Beyond Value: Investigating Reputation Effect on Resale Prices in NFT Auctions

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January 16, 2025

Abstract

This paper examines the dynamics of repeated NFT auctions on the Foundation platform, focusing on how buyer and seller reputation and experience—measured by the number of followers and Katz centrality—impact resale prices. Our findings reveal that the popularity of sellers in primary sales who is also the creator of digital art positively influences both resale prices and the likelihood of resale. The trading experience of buyers raises relative prices but negatively affects the likelihood of trade in matched samples. Extensive trading networks among buyers show varied effects on resale dynamics, demonstrating cautious consideration of opportunities to buy but aggressive bidding behavior when they do. This study provides valuable insights into the evolving digital art market, highlighting factors that drive resale likelihood and prices, and contributing to a deeper understanding of digital asset markets and their parallels with the traditional art market.

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1 Introduction

The rise of digital art and the emergence of Non-Fungible Tokens (NFTs) have revolutionized the traditional art market, introducing new dynamics and challenges for market participants. As digital assets, NFTs provide a unique framework for understanding how networks and followers impact the resale price of art. Repeated auction sales have garnered significant attention due to their dynamic nature and potential for enhancing market efficiency. In this paper, we explore the intricate dynamics of repeated NFT auctions on the Foundation platform, with a particular focus on how buyer and seller reputation—reflected in the number of followers and information transmission, as indicated by Katz centrality of previous activity—affect resale prices.

The study of repeated auctions is a significant area within auction theory, examining how different auction designs and rules affect outcomes. Researchers analyze bidder behavior, auction formats, and market dynamics to understand and improve auction performance. Understanding the dynamics of repeated auction sales is crucial, as these mechanisms are pivotal in various markets, including online platforms like the Foundation. Participants in these decentralized markets continually adapt their strategies based on past outcomes, which influences market efficiency and dynamic pricing. These auctions are characterized by several key aspects:

- Learning and Adaptation: Participants, both buyers and sellers, refine their strategies based on historical outcomes. Buyers may adjust their bidding behavior to enhance their chances of winning at lower prices, while sellers select their reserve prices to maximize revenue.

- Reputation Effects: The reputation of both buyers and sellers plays a crucial role in repeated auctions. A well-regarded seller can attract higher bids, while a buyer with a history of winning auctions may influence the bidding behavior of others.

- Market Efficiency: Repeated auctions tend to lead to more efficient market outcomes as participants accumulate information about the value of items and the strategies of their competitors.

• Dynamic Pricing: Prices in repeated auctions can fluctuate based on demand, competition, and market conditions, allowing for dynamic price discovery and revealing the true market value of items.

Previous studies have highlighted the importance of reputation in online auctions. Bajari and Hortaçsu (2003) examined eBay coin auctions, revealing that seller reputation crucially influences auction revenues. Positive reputations increased revenues, while negative feedback could reduce revenues by up to 15%. Bidder experience, however, did not notably affect auction outcomes. Dellarocas (2005) explored reputation mechanisms in electronic markets, showing that simpler mechanisms, which publish only recent ratings, can achieve maximum efficiency by ensuring punishment for negative behavior. Bolton et al. (2008) found that competition enhances feedback systems' effectiveness in fostering trust and market efficiency. Ba and Pavlou (2002) demonstrated that proper feedback mechanisms foster trust and generate price premiums for reputable sellers. Lucking-Reiley et al. (2007) found that negative feedback significantly lowers auction prices for collectible coins, emphasizing the importance of maintaining a good reputation.

Khademorezaian et al. (2022) have studied the impact of networks and platform followers on NFT prices, specifically focusing on original sales within the Cryptoart market. Their research uncovers significant heterogeneous effects across the distribution of Cryptoart prices, providing valuable insights into how network connections and platform popularity influence market outcomes. Sellers with extensive trading networks and a significant number of followers are able to leverage the information and reputation built through these connections to achieve better sales outcomes for lower-priced NFTs. Their findings suggest that trading network effects for sellers are dominant for low valued NFTs while platform popularity gains importance for high valued NFTs. A combination of a substantial follower count and a limited number of connections made by following others on the platform can have a significant impact on the price of Cryptoart sold on the Foundation platform. On the buyer's side, the study reveals that there are no significant platform effects while network effects are more muted. Grover et al. (2022) in their survey paper on the evolution of social media influence underscore the limited exploration in the literature of topics such as information diffusion, and social media or platform influence in a market context. Their work emphasizes the need for more research to understand how social media and platform interactions shape market dynamics and outcomes. Oh et al. (2022) assess investor performance in the NFT market with a particular emphasis on experience. While a broad network often suggests substantial experience, our research focuses on understanding the distinct effects of the sales network structure and platform reputation on resale prices.

In the context of art as an investment, constructing an accurate index of art prices has been challenging due to the heterogeneous nature of art objects and infrequent trading. The hedonic approach and the Repeat Sales Regression have been employed to compute the rate of return on paintings over time, each with its strengths and limitations (Ashenfelter and Graddy, 2006). NFTs offer a unique opportunity to assess price movements over time for digital art, which bears common value and does not depreciate in the traditional sense. This paper aims to analyze repeated auctions of NFTs on the Foundation platform, exploring the interplay between buyer and seller reputation and their implications for market dynamics. By shedding light on these dynamics, we contribute to a deeper understanding of the evolving landscape of digital asset markets and their parallels with traditional art markets. Through our analysis, we aim to provide insights into the factors driving the likelihood of resale and resale prices in the NFT market, offering valuable insights for participants and policymakers alike.

The remainder of the paper is organized as follows. Section 2 provides an overview of the Foundation platform and the data. Section 3 presents an empirical investigation of the impact of trading networks and platform connections on resale prices. Finally, Section 4 concludes with a summary of our findings.

2 Platform and Data Overview

Foundation, a platform dedicated to CryptoArt, launched in February 2021 with an invitation-based model that allows users to mint and sell NFTs directly. The platform supports various wallets and utilizes smart contracts to manage transactions. In particular, users mint new NFTs by uploading their Cryptoart, which is registered on the blockchain via a smart contract linked to their wallet. The process involves inputting metadata, and listing the NFT for sale. This process is decentralized without the use of intermediaries unlike sales in traditional auction markets mostly controlled by dealers. Ownership is recorded on the blockchain's distributed ledger, with sellers paying a percentage of subsequent sales as royalties to the original creator.

An NFT can be listed for sale with a "Buy Now" option or a reserve price for auction. The auction starts when a bid meets the reserve price and concludes 24 hours later. The highest bidder transfers the bid amount to the seller's wallet, and the NFT is transferred accordingly.

Foundation also functions as a social network, allowing users to follow profiles and build reputations through sales. The market experienced significant changes from rapid growth in early 2021 to maturity by mid-2022, aligning with Ethereum's price fluctuations. The number of auctions eventually stabilized post-cryptocurrency crash, with reduced volatility. Currently, the price of Ethereum has recovered most of its losses and is now at approximately 82 percent of its peak value, reinvigorating the level of activity on the platform.

We created a dataset of repeated sales from auctions on the Foundation platform, ranging from February 5, 2021, to December 5, 2022. We retrieved all auction data from the Ethereum blockchain via thegraph.com and identified the NFTs that were auctioned twice. We use the unique user IDs from the blockchain to retrieve additional information about the participants from the Foundation platform, including their number of followers, followings on the platform, and social media accounts. We collected auction information that includes the time of creation, the reservation price, history of any reservation price changes, and details about bidders and their bid amounts. We retrieve the Ethereum to US Dollar exchange rate from Etherscan.io, which tracks this information. After excluding auctions involving participants banned or suspended from the platform due to terms of service violations, the remaining count totals 1274 repeated sales. Table 1 provides summary statistics for the auctions used in our regression analysis during the period under consideration.[1] The average winning bid is of primary sales was 0.72 ETH, with a standard deviation of 1.35 ETH. The corresponding winning bid for NFT resales was 1.52 ETH, with a standard deviation of 3.54 ETH. On average, the duration between listing and final sale for primary sales was 30.4 hours while for secondary sales the listing to final sales was 58.13 hours. This duration offers a more realistic assessment of the time taken to successfully sell an NFT compared to the standard 24-hour auction duration. We classify participants into four groups based on their prior actions within the platform. A seller is defined as a participant who has successfully sold an NFT, while a collector is a participant who has won an auction. An artist refers to a creator who has minted an NFT, and a bidder is a participant who has placed bids at the auction, irrespective of whether they won the auction or not. There is a lot of overlap across participant groups. On average, there were 6.85 participants in each primary sale and 5.33 in the secondary sale. The latter group is dominated by the number of collectors. Sellers have a larger number of followers in primary sales and a smaller in secondary sales.

We use all the auctions that occurred during this period to construct a network of trades between sellers and buyers (Kranton and Minehart, 2001), where a node represents a user in the Foundation platform and an edge represents an auction weighted by the winning bid value in Ethereum. We measure the centrality of each node k at time t using:

$$kc_{k,t}(N_t) = \sum_{l} \sum_{j} \delta^l \mathbf{A}^l_{t,k,j}, \tag{1}$$

where N_t represents the network of sellers and buyers form the transactions in the last 30 days, but excluding those at t. $\mathbf{A}_t$ representing its corresponding adjacency matrix where

[1] Due to the lack of availability of data for some of those measures created for the analysis we dropped 69 observations.

Figure 1: Heat Map of Average Percentage Change in Prices

$\mathbf{A}_{t,k,j} \neq 0$ indicates the presence of transactions between node k and j during the time frame before t. The index l denotes the length of walks emanating from node k and δ represents the discount factor. Following standard practice (Bloch et al., 2023), the discount factor is determined by establishing an upper bound based on the maximum eigenvalue of matrix $\mathbf{A}_t$.

Figure 1 presents a heat map showing the average percentage change in prices across quartiles, based on the number of followers and accounts followed by original sellers/creators, secondary sellers, and buyers. The data suggests that price changes tend to be higher for creators and secondary buyers with many followers but who follow few others. In contrast, no clear pattern emerges for secondary sellers. To better understand the impact of sales networks and follower counts on prices, our regression analysis will control for NFT characteristics, auction details, and bidder profiles.

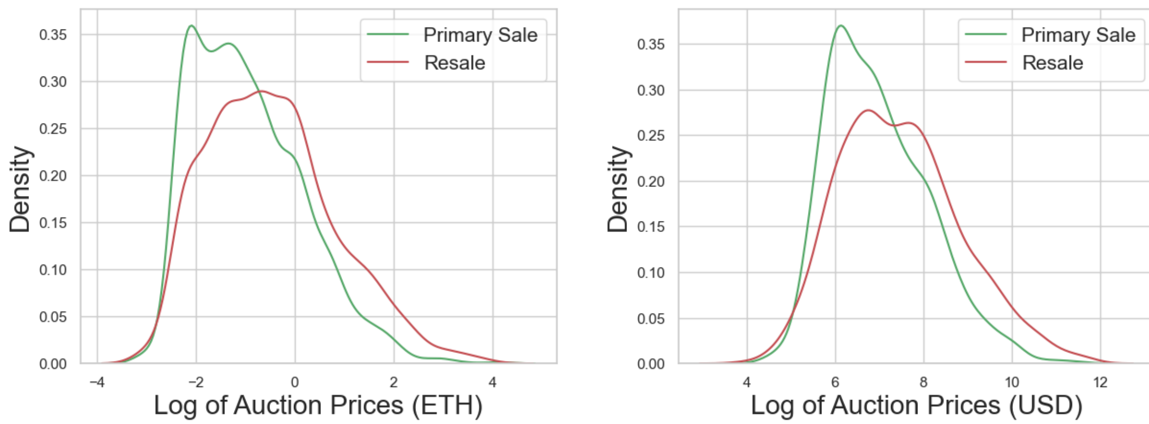
Finally, for each NFT, we obtained the creator's unique blockchain identifier, mint date, and IPFS path, allowing us to locate the NFT's metadata. Using these addresses, we retrieved metadata from ipfs.tech, which includes the NFT's name, description, and link to the stored file. We used this link to extract both the file name and its extension, enabling us to identify the specific file type. We categorized the files into three groups: static images (.jpg, .png, .svg), animated files (.gif, .mov, .mp4), and 3D images (.glb, .gltf). Creators often add descriptions, averaging around 212 characters. There were no 3D images resold in this market with 59 % of the images that sold twice being still. Summary statistics for the NFTs are listed in Table 1.

Table 1: Descriptive Statistics

	Primary Sale					Secondary				
Variable	Mean	Deviation Standard	Min	Max	Number of Observations	Mean	Deviation Standard	Min	Max	Number of Observations
A. Summary of Auctions										
Winning Bid Amount	0.72	1.35	0.05	19.80	1,205	1.52	3.54	0.05	50.00	1,205
Listing-to-Sale duration (Hours)	14.45	30.40	1.00	387.42	1,205	58.13	78.80	0.96	529.34	1,205
Reservation Price Change	0.23	0.42	0.00	1.00	1,205	0.37	0.48	0.00	1.00	1,205
B. Participants Type in Auctions										
No. of Bidder Never Won	0.18	0.67	0.00	10.00	1,205	0.08	0.53	0.00	9.00	1,205
No. of Artist and Seller	0.77	1.02	0.00	7.00	1,205	0.02	0.15	0.00	2.00	1,205
No. of Artist and Collector	2.29	2.32	0.00	19.00	1,205	1.15	1.69	0.00	12.00	1,205
No. of Collector	2.91	2.67	0.00	18.00	1,205	4.08	2.40	0.00	20.00	1,205
C. Network and Social Media										
Katz Centrality of Seller	0.02	0.08	0.00	1.00	1,205	0.01	0.06	0.00	1.00	1,205
Katz Centrality of Buyer	0.02	0.08	0.00	1.00	1,114	0.06	0.17	0.00	1.00	1,205
No. of Followers of Seller	1322.64	1620.82	3.00	13000.00	1,205	1233.32	1661.24	12.00	12900.00	1,205
No. of Seller Following	402.97	2932.01	0.00	93700.00	1,205	344.32	1892.92	0.00	41900.00	1,205
No. of Followers of Buyer	1197.40	1630.78	6.00	9611.00	1,205	1810.83	2564.68	4.00	12600.00	1,205
No. of Buyer Following	290.27	978.05	0.00	16100.00	1,205	210.73	427.25	0.00	3581.00	1,205
Seller has Twitter	0.96	0.19	0.00	1.00	1,205	0.77	0.42	0.00	1.00	1,205
Seller has Instagram	0.78	0.42	0.00	1.00	1,205	0.44	0.50	0.00	1.00	1,205
Buyer has Twitter	0.73	0.44	0.00	1.00	1,205	0.62	0.49	0.00	1.00	1,205
Buyer has Instagram	0.39	0.49	0.00	1.00	1,205	0.24	0.43	0.00	1.00	1,205
D. NFT characteristics										
Length of NFT's Description	212.49	202.77	0.00	1000.00	1,205					
Still Image	0.59	0.49	0.00	1.00	1,205					
Animated	0.41	0.49	0.00	1.00	1,205					
3D Format	0.00	0.03	0.00	1.00	1,205					

Notes: The computation of Katz centrality follows (1). The description of participant types in Panel B is explained in section 2.

Figure 2: Log-transformed Auction Prices



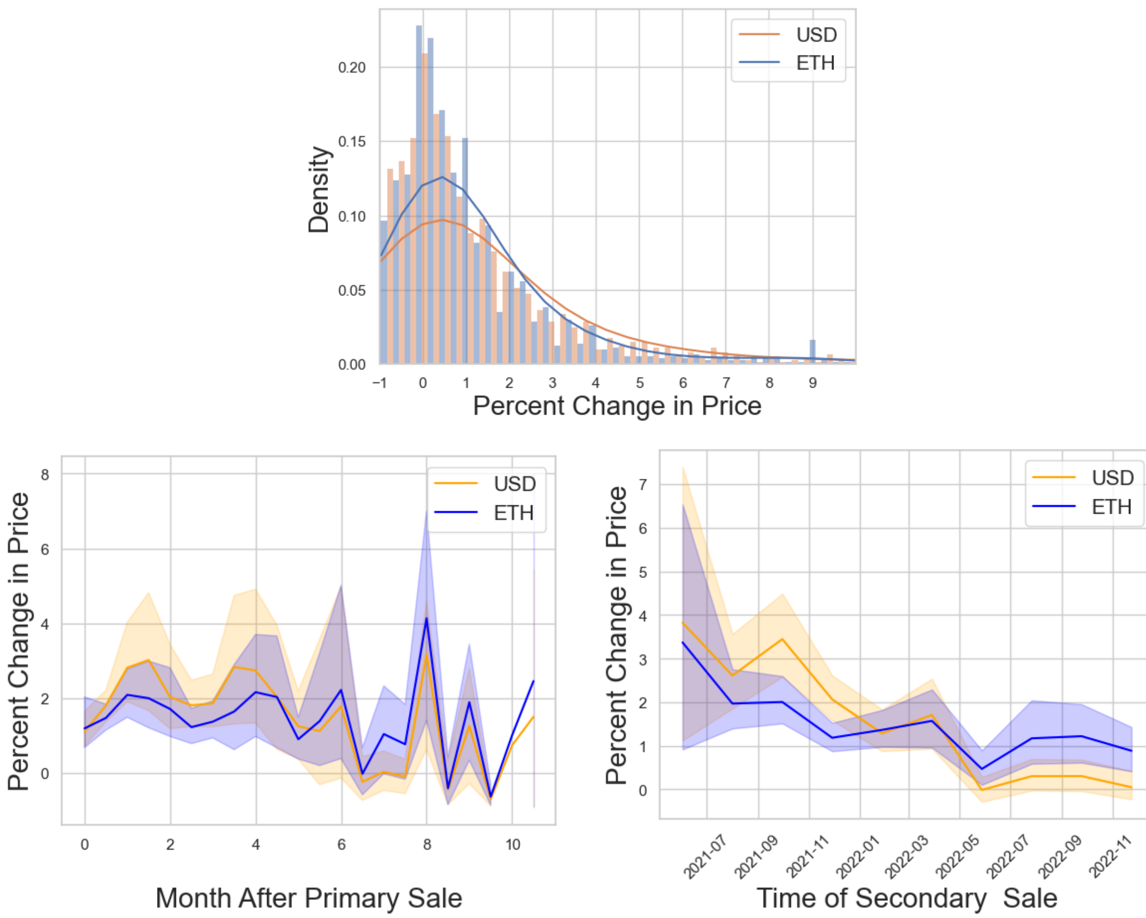
Note: The plot on the left displays the density plot of the logarithm of the winning bids in Ethereum. The plot on the right uses the exchange rate at the time of the auction to convert these values into US Dollars.

Figure 2 presents the density of winning bids in both Ethereum and USD, indicating that resale prices tend to be higher overall with the main differentiation happening beyond the lower valued NFTs.

Figure 3 presents additional information on the percentage price change between the primary and secondary sales. Based on this data, only 25% percent of Cryptoart experienced a price decline in secondary sales. The distribution is skewed to the right with a few sales (49 sales in terms of USD and 29 in ETH) achieving an appreciation of more than 10%. As the left bottom panel of the figure suggests, most of the NFTs that resold at the beginning of the time window, during the periods of initial market surge and eventual stabilization, experienced more significant price increases. Those resold many months after their initial sale experienced smaller increases in price, and sometimes decreases, with greater fluctuations in the percentage change for those sold 10 months or more after the initial sale. The bottom right panel confirms that resale returns were higher in the earlier part of our time window.

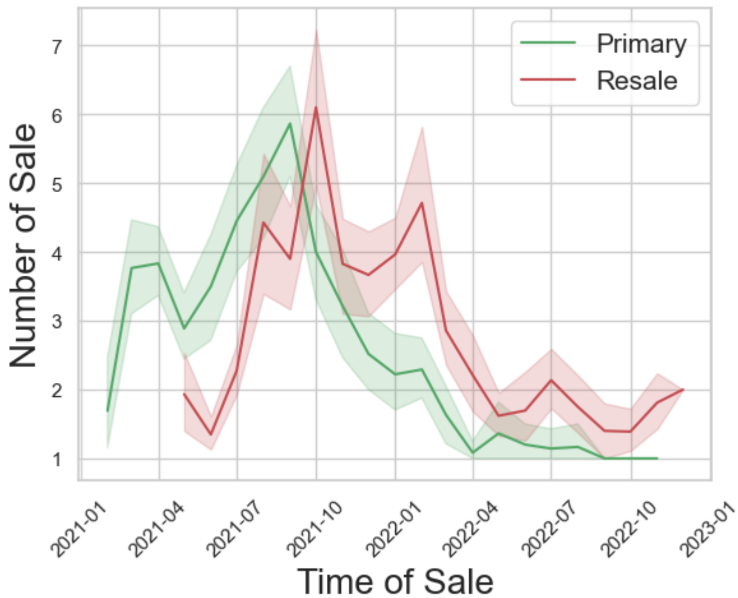
Finally, Figure 4 shows that primary and secondary sales volume decreased in the latter part of the period coinciding with the crush of the cryptocurrency market. The figure captures the daily number of transactions for all NFTs that were resold in the entire period peaking around the time when Ethereum value was at its highest.

Figure 3: Percentage Change in Price between Primary and Secondary



Note: The exchange rate at the time of sale is used to calculate the value in USD. In the top figure, there are some observations spread above 10 percent, with very low density (49 in USD and 29 in ETH), that are not shown in the figure for better visualization. On the left, the figure shows the density of change in resale price. The plot on the right charts this percentage change over the period between the two sales. The lines denote the mean, while the shaded areas represent the 95th percentile.

Figure 4: Primary and Secondary Sales over Time



Note: The lines are the average number of actions for each month and the shaded areas are the 95th percentiles.

3 Empirical Analysis

In this section, we will consider how the relative price of an NFT is affected by trading networks and buyer and seller popularity. We will also examine the factors that affect the probability of a resale.

3.1 Resale Price

We first estimate the change in relative price when an NFT is resold as a fuction of auction, NFT and bidder characteristics including network variables capturing popularity and trading experience. We consider the following semiparametric equation:

$$\log(\frac{y_{isrt_2}}{y_{iast_1}}) = \boldsymbol{N}'_{isrt_2}\boldsymbol{\delta}_1 + \boldsymbol{F}'_{iasrt_2}\boldsymbol{\delta}_2 + \boldsymbol{W}'_{isrt_2}\boldsymbol{\theta} + f_d(D_{it_2}) + f_e(E_{t_2}) + \mu_{t_2} + u_{iasrt_2}, \quad (2)$$

where y_{isrt_2} denotes the winning bid of an NFT i, bought by buyer r, and sold by seller s at time t_2 and y_{iast_1} denotes the winning bid received by the creator a at time t_1 paid by buyer s. The vector $\boldsymbol{N}_{isrt_2}$ denotes network variables at the time of resale and $\boldsymbol{F}_{iasrt_2}$ includes the number of accounts following creators, buyers, and sellers on the Foundation platform, and the number of accounts the creator, buyer or the seller follows. The vectors $\boldsymbol{W}_{isrt_2} = (\boldsymbol{S}'_{isrt_2}, \boldsymbol{B}'_{it_2}, \boldsymbol{X}'_i)'$ include various controls. $\boldsymbol{S}_{isrt_2}$ contains indicators for social media presence (i.e, the buyer has a Twitter or Instagram account connected to the Foundation platform), $\boldsymbol{B}_{it_2}$ are auction-related controls, including bidder type and an indicator denoting changes in the reservation price, and the time between the primary and secondary sale, $\boldsymbol{X}_i$ are NFT related controls including the type of NFTs auctioned off and the length of their description. μ_{t_2} are time dummies and u_{iasrt_2} is an error term.

The model also includes two unknown functions in terms of the listing-to-sale duration of the auction D_{it_2} and the exchange rate E_{t_2}. We estimate the functions f_e and f_d using cubic B-spline functions with five knots. A detailed description of all the variables used in our analysis is provided in Table A.1 in the appendix.

The first column of Table 2 provide the mean level regression results and the following columns present the estimated coefficients at various quantiles. The number of followers of the primary seller capturing the popularity of the creator, has a positive effect on the rate of change of prices. This effect is significant for low quartiles and at the median. In other words, the seller's popularity drives small changes in the price but is not having an effect in NFTs whose prices increased substantially. The number of accounts that the creator follows does not seem to make a discernible difference. The popularity of the secondary seller, which is also the buyer in the primary sale does not have a statistically significant impact on the price ratio which suggests that the buyers in the secondary market rely more on the popularity of the first seller and creator of the NFT to determine its value than on the seller who resales. The number of accounts following the secondary buyer have a positive impact and the number of accounts followed have a negative impact. These effects increase across quantiles, indicating that more popular buyers in the secondary market generate relatively higher prices.

Table 2: Estimation Results

	OLS	Q0.1	Q0.25	Q0.5	Q0.75	Q0.9
Number of Followers Primary Seller	0.093***	0.073**	0.082***	0.097***	0.047	0.049
	(0.028)	(0.036)	(0.031)	(0.029)	(0.037)	(0.056)
Number of Following Primary Seller	−0.025	−0.020	−0.018	−0.020	0.003	−0.006
	(0.018)	(0.024)	(0.020)	(0.020)	(0.024)	(0.036)
Number of Followers Secondary Seller	−0.019	−0.033	−0.016	−0.017	0.018	0.082*
	(0.026)	(0.036)	(0.029)	(0.028)	(0.034)	(0.048)
Number of Following Secondary Seller	0.009	−0.004	0.008	0.004	−0.017	−0.029
	(0.018)	(0.026)	(0.018)	(0.018)	(0.025)	(0.035)
Number of Followers Secondary Buyer	0.208***	0.134***	0.103***	0.141***	0.230***	0.274***
	(0.023)	(0.032)	(0.025)	(0.027)	(0.033)	(0.042)
Number of Following Secondary Buyer	−0.161***	−0.100***	−0.077***	−0.127***	−0.197***	−0.234***
	(0.020)	(0.025)	(0.021)	(0.024)	(0.027)	(0.034)
Centrality Secondary Seller	0.205	−0.001	0.468	0.156	0.154	−0.304
	(0.384)	(0.509)	(0.384)	(0.372)	(0.367)	(0.348)
Centrality Secondary Buyer	0.572***	0.454***	0.337**	0.436**	0.711**	0.740**
	(0.160)	(0.165)	(0.143)	(0.178)	(0.287)	(0.372)
Months from Primary Sale	−0.041***	−0.130***	−0.090***	−0.030**	−0.015	0.015
	(0.012)	(0.022)	(0.022)	(0.014)	(0.018)	(0.020)
Auctions Controls	Yes	Yes	Yes	Yes	Yes	Yes
NFT Controls	Yes	Yes	Yes	Yes	Yes	Yes
Semiparametric Functions	Yes	Yes	Yes	Yes	Yes	Yes
Month and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Social Media Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,205	1,205	1,205	1,205	1,205	1,205

Notes: The dependent variable is the logarithm of the ratio of the winning bid in the primary sale to the secondary in Ethereum for an NFT. Number of followers and following are logged. All models include a constant. Statistical significance levels are denoted as follows: *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. Standard errors are enclosed in parentheses.

Table 3: Estimation Results

	OLS	Q0.1	Q0.25	Q0.5	Q0.75	Q0.9
Primary Sale Price	0.638***	0.629***	0.712***	0.747***	0.691***	0.660***
	(0.031)	(0.047)	(0.038)	(0.036)	(0.045)	(0.061)
Number of Followers Primary Seller	0.196***	0.197***	0.164***	0.132***	0.147***	0.173***
	(0.028)	(0.041)	(0.032)	(0.031)	(0.040)	(0.060)
Number of Following Primary Seller	−0.077***	−0.080***	−0.070***	−0.051**	−0.042	−0.039
	(0.018)	(0.025)	(0.020)	(0.021)	(0.026)	(0.036)
Number of Followers Secondary Seller	0.041	0.010	0.004	0.033	0.047	0.049
	(0.025)	(0.032)	(0.028)	(0.028)	(0.032)	(0.045)
Number of Following Secondary Seller	−0.022	−0.004	−0.018	−0.013	−0.023	−0.005
	(0.018)	(0.024)	(0.019)	(0.019)	(0.024)	(0.030)
Number of Followers Secondary Buyer	0.249***	0.159***	0.164***	0.208***	0.245***	0.364***
	(0.022)	(0.031)	(0.026)	(0.028)	(0.032)	(0.045)
Number of Following Secondary Buyer	−0.182***	−0.102***	−0.109***	−0.170***	−0.202***	−0.279***
	(0.019)	(0.025)	(0.022)	(0.025)	(0.026)	(0.034)
Centrality Secondary Seller	0.300	−0.309	0.612*	0.279	0.526	0.297
	(0.363)	(0.508)	(0.327)	(0.440)	(0.375)	(0.421)
Centrality Secondary Buyer	0.552***	0.285*	0.254*	0.317*	0.582**	0.581
	(0.151)	(0.172)	(0.138)	(0.169)	(0.237)	(0.373)
Months from Primary Sale	−0.020*	−0.092***	−0.057***	−0.026*	0.007	0.021
	(0.011)	(0.024)	(0.018)	(0.014)	(0.019)	(0.019)
Auctions Controls	Yes	Yes	Yes	Yes	Yes	Yes
NFT Controls	Yes	Yes	Yes	Yes	Yes	Yes
Semiparametric Functions	Yes	Yes	Yes	Yes	Yes	Yes
Month and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Social Media Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,205	1,205	1,205	1,205	1,205	1,205

Notes: The dependent variable is the logarithm of the winning bid in Ethereum from the secondary sale. Number of followers and following are logged. All models include a constant. Statistical significance levels are denoted as follows: *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. Standard errors are enclosed in parentheses.

Here, the resale seller as the middleman between the creator and the second buyer does not have substantial effect on relative prices. Buyers with extensive networks are more inclined to bid up prices in the secondary market and that is more significant at the upper quartiles. Lastly, the number of months that elapsed since the primary sale, negatively impacts the price. In this analysis, the creator's popularity and the popularity and network of the buyer in the secondary sale are the most critical factors affecting change in relative prices. The secondary seller's experiences has a no statistically significant effect.

Table 3 presents a logarithmic model of the resale price as a function of the logarithm of primary sale price and other NFT, auction, bidder characteristics and time controls. Here we don't only see the relative price movements but we can see if the characteristics of bidders such as popularity and experience have a differential effect on prices across the distribution, conditional on the price levels achieved in the primary market. As in table 2, our results reveal that the popularity of the creator and the buyer in the resale market were critical in boosting the sales price. While the seller's popularity is affecting prices uniformly across quartiles, the popularity and experience of the secondary buyer has a larger effect at higher quartiles.

3.2 Likelihood of Resale

In this section, we examine the likelihood of resale as a function of the network ($\boldsymbol{N}_{iast}$) and Foundation variables ($\boldsymbol{F}_{iast}$) to investigate the effect of popularity and network connections in the primary sale on the probability of resale. We estimate the following Probit model:

$$\begin{aligned} \Pr(R_{ias} = 1 | y_{iast_1}, &\boldsymbol{N}_{iast_1}, \boldsymbol{F}_{iast_1}, \boldsymbol{W}_{iast_1}, D_{it_1}, E_{t_1}, \mu_{t_1}) \\ &= \Phi(y_{iast_1} + \boldsymbol{N}'_{iast_1}\boldsymbol{\delta}_1 + \boldsymbol{F}'_{iast_1}\boldsymbol{\delta}_2 + \boldsymbol{W}'_{iast_1}\boldsymbol{\theta} + f_d(D_{it_1}) + f_e(E_{t_1}) + \mu_{t_1}), \end{aligned} \tag{3}$$

where ($R_{ias} = 1$) denotes an NFT that will be resold in the future, and it equals one if we observe another auction for this NFT in our sample. We use the primary sales data. We are interested in the probability of resale based on primary sale value (y_{iast_1}), sales network

($\boldsymbol{N}_{iast}$) and Foundation followers ($\boldsymbol{F}_{iast}$). Variable $\boldsymbol{W}_{isrt_1} = (\boldsymbol{S}'_{iast_1}, \boldsymbol{B}'_{it_1}, \boldsymbol{X}'_i)'$ contains the NFT characteristics such as file type, length of description and types of participants in the auction.

Table 4 presents the estimation results of Equation 3. Column (1) presents the results using all auctions. Because some NFTs may not have had sufficient time to be resold, we use different subsamples of the auctions as control groups. Column (2) presents the results using NFTs that their original sales is before 2022. This is based on Figure 4, which shows that the majority of primary sales for resold items occurred by that time. In the next columns, we use propensity score matching to select a subsample of auctions without resale. The concern is that the treated and control groups (the NFTs that were resold and those that didn't during our sample period) may share different characteristics along a number of dimensions including the type of art, the timing of sale and the ETH exchange rate after the item was first sold. In this effort, we use subsamples of the control group that best mimic the treatment group in these dimensions.

We used nearest neighbor matching to select a control group. This process involves calculating the distance between observations. We used logistic, random forests, and Mahalanobis distances, which are commonly used in matching methods (Abadie and Imbens, 2016; Athey and Imbens, 2019), and picked the closest observation without replacement. The logistic distance is the predicted values of a GLM model with a binomial link, random forests uses the predicted values of fitted forest, and the Mahalanobis distance is defined as $d_{i,j} = \sqrt{(x_i - x_j)\Sigma^{-1}(x_i - x_j)'}$, where Σ is the pooled within-group covariance matrix of covariates computed by the treatment group-mean. Column (3) uses random forests and finds the 5 nearest neighbors, and Column (4) uses only the nearest neighbor. Column (5) uses logistic distance as scores and column (6) uses Mahalanobis distance. As mentioned above, we used auction and NFT-specific controls, time, and exchange rates for matching. The matching is performed across all auctions without resale. We then run our regression on network variables. Table A.2 compares these matching processes by examining the means of matched variables. The matched variable means are closer to those of auctions with resales, creating a more effective control group.

Table 4: Likelihood of Resale

	(1)	(2)	(3)	(4)	(5)	(6)
Winning Bid	$-0.069***$	$-0.075***$	$-0.086***$	$-0.133***$	$-0.140***$	$-0.055*$
	(0.016)	(0.018)	(0.021)	(0.030)	(0.029)	(0.030)
Number of Followers Seller	$0.272***$	$0.292***$	$0.385***$	$0.447***$	$0.344***$	$0.308***$
	(0.014)	(0.017)	(0.021)	(0.031)	(0.030)	(0.029)
Number of Following Seller	$-0.062***$	$-0.072***$	$-0.089***$	$-0.108***$	$-0.091***$	$-0.086***$
	(0.009)	(0.010)	(0.013)	(0.019)	(0.019)	(0.019)
Number of Followers Buyer	$-0.149***$	$-0.147***$	$-0.187***$	$-0.220***$	$-0.201***$	$-0.205***$
	(0.013)	(0.015)	(0.018)	(0.027)	(0.026)	(0.026)
Number of Following Buyer	$0.108***$	$0.103***$	$0.129***$	$0.141***$	$0.116***$	$0.133***$
	(0.011)	(0.012)	(0.015)	(0.021)	(0.021)	(0.020)
Centrality Seller	$0.326*$	$0.346*$	0.294	-0.332	0.545	0.032
	(0.167)	(0.203)	(0.255)	(0.326)	(0.407)	(0.360)
Centrality Buyer	$-0.791***$	$-0.894***$	$-0.952***$	$-1.032***$	$-1.245***$	$-0.875***$
	(0.142)	(0.174)	(0.194)	(0.253)	(0.243)	(0.261)
Auctions Controls	Yes	Yes	Yes	Yes	Yes	Yes
NFT Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Social Media Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82,091	44,585	7,710	2,570	2,570	2,570

Notes: The dependent variable is resale ($R \in \{0,1\}$). Number of followers and following are logged. All models include a constant. Statistical significance levels are denoted as follows: *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. Standard errors are enclosed in parentheses.

The results suggest that the likelihood of resale is lower when prices in the original sale are higher. Additionally, the number of followers of a seller and creator has a positive impact on resale likelihood, while the number of accounts the seller is following has a negative impact. The number of followers a buyer has impacts negatively the likelihood of resale, whereas the number of accounts the buyer is following increases the likelihood. Popular buyers typically drive prices up in the original sale creating less opportunity for a bargain buy in a secondary market. The centrality of the seller does not impact the likelihood of resale when the sample is reduced to create a balance with respect to auction and NFT-specific controls, time, and exchange rates, but the centrality of the buyer decreases the likelihood. This indicates that more experienced traders are less likely to sell the NFTs they acquire.

4 Conclusion

In conclusion, our analysis reveals that the popularity of both primary sellers (creators) and secondary buyers significantly influences NFT price dynamics and resale likelihood. The primary seller's popularity drives modest price increases, particularly at lower price levels, while the secondary buyer's popularity tends to boost prices more significantly in higher quantiles. Interestingly, the centrality of secondary sellers has no statistically significant effect on prices. On the one hand, when considering relative prices, if the popularity and information acquired by a buyer in the primary market (seller in resale market) do not change much between sales the relative price is not expected to change a lot. On the other hand, if you consider the logarithm of prices, modeling the NFT auction as a common value auction as in Khademorezaian et al. (2022), we expect the information coming from the buyer in the primary sale (seller in the secondary sale) to affect the price as it adds valuable information about the perception of the value at the auction, Nevertheless, the price in the primary auction already incorporates the information coming from bidder participation at this auction. As long as this participant does not gain new insights, the auction price in the resale market will not be affected substantially. Buyers with extensive networks, however, bid up prices in resale and more so at the upper quartiles. The likelihood of resale is inversely related to the original sale price and positively influenced by the seller's popularity, yet negatively impacted by the buyer's popularity. These findings suggest that highly networked and experienced market participants are more strategic and selective in their trading, underscoring the nuanced role of social dynamics and market experience in shaping NFT market behavior.

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1 Appendix

Table A.1: Variable Descriptions

Vector	Variable	Description
y_{iast}	Log of Price	Logarithm of the winning bid value in Ethereum (ETH)
$\boldsymbol{N}_{iast}$	Centrality Seller	Measures the Katz centrality of the seller within the buyer-seller network over the past 30 days, following Equation (1). The network is constructed based on transactions, with the edges weighted by the value of the transactions in Ethereum.
	Centrality Buyer	Measures the Katz centrality of the buyer within the buyer-seller network over the past 30 days, following Equation (1). The network is constructed based on transactions, with the edges weighted by the value of the transactions in Ethereum.
$\boldsymbol{F}_{iast}$	No. of Followers Seller	The logarithm of the number of accounts following the seller on the Foundation.app platform.
	No. of Following Seller	The logarithm of the number of accounts that the seller follows on the Foundation.app platform.
	No. of Followers Buyer	The logarithm of the number of accounts following the buyer on the Foundation.app platform.
	No. of Following Buyer	The logarithm of the number of accounts that the buyer follows on the Foundation.app platform.
$\boldsymbol{S}_{iast}$	Seller Has Twitter	Indicator variable denoting whether a seller has associated their Twitter account with the Foundation platform.
	Seller Has Instagram	Indicator variable denoting whether a seller has associated their Instagram account with the Foundation platform.
	Buyer Has Twitter	Indicator variable denoting whether a buyer has associated their Twitter account with the Foundation platform.
	Buyer Has Instagram	Indicator variable denoting whether a buyer has associated their Instagram account with the Foundation platform.
$\boldsymbol{B}_{it}$	No. of Bidders Never Won	Count of auction participants categorized as bidders that never won an auction.
	No. of Artist and Seller	Count of auction participants categorized as both artist and seller.
	No. of Artist and Collector	Count of auction participants categorized as both artist and collector.
	No. of Collector	Count of auction participants categorized as only collectors.
	Reservation Price Change	Binary variable indicating whether the auction reservation price was changed during the auction.
$\boldsymbol{X}_{i}$	Description Length	The NFT description's length divided by 100
	Animated	An indicator variable that determines whether the NFT is animated (.MP4, .MOV, or .GIF format).
	3D	An indicator variable that determines whether the NFT is 3D (.GLB or .GLTF format).

Table A.2: Matching Summary

	No Resale	Resale	(3)	(4)	(5)	(6)
No. of Bidder Never Won	0.096	0.163	0.136	0.147	0.169	0.138
No. of Artist and Seller	1.059	0.758	0.956	0.855	0.749	0.769
No. of Artist and Collector	1.656	2.275	2.003	2.133	2.330	2.174
No. of Collector	2.459	2.782	2.597	2.684	2.784	2.664
Price Changed	0.222	0.237	0.257	0.251	0.239	0.233
Length of NFT's Description	2.345	2.106	2.357	2.247	2.110	2.091
Animated	0.332	0.407	0.407	0.415	0.402	0.404
3D Format	0.007	0.002	0.007	0.005	0.001	0.002
Creator has Twitter	1.960	1.958	1.953	1.956	1.959	1.958
Creator has Instagram	1.749	1.774	1.772	1.787	1.771	1.782
Buyer has Twitter	1.688	1.714	1.695	1.710	1.709	1.721
Buyer has Instagram	1.310	1.371	1.368	1.373	1.378	1.368
Number of Observations	80806	1285	7710	2570	2570	2570

Notes: Each column presents the mean of the variables used in matching. Column (3)-(6) corresponds to columns in Table 2. In (3) and (4), distance is calculated using random forests, in (5) using logistic regression, and in (6) using Mahalanobis distance. In (3), matching selects the 5 nearest neighbors, while in the other columns, it selects the nearest neighbor.