, counteroffers, and price adjustments. Market participants are often anonymous and difficult to track across assets and over time. These limitations make it challenging to separate investor-level heterogeneity from other factors, i.e., to assess whether round pricing primarily reflects persistent differences across agents in how precisely they value assets or instead is generated by transitory market features.

We overcome these challenges using detailed transaction-level data from non-fungible token (NFT) markets. NFTs are blockchain-based digital assets that resemble real and private-value assets: each token is unique and traded through decentralized peer-to-peer transactions. As in other private-value markets, valuations reflect both resale considerations and consumption or enjoyment benefits (Whitaker and Abrams 2023).

Two features of NFT markets provide unusually sharp empirical leverage. First, some platforms record listings, offers, accepted offers, and list-price adjustments on-chain, allowing us to observe the bargaining path rather than only the final price. Second, wallets are persistent and identifiable across assets and over time, which allows us to study investor behavior, experience, and heterogeneity directly. At the same time, prices are not constrained by tick sizes or centralized quoting rules, making NFT markets a natural laboratory for studying voluntary price discretization. This empirical leverage parallels recent work that exploits detailed bargaining sequences in real-world markets to study fundamental properties of negotiated outcomes (e.g., Backus et al. 2020; Larsen 2020).

To organize the analysis, we adopt a parsimonious valuation-grid framework in which investors differ in the precision with which they form and express valuations. Agents with fine grids state precise prices, while agents with coarse grids systematically round to salient values. The framework is not intended as a psychological model of numerical cognition, but rather as an organizing device that clarifies how heterogeneity in valuation precision maps into observable predictions for listings, offers, bargaining dynamics, and transaction outcomes. Within this framework, round pricing can arise through three channels: price-level focal points common to all agents; asset-specific conditions that shift the range of plausible valuations; and persistent differences across investors in valuation precision and participation motives.

We bring this framework to the data using two complementary sources from the Ethereum NFT ecosystem. The first is SuperRare, a curated marketplace for single-edition digital artworks. On SuperRare, we observe listings, offers, accepted offers, and list-price adjustments at the NFT level, which allows us to study bargaining paths and counteroffers directly. The second is a large transaction-level dataset of Ethereum-based generative collections (the GC Ethereum, or GCE, dataset) introduced by Oh et al. (2025). This dataset aggregates millions of secondary-market trades across major platforms such as OpenSea and Blur, providing dense cross-sectional and time-series coverage across thousands of collections. While the GCE data do not include listings or offers, they are well suited for analyzing persistence in investor behavior, experience effects, and collection-level price dynamics.

Our empirical analysis proceeds in three steps. First, we test whether investors behave as if they operate on valuation grids of different granularity. Using SuperRare data, we show that round-price usage is highly persistent within wallets; that round list prices and offers predict distinct bargaining dynamics, including concession patterns and acceptance probabilities; and that round list prices are adjusted less frequently but by larger amounts, typically between round values. Using the GCE data, we document persistent within-wallet rounding behavior across trades, show that round purchase prices predict lower subsequent resale returns, and find that collections with a high share of round-price trades experience lower short-run returns. Together, these results indicate that valuation precision leaves systematic footprints in prices, bargaining paths, and returns.

Second, we examine the sources of heterogeneity in valuation precision. Consistent with the framework, we find that more experienced traders are less likely to use round prices, suggesting finer valuation grids as investors learn about the market. Using external blockchain analytics labels, we show that wallets identified as wash traders, plausibly reflecting sophisticated, profit-motivated behavior, are significantly less likely to submit round offers. In contrast, NFT artists who collect peers' work and wallets that behave like long-horizon collectors are more likely to transact at round prices. These patterns support the interpretation that valuation precision varies systematically with investor type and motivation.

Third, we quantify the relative importance of price-level, asset-level, and investor-level forces using a Shapley value decomposition. Applying this approach to linear probability models of round-price usage in the GCE data, we show that while price-level focal points and collection-by-date conditions explain meaningful variation, investor identity—particularly when allowed to vary over time—accounts for the largest share. Static wallet effects explain roughly one quarter of the explained variation, while wallet-by-date effects account for nearly one half, with the remainder split between price-level and asset-level components. These results highlight investor heterogeneity as a central driver of observed price discretization.

This paper makes two contributions. First, we document persistent heterogeneity in valuation precision using round pricing as a revealed, agent-level measure in decentralized

markets without mechanical pricing constraints. While price clustering has been widely documented in financial and real-asset markets (e.g., Niederhoffer 1965; Harris 1991; Ball et al. 1985; Bhattacharya et al. 2012; Pope et al. 2015), existing evidence has largely focused on transaction-level regularities rather than stable differences across market participants. We show that rounding behavior is highly persistent within investors and systematically predicts bargaining paths, price adjustments, and transaction outcomes. Valuation precision varies with experience and investor type, and these differences are associated with predictable patterns in negotiation dynamics and realized returns, consistent with evidence that market experience disciplines behavioral regularities in field settings (List 2003). By linking a stable agent-level attribute to observed bargaining paths and outcomes, our analysis complements recent field evidence that uses rich negotiation sequences to study economically meaningful heterogeneity in bargaining environments (e.g., Larsen (2020); Backus et al. (2020)). Together, these results establish valuation precision as a persistent and economically meaningful investor characteristic, extending empirical work on bargaining and numeric precision in negotiated settings (Backus et al. 2019; Mateen et al. 2023).

Second, we provide a unified empirical decomposition of round-price usage that separates the roles of price-level focal points (Pope et al. 2015), asset-level conditions (Binder 2017), and investor-level heterogeneity (Kuo et al. 2015; Lin and Pursiainen 2021). Using a Shapley value decomposition, we show that investor-level components, particularly time-varying wallet behavior, account for the largest share of observed price discretization and exceed the contribution of asset-level fundamentals and price-level focal points. This decomposition demonstrates that round pricing is driven primarily by persistent differences in how agents express valuations, rather than by transitory market conditions or mechanical features of prices.

The remainder of the paper proceeds as follows. Section 2 presents the valuation-grid framework. Section 3 describes the data. Sections 4 and 5 present the empirical results. Section 6 provides the variance decomposition. Section 7 concludes.

2 Conceptual Framework

To formalize the sources of round-price usage emphasized in the introduction, we develop a simple conceptual framework in which investors differ in the precision with which they form and express valuations. The framework is intentionally parsimonious. Its purpose is not to model the full strategic or institutional complexity of NFT trading, but to isolate how heterogeneity in valuation precision shapes listing behavior, bargaining dynamics, and transaction outcomes in decentralized markets without mechanical pricing constraints.

We introduce a valuation structure that captures how heterogeneous valuation grids map into observable prices, offers, and bargaining paths. The framework serves as an organizing device that delivers transparent empirical predictions, which we test directly using the transaction-level blockchain data described in Section 3.

2.1 Valuations and Valuation Grids

Consider a unique, durable utility-bearing asset such as an artwork or NFT held by agent i at time t. Let $V_{i,t}$ denote i's pre-rounding valuation of the asset at time t, and suppose the agent expects to hold the asset until time t'. We can write

$$V_{i,t} = PV_t(\text{revenues}_{t'}) + PV_t(\text{enjoyment}_{i,t\to t'}), \tag{1}$$

where the first term is the present value of expected resale revenues at time t' and the second term is the present value of the flow of emotional dividends (Lovo and Spaenjers 2018) between t and t'. In the spirit of Grossman and Stiglitz (1980) and Ball et al. (1985), $V_{i,t}$ is an equilibrium valuation that incorporates information up to the point where the marginal cost of information acquisition equals the marginal benefit. Yet it remains noisy because both resale conditions and future enjoyment are uncertain.

Motivated by evidence that individuals round in settings with uncertainty or imprecision (e.g., Kuo et al. 2015; Binder 2017), we assume that agent i quotes a rounded valuation

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

where $\rho^{k_{i,t}}(\cdot)$ rounds to the nearest $k_{i,t}$ units. The parameter $k_{i,t}$ captures the resolution of the valuation grid at time t: small $k_{i,t}$ implies a fine grid (high precision), while large $k_{i,t}$ implies a coarse grid (low precision). We use a simple binary distinction in the theory for clarity, but in the data $k_{i,t}$ varies continuously across agents and over time. Our central hypothesis is that heterogeneity in $k_{i,t}$ manifests systematically in the use of round numbers when listing and bidding.

2.2 *Trading Mechanics and Heterogeneous Grids*

We introduce a stylized trading environment to map heterogeneity in $k_{i,t}$ into predictions for list prices, offers, and outcomes. Consider a market for a single asset in which an owner j lists the item for sale at time $t = 0$, and a potential buyer i either buys at the list price or makes a counteroffer at time $t = 1$. To highlight the role of valuation grids, suppose there are two types of agents:

- Type f (fine grid): $k_{f,t} = 0$ for all t, so $V_{f,t}^{*} = V_{f,t}$.
- Type c (coarse grid): $k_{c,t} > 0$ for all t, so $V_{c,t}^{*} = V_{c,t} + \rho^{k_{c,t}}(V_{c,t})$.

Agents list at prices strictly above what they would be willing to pay for the same asset. Let $l(\cdot)$ denote the underlying listing strategy, which we assume to be increasing in the valuation. Then

$$L_{f,t} = l(V_{f,t}), \qquad L_{c,t} = l(V_{c,t}) + \rho^{k_{c,t}}(l(V_{c,t})), \tag{3}$$

so type-c agents tend to post round list prices.

We assume truthful bidding. If agent i encounters the listing at time $t = 1$, they either buy at the list or place an offer:

$$B_{f,1} = V_{f,1}, \qquad B_{c,1} = V^*_{c,1}, \tag{4}$$

unless $B_{i,1} \geq L_{j,0}$, in which case they buy at the list price. The list price $L_{j,0}$ may lag the seller's current valuation $V^*_{j,1}$. This setup reflects frictions such as limited attention or rigid updating.

The seller accepts an offer if and only if it meets or exceeds their contemporaneous (potentially rounded) valuation:

$$\text{Accept at } t = 1 \iff B_{i,1} \geq V^*_{j,1}. \tag{5}$$

If the offer is rejected, the seller updates their list price to $L_{j,1}$ and the process repeats.

The framework abstracts from strategic or informational feedback. Agents do not choose $k_{i,t}$ strategically, do not infer types from observed prices, and only a single potential buyer arrives in each period. The goal is not to claim that NFT markets operate exactly in this manner but rather to show that a simple structure with heterogeneous rounding grids produces patterns that align with the data.

2.3 Empirical Predictions

The coarse-versus-fine grid structure generates several empirical predictions:

1. **Persistence in round-price usage.** A coarse-grid agent uses round numbers consistently across listings and offers, implying strong within-wallet persistence in round-price usage.

2. **Returns on resales at round list prices.** If a coarse-grid seller posts a round list price, sales that occur at the list price disproportionately reflect downward rounding, increasing the likelihood of sale at a relatively low price. Resales at round list prices should therefore be associated with lower realized returns on average.

3. **Returns following accepted round offers.** Coarse-grid buyers submit rounded offers. Although rounding can push offers above or below true valuations, accepted round offers are relatively high on average, implying higher realized returns for the seller.

4. **Relative size of counteroffers.** If a round list price does not immediately result in a sale, it is likely to be relatively high due to rounding. Given truthful bidding, first counteroffers should therefore lie farther below the list price on average for round listings.

5. **Acceptance of round counteroffers.** Upward rounding by coarse-grid buyers increases the probability that an offer meets a seller's coarse valuation threshold. As a result, round offers should be more likely to be accepted when the list price itself is round.

6. **List price adjustments.** Small valuation changes may not trigger adjustments for coarse-grid sellers, while larger changes lead to discrete jumps between round value. Unsold round listings should thus exhibit less frequent but larger price adjustments that cluster at round values, whereas non-round listings should adjust more quickly and in smaller steps.

Sections 4 and 5 test these predictions using the two datasets described next. The empirical focus is first on the implications for transaction outcomes and bargaining dynamics and then on the determinants of $k_{i,t}$ itself.

2.4 Determinants of Valuation Grids

The framework treats valuation precision, captured by the grid parameter $k_{i,t}$, as an economically meaningful but exogenous source of heterogeneity. In the empirical analysis, we examine how observed differences in valuation precision relate systematically to investor characteristics and trading behavior.

Two factors are of particular interest. First, informedness and experience. Investors who trade more frequently and acquire more market-specific information may form more

precise valuations, implying finer grids and less reliance on round numbers. Second, participation motives. Valuations combine expected resale revenues with enjoyment or consumption benefits. For short-horizon speculators, the resale component dominates and relates more closely to observable market conditions. For long-horizon collectors, the enjoyment component is harder to pin down (Butler and Loomes 2007; Pope et al. 2015; Lovo and Spaenjers 2018), meaning that they can be expected to operate on coarser grids than speculators. Section 5 evaluates these relationships empirically by linking observed rounding behavior to measures of experience, trading intensity, and investor type.

3 Empirical Setting and Data

We study two transaction-level datasets from Ethereum-based NFT markets: SuperRare and the GC Ethereum (GCE) dataset. The datasets are complementary for our purposes. SuperRare records the full sequence of listings, offers, accepted offers, and list-price adjustments, allowing us to observe bargaining paths directly. The GCE dataset provides a large, high-frequency panel of realized trades across thousands of collections and wallets, which is well suited for quantifying investor heterogeneity and estimating rich fixed-effects specifications.

Our study follows a small but growing literature that exploits the unusually transparent data generated by decentralized NFT markets to study fundamental economic questions (e.g., Lundy et al. 2025; Huang and Goetzmann 2023; Oh et al. 2025). Importantly for our analysis, NFT markets share key features with other decentralized trading environments in which prices are negotiated, agents differ in sophistication and objectives, and coarse adjustments play a central role in shaping outcomes (Goetzmann et al. 2021).

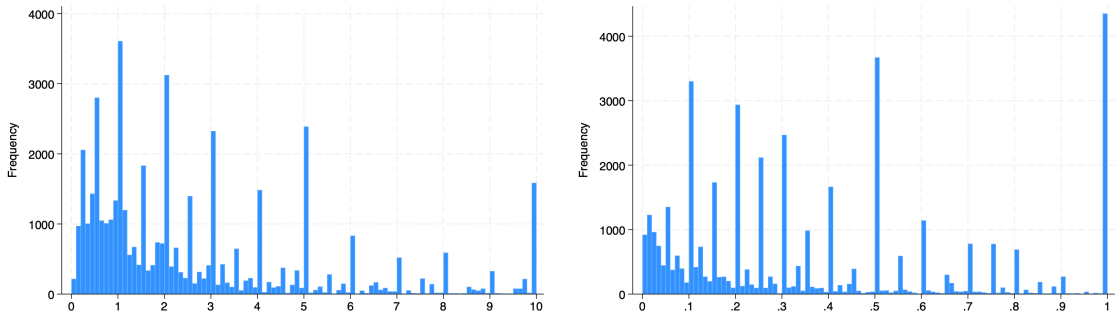
3.1 SuperRare

SuperRare is a peer-to-peer marketplace for unique, single-edition digital artworks. The platform vets artists through an application process. After an artist has minted an NFT on SuperRare, three types of transactions can take place. Collectors can make offers on

any artwork. Owners can set list prices. Since December 2020, owners can also initiate auctions.

SuperRare provided us with a dataset containing all events on their platform between early April 2018 and mid-October 2021. We focus on all instances where the owner listed an item for sale. We remove listings with price equal to zero. The resulting dataset contains 56,703 listings across 15,958 NFTs and 2,599 wallet addresses. We track all offers after a listing. For 15.6% of listings we observe at least one offer. In terms of final outcomes, 11.8% of listings result in a transaction at the list price and 8.1% in an accepted offer. The remaining listings do not result in a transaction before the list price is adjusted, ownership transfers, or the sample ends.

The median list price is 2.5 ETH and the median offer is 0.35 ETH. Figure 1 shows histograms of list prices and offers, truncated at 10 ETH and 1 ETH respectively. Both distributions exhibit spikes at round values.



Panel A. List Prices (0–10 ETH) **Panel B.** Offers (0–1 ETH)

Figure 1. List Prices and Offers on SuperRare

Notes: Histograms of list prices and offers on SuperRare. List prices are truncated at 10 ETH and offers at 1 ETH. Round-price definitions for SuperRare are described in Section 3.1.

For our analysis, we classify a list price or offer as round if it is a multiple of 0.01 for amounts up to 0.50 ETH, a multiple of 0.05 for 0.50 to 1 ETH, a multiple of 0.10 or 0.25 for 1 to 5 ETH, a multiple of 1 for 5 to 20 ETH, and a multiple of 5 above 20 ETH. These definitions reflect the coarser structure of prices in this thinner market. Using these definitions, 64% of listings, 74% of offers, and 77% of transactions are round. Figure 2 shows the proportion of list prices and offers classified as round within each value band.

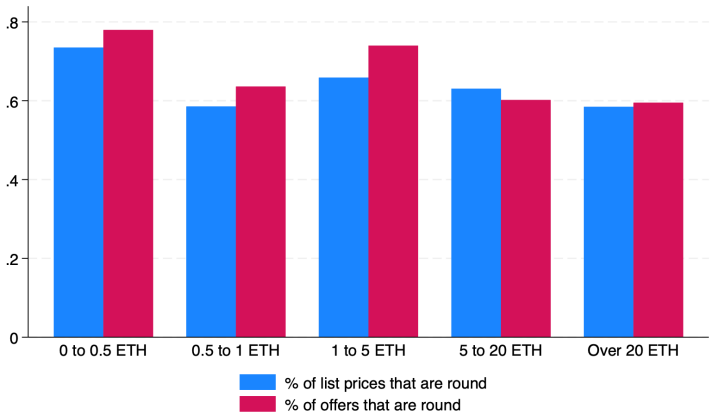


Figure 2. Proportion of Round List Prices and Offers on SuperRare
Notes: Bar chart showing the fraction of list prices and offers classified as round within each value band defined in Section 3.1.

3.2 GC Ethereum (GCE) Dataset

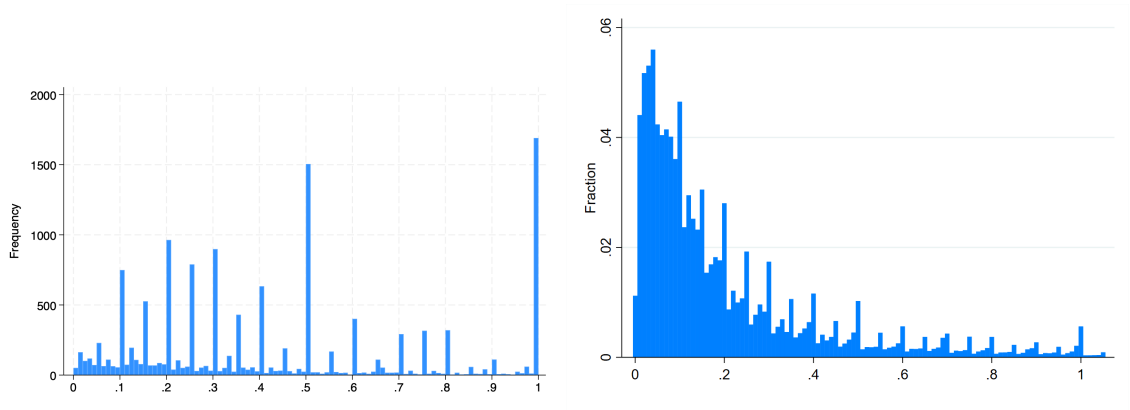
Our second dataset consists of secondary-market transactions for Ethereum-based generative collections (GCs). GCs are large, algorithmically generated sets of NFTs that share a common artistic template but differ in attributes. They represent a major segment of the NFT market and are the focus of Oh et al. (2025), which describes the institutional environment and documents the properties of the dataset.

The GCE dataset aggregates secondary-market trades across major NFT marketplaces, most notably OpenSea and Blur. This consolidation reflects the fact that NFT trading during 2021 to 2024 occurred across multiple venues. The dataset provides a comprehensive view of trading activity for the GC collections we study.

We focus on all secondary-market trades for the GCs identified in Oh et al. (2025). The dataset contains thousands of collections, millions of individual trades, and more than half a million unique wallets. Unlike SuperRare, we do not observe listings or bids, only realized transactions. This limits certain analyses but provides two key advantages. First, the scale of the data allows precise estimation of wallet-level heterogeneity and supports rich fixed effects. Second, prices within a collection tend to comove strongly, meaning that collection-level fixed effects capture much of the cross-sectional variation in valuations.

For the GCE data, where most transaction prices lie below 0.2 ETH and price increments are very fine, we adopt a transparent definition of round prices: a price is round if it is an exact multiple of 0.001 ETH. This definition is well suited to a high-frequency dataset with dense support over small price increments. We apply each round-price definition only within its respective dataset. We do not mix definitions across SuperRare and GCE.

Under the 0.001 ETH definition, approximately 80 percent of GCE transactions occur at round prices. Figure 3 shows that the distribution of transaction prices in the GCE dataset is heavily concentrated below 0.25 ETH.



Panel A. SuperRare Dataset **Panel B.** GC Ethereum Dataset

Figure 3. Transaction Prices Up to 1 ETH by Dataset
Notes: Histograms of transaction prices between 0 and 1 ETH for (a) SuperRare and (b) the GC Ethereum (GCE) dataset. Both datasets are described in Section 3.

4 Investors with Coarse vs. Fine Valuations

We begin by testing the core empirical predictions of the conceptual framework in Section 2 using our SuperRare and GCE datasets. The central question is whether observed pricing and trading patterns are consistent with persistent heterogeneity in valuation precision, with some investors operating on finer grids and others relying on coarser, round-number grids.

4.1 Persistence in Use of Round Numbers

A central implication of the conceptual framework in Section 2 is that if valuation precision is a persistent investor-level attribute, then rounding behavior should be stable within wallets over time. We begin with simple persistence measures based on successive actions by the same participant. In the SuperRare data, the correlation between the round-list indicator for a listing and the same wallet's previous listing is 0.40. For offers, the analogous correlation is 0.22. Table I shows that both relationships remain highly significant in regressions that control for year-month and NFT-creator fixed effects. These results indicate that round-price usage is persistent within investor identities, consistent with heterogeneous valuation grids rather than transitory noise.

Table I
SuperRare Dataset: Persistence of Round Price Usage

Notes: This table reports OLS regressions where the dependent variable is an indicator for whether a list price or an offer is round. The main explanatory variable is the same indicator for the wallet's previous listing or offer. Regressions include year-month and NFT-creator fixed effects. Standard errors are clustered at the wallet level. Round-price definitions are described in Section 3.1.

	(1)	(2)
	Round list price?	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 GCE data. To ensure we are comparing a consistent type of trade over time, we restrict attention to wallets that realized at least 20 returns from a primary-market purchase followed by a secondary-market sale executed through a listing rather than a bid. Focusing on these resale events serves two purposes. First, by conditioning on mint purchases, we hold fixed the nature of the initial acquisition, so cross-wallet differences in purchase channels do not confound the analysis. Second, by requiring that the subsequent sale occur through a seller-posted listing, we know that the seller—not a bidder—chose the resale price, making the round-price indicator directly interpretable as the seller's chosen pricing grid. We then compute, for each wallet, the fraction of these resale transactions that occur at round prices.

Figure 4 shows a binned scatter comparing each wallet's round-price fraction in its first 20 qualifying resales with its fraction in all subsequent qualifying resales. The strong positive relationship indicates that round-price usage is highly persistent within wallet identities.

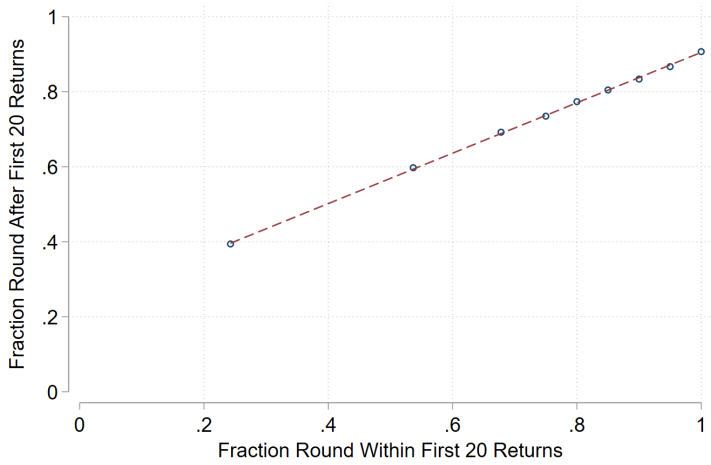


Figure 4. GC Ethereum Dataset: Persistence of Round Price Usage at the Wallet Level. *Notes:* Binned scatter plot comparing each wallet's fraction of round-price resale transactions in its first 20 qualifying trades with its fraction in all subsequent trades. We restrict the sample to resales that (i) follow a primary-market purchase and (ii) occur through a seller-posted listing rather than an accepted bid, ensuring that the resale price is chosen by the seller. The round-price definition used for the GCE dataset is described in Section 3.2.

4.2 *Returns on Resales*

The conceptual framework in Section 2 implies that rounding behavior has systematic implications for transaction prices and investment performance. When a seller operating on a coarse valuation grid posts a round list price, the price may be rounded downward relative to the underlying valuation, increasing the likelihood of a sale but at a lower realized price. When a buyer submits a round offer, successful transactions tend to occur at relatively high prices. We test these implications first in the SuperRare data, where the full bargaining sequence is observed, and then in the GCE data, where only realized transactions are available.

We begin by examining resales executed at the seller's list price. If round list prices reflect downward rounding by sellers, then resales at round list prices should be associated with lower realized returns. Columns 1–2 of Table II test this prediction by regressing log resale returns on an indicator for whether the resale price is round, controlling for purchase and resale year-month fixed effects, price-band indicators, and, in the richer specification, NFT-creator fixed effects. Consistent with the framework, resales at round list prices underperform: items that sell at round list prices generate significantly lower capital gains than those sold at non-round prices.

Table II
SuperRare Dataset: Returns on Resales

Notes: This table reports OLS regressions of log resale returns on an indicator for whether the resale price is round. Columns distinguish resales executed at the list price and resales following accepted offers. Regressions include purchase and resale year-month fixed effects, price-band fixed effects, and, in selected specifications, NFT-creator fixed effects. Standard errors are clustered at the resale year-month level. Round-price definitions are described in Section 3.1.

	(1)	(2)	(3)	(4)
	Transactions at list	Transactions at list	Accepted offers	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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table II confirms this prediction: resales following round offers outperform resales at non-round offers. In other words, successful round offers reflect upward-rounded valuations, generating systematically higher returns for the seller.

We next turn to transactions executed after an offer is accepted. When buyers operating on coarser valuation grids submit round offers, those offers may be rounded upward or downward relative to the underlying valuation. Conditional on acceptance, however, round offers tend to be relatively high, implying higher realized prices for sellers. Columns 3–4 of Table II confirm this prediction: resales following round offers outperform resales following non-round offers. Successful round offers therefore reflect upward-rounded valuations and generate systematically higher returns for sellers.

We test an analogous implication in the GCE dataset, where only realized secondary-market trades are observed. If paying a round price reflects an upward-rounded valuation, then buyers who transact at round prices should subsequently earn lower resale returns. We evaluate this prediction by regressing resale returns on an indicator for round purchase prices and a comprehensive set of fixed effects capturing transaction dates, collection identity, and whether the purchase and resale legs involved accepted bids.[1] Table III shows that round purchase prices significantly predict lower resale performance, mirroring the SuperRare results in a reduced-form setting and complementing recent evidence that round-number pricing is associated with predictable return patterns in financial markets (Blau et al. 2022).

Across both datasets, the resale evidence aligns with the same mechanism: round-price transactions occur at valuations that are systematically low for sellers (round list prices) or systematically high for buyers (round offers or round purchases). SuperRare allows us to see the bargaining channel directly; the GCE data show the same pattern in realized returns.

Finally, we examine how round-price usage covaries with valuation dynamics at the collection level. Because prices within generative collections comove strongly (Oh et al. 2025), these aggregates provide a natural complement to the wallet-level evidence. We

[1] In the platforms captured by the GCE data (for example, OpenSea and Blur), transactions can be executed after a seller accepts a bid offer, either in response to a listing or unsolicited. The data record only the final transaction outcome, not the full bargaining sequence.

Table III
GC Ethereum Dataset: Returns on Resales

Notes: This table reports OLS regressions of resale returns on an indicator for whether the purchase price is round. Regressions include fixed effects for transaction dates, collections, and whether the purchase or resale leg involved an accepted offer. Returns are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the resale date–collection level. Round-price definitions are described in Section 3.2.

	(1)	(2)	(3)
Round purchase price	-0.016***	-0.015***	-0.014***
	(0.002)	(0.002)	(0.002)
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	0.775	0.782	0.788
N	5,113,014	4,957,681	4,850,945

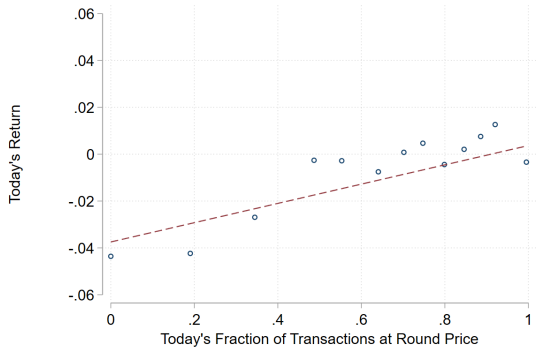
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

construct daily collection-level price indexes using the median transaction price (when at least five trades occur) and compute daily returns as changes in these indexes. Figure 5 presents binned scatter plots relating collection-level returns to the fraction of round-price trades. The contemporaneous relationship is positive: collections experiencing relatively high prices also see more round-price transactions. More strikingly, higher round-price usage on day t predicts lower returns on day $t+1$. Together with the wallet-level results, these patterns suggest that round prices tend to occur at valuations that are high relative to subsequent market movements.

Overall, the resale evidence across SuperRare and the GCE dataset provides consistent support for the valuation-grid interpretation: round-price transactions tend to occur at prices that are relatively high for buyers or relatively low for sellers, generating predictable return differentials in both bargaining and reduced-form settings.

4.3 Relative Size of Counteroffers

The analysis so far has focused on how valuation precision affects realized transaction prices and returns. We now examine listing–counteroffer dynamics in more detail. For this purpose, we focus on the SuperRare data, which allow us to observe each step of the sequential bargaining process.



Panel A. Contemporaneous Round-Price Fraction



Panel B. Lagged Round-Price Fraction

Figure 5. GC Ethereum Dataset: Round Price Usage and Collection-level Returns.
Notes: Binned scatter plots showing the relation between collection-level daily returns and the fraction of transactions at round prices, measured contemporaneously (left panel) and with a one-day lag (right panel). Returns are winsorized at the 1st and 99th percentiles. Round-price definitions for the GCE data are provided in Section 3.2.

If round list prices reflect upward rounding by sellers operating on coarser valuation grids, then such listings are more likely to remain unsold at the list price and to attract counteroffers. Because offers reflect buyers' valuations, counteroffers submitted in response to round list prices should be lower relative to the list price on average. We test this implication by comparing the size of counteroffers following round versus non-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. The estimate in column 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.

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.

Table IV
SuperRare Dataset: Round List Prices and Counteroffers

Notes: This table reports OLS regressions examining how the size of counteroffers varies with the roundness of the list price. The dependent variable is the ratio of the first offer or accepted offer to the list price. Regressions include year-month and list price band fixed effects and, in selected specifications, owner fixed effects. Standard errors are clustered at the owner level. Round-price definitions are described in Section 3.1.

	(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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4 Probability of Accepting Counteroffers

In the previous subsection, we examined how the relative size of counteroffers varies with the roundness of the list price. We now study whether rounding also affects the likelihood that a counteroffer is accepted. Unconditionally, a round offer need not be more likely to succeed, since rounding can push an offer either upward or downward. The conceptual framework in Section 2, however, yields a conditional prediction: round offers should be more likely to be accepted when the list price itself is round.

The intuition is straightforward. A round list price signals that the seller is operating on a coarse valuation grid and therefore evaluates offers using rounded valuation thresholds. When a buyer also submits a round offer, upward rounding increases the probability that the offer meets or exceeds the seller's acceptance threshold, while downward rounding does not reduce the probability of acceptance relative to a precise offer. As a result, round offers are more likely to be accepted in the presence of a round list price. We test this implication directly in the SuperRare data.

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 Dataset: Round List Prices and Round Counteroffers

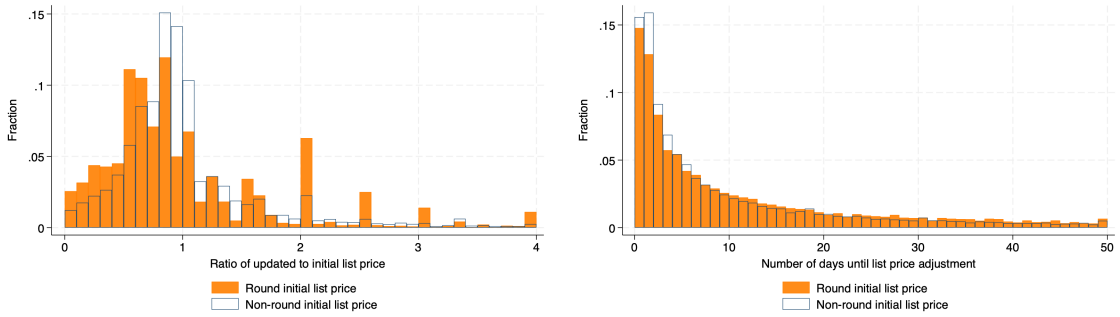
Notes: This table reports OLS regressions where the dependent variable equals one if a counteroffer is accepted by the seller. Explanatory variables include indicators for round list prices, round offers, and their interaction. Regressions include year-month and list price band fixed effects and, in selected specifications, NFT-creator or owner fixed effects. Standard errors are clustered at the owner level. Round-price definitions are described in Section 3.1.

	(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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5 List Price Adjustments

The conceptual framework in Section 2 also implies distinct patterns in how list prices are adjusted over time. When an item is listed at a round price and does not sell, small changes in the seller's underlying valuation need not trigger a price update. As a result, round list prices should be adjusted less frequently but by larger amounts, typically jumping between salient round values. In contrast, when an item is listed at a non-round price, even small changes in valuation are more likely to translate into price revisions, leading to more frequent but smaller adjustments. We examine these predictions using observed list-price changes in the SuperRare data.



Panel A. Size of List Price Adjustments

Panel B. Timing of List Price Adjustments

Figure 6. SuperRare Dataset: Size and Timing of List Price Adjustments.
Notes: Histograms showing the size (left panel) and timing (right panel) of list price adjustments on SuperRare, split by whether the initial list price was round. Round-price definitions for the SuperRare data are provided in Section 3.1.

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 the ratio of the new list price to the old list price separately for round and non-round (initial) list prices. Two patterns stand out. First, as expected, we find that downward price adjustments tend to be larger for round list prices. Second, we see that price adjustments cluster at round multiples (e.g., 0.5; 1.5; 2) for round (initial) list prices. In Panel B of Figure 6, we plot histograms of the number of days it took for the list price to be adjusted. In line with our conceptual framework in Section 2, non-round list prices are adjusted faster.

5 Drivers of Investors' Valuation Grids

The results in Section 4 show that rounding behavior is persistent within wallets and systematically related to bargaining dynamics and returns, consistent with heterogeneous valuation precision. In this section, we examine correlates of this heterogeneity, focusing on investor experience and type as suggested by the framework in Section 2.

Table VI
SuperRare Dataset: Experience and Use of Round List Prices

Notes: This table reports OLS regressions where the dependent variable equals one if a list price is round. Experience measures capture cumulative sales, purchases, or bids by the seller through the month prior to listing. Regressions include year-month and NFT-creator fixed effects and, in selected specifications, owner fixed effects. Standard errors are clustered at the owner level. Round-price definitions are described in Section 3.1.

	(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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.1 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 with the NFT owner's market experience. The coefficient remains strongly significant for seller experience once exploiting only within-owner variation in experience and rounding behavior.

We observe the same pattern in the GCE data: the fraction of returns realized at a round price declines 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).

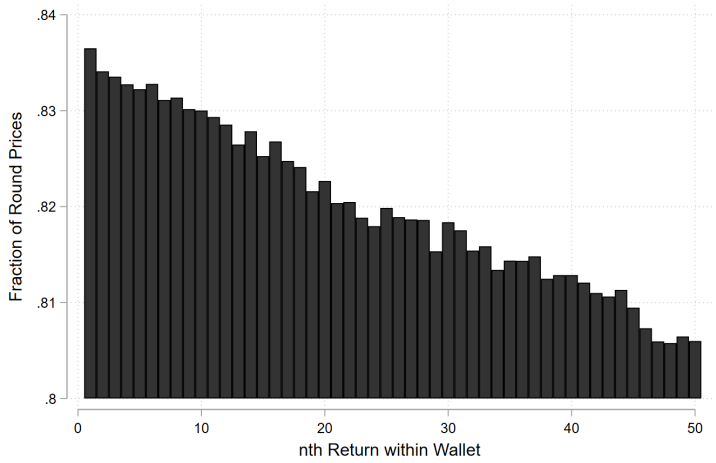


Figure 7. GC Ethereum Dataset: Round Price Usage and Experience.
Notes: Fraction of realized returns occurring at round prices, plotted by the wallet's nth resale. Round-price definitions for the GCE data are provided in Section 3.2.

5.2 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 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 made 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 dataset. Arguably, these market participants are less likely to be buying with the expectation of making a quick profit.

Table VII
SuperRare Dataset: Bidder Characteristics and Use of Round Offers

Notes: OLS regressions where the dependent variable equals one if an offer is round. Bidder characteristics include indicators for wash traders and artists. Round-price definitions for the SuperRare data are provided in Section 3.1. 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 then 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 GCE 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) in the GCE dataset are more likely to transact at round prices.

6 Variance Decomposition of Round-Price Usage

The evidence so far indicates that round-price usage is persistent, linked to returns, and correlated with experience and investor type. We now quantify the relative importance of

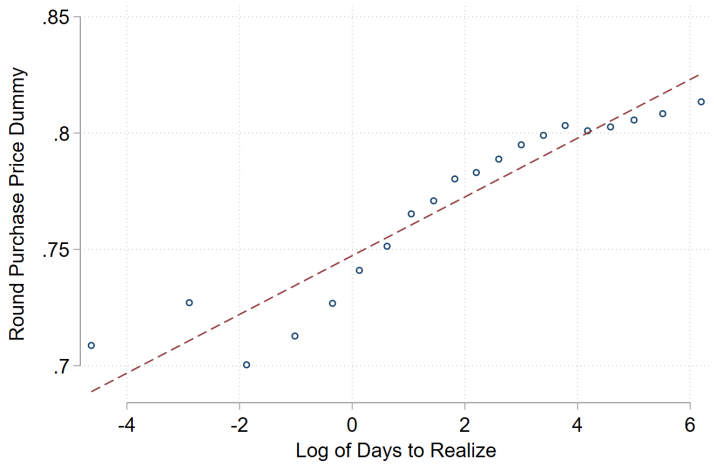


Figure 8. GC Ethereum Dataset: Round Purchase Prices and Holding Period.
Notes: Binned scatter plot comparing the use of round purchase prices in the secondary market with the log of the subsequent holding period. Round-price definitions for the GCE data are provided in Section 3.2.

three channels emphasized in the framework: price-level focal points, time-varying asset conditions, and investor behavior (both persistent and time-varying). Using the GCE dataset, we estimate fixed-effects specifications for the round-price indicator and apply a Shapley-value decomposition of adjusted R^2 across fixed-effect groups. The objective is descriptive: we quantify how much variation in round-price usage is associated with different components, without estimating structural parameters.

We work at the transaction level and use as the dependent variable an indicator for whether the transaction price is round under the 0.001 ETH definition. Let i index transactions, c collections, d dates, and p wallets. We consider four sets of fixed effects:

- R: price-level fixed effects for the nearest 0.001 ETH price level,
- N: collection-by-date fixed effects N_{cd},
- P: wallet fixed effects P_p,
- D: wallet-by-date fixed effects D_{pd}.

We estimate linear probability models because variance decompositions are well defined for linear models and interpreted naturally in terms of R^2. In practice, logit and probit models yield marginal effects and patterns that are very similar to the linear estimates, confirming that our choice is not driving the results.

Table VIII reports adjusted R^2 values for seven benchmark specifications. Columns differ only in which fixed effects are absorbed. All regressions use the same sample. Specifically, we restrict the data to observations retained under the most restrictive specification with R, N, and D jointly included. This ensures comparability of R^2 across specifications. Using alternative definitions of the common sample, including the union of rows across specifications, yields very similar decomposition patterns.

Table VIII
GC Ethereum Dataset: Fixed-Effects Specifications for Round-Price Usage

Notes: This table reports OLS regressions of the round-price indicator on different combinations of fixed effects using the GCE transaction-level dataset. "R" denotes round-value fixed effects, "N" denotes collection-by-date fixed effects, "P" denotes wallet fixed effects, and "D" denotes wallet-by-date fixed effects. Each column absorbs only the fixed-effect sets indicated and includes no covariates. All regressions use the same sample, defined as the intersection of observations retained under the specification with R, N, and D. Robust standard errors are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FE Specification	R	N	P	D	RN	RP	RD	RNP	RND
R^2	0.261	0.330	0.395	0.699	0.415	0.529	0.756	0.591	0.780
Adj. R^2	0.260	0.302	0.365	0.599	0.390	0.504	0.674	0.551	0.693
N	8,510,349	8,510,349	8,510,349	8,510,349	8,510,349	8,510,349	8,510,349	8,510,349	8,510,349

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

To quantify how much explanatory power each fixed-effect group contributes, we apply a Shapley-value decomposition of adjusted R^2. Conceptually, adjusted R^2 is treated as a cooperative surplus, meaning the total explanatory power produced jointly by the fixed-effect groups when they are included together in the model. The Shapley value for a given group is its average marginal contribution to adjusted R^2 across all inclusion orders. The method is additive and order invariant, which makes it particularly suitable for high-dimensional fixed effects. Results using unadjusted R^2 are nearly identical.

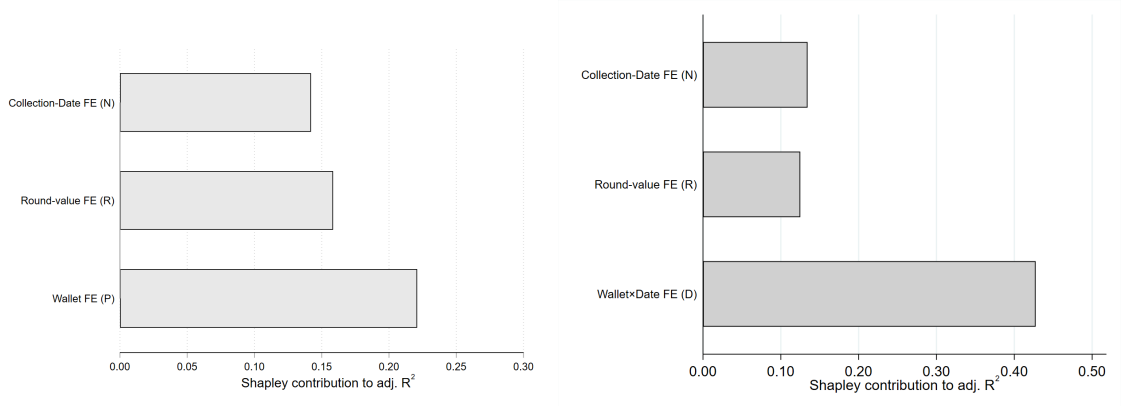
A subtle issue arises because wallet fixed effects P are nested within wallet-by-date fixed effects D. To avoid double counting, we perform two separate decompositions: one for (R, N, P) and one for (R, N, D). In each case, we use the common sample across the relevant specifications.

Panel A of Figure 9 reports the decomposition for (R, N, P). The adjusted R^2 of the full model with R, N, and P is approximately 0.50. The Shapley values attribute about

0.16 to R, 0.14 to N, and 0.22 to P. Thus investor identity accounts for the largest share of explained variation (over 40 percent), with price-level focal points and time-varying collection-level conditions contributing roughly equal shares.

Panel B presents the decomposition for (R, N, D). Allowing for wallet-by-date heterogeneity raises the adjusted R^2 of the full model to about 0.64. The Shapley values attribute roughly 0.13 to R, 0.14 to N, and about 0.43 to D. The wallet-by-date component therefore explains the largest share of round-price variation, reflecting systematic wallet-specific behavior that evolves over time. This aligns with the earlier evidence: persistent differences across wallets (Figure 4), learning with experience (Figure 7), and the role of motives (Figure 8), all of which are naturally absorbed by the wallet-by-date fixed effects.

Taken together, the variance decompositions confirm that all three conceptual channels introduced in the framework play meaningful roles in explaining round-price usage. Price-level focal points and time-varying asset-level conditions matter, but investor behavior is the dominant driver, especially once time variation within wallets is allowed. These conclusions are robust to using unadjusted R^2, to alternative round-price thresholds, and to modest changes in sample definition.



Panel A. Decomposition across R, N, and P **Panel B.** Decomposition across R, N, and D

Figure 9. GC Ethereum Dataset: Shapley Decomposition of Round-Price Usage

Notes: This figure reports Shapley-value decompositions of adjusted R^2 from regressions of the round-price indicator on groups of fixed effects in the GCE dataset. Panel A decomposes across price-level fixed effects R, collection-by-date fixed effects N, and wallet fixed effects P. Panel B decomposes across R, N, and wallet-by-date fixed effects D. All decompositions use the common sample across the relevant specifications.

7 Conclusion

This paper studies the widespread use of round prices as a manifestation of heterogeneity in valuation precision and its implications for bargaining behavior and economic outcomes. Using transaction-level data from decentralized NFT markets without mechanical pricing constraints, we show that round pricing serves as a revealed measure of how precisely investors form and express valuations. Across two complementary datasets, round-price usage reflects the interaction of price-level focal points, time-varying asset conditions, and persistent investor-level heterogeneity.

Empirically, rounding behavior is highly persistent within wallets and predicts systematic differences in bargaining paths and returns. Transactions executed at round list prices yield lower resale returns, while transactions following round offers generate higher returns for sellers. Round listings attract lower counteroffers, round offers are more likely to be accepted when list prices are round, and round list prices are adjusted less frequently but by larger amounts. Valuation precision varies across investors: rounding declines with experience, is less prevalent among profit-motivated traders, and is more common among participants who behave like long-horizon collectors. A Shapley decomposition shows that investor-level components explain the largest share of observed round-price variation, alongside price-level focal points and asset-level conditions.

Our contribution is not to provide a psychological explanation for the appeal of round numbers or a fully strategic model of bargaining. Rather, we show that valuation precision is a distinct and persistent dimension of economic heterogeneity that leaves systematic footprints in prices, negotiations, and returns. By using round pricing as a transparent empirical proxy for valuation precision, the paper highlights how differences in numerical granularity can shape market outcomes in decentralized, negotiated settings.

More broadly, these findings suggest that incorporating heterogeneity in valuation precision may be important for understanding price formation in markets where agents negotiate over assets with both financial and consumption value. Future work could explore how valuation precision interacts with learning, market design, and institutional features across a wider range of decentralized trading environments.

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