Networks, Platforms, and Auction Pricing: Evidence from the NFT Art Market*

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Abstract

This paper studies the Non-fungible Token (NFT) art marketplace to gain insights into how trading networks, platform connections, and social media interactions impact prices. We focus on daily online auctions hosted on the Foundation platform. Our findings reveal that a larger seller's trading network leads to higher winning bids, while the influence of platform connections, specifically popularity, emerges as a critical factor among the most expensive NFTs. Our research underscores that in decentralized online markets, the power to set prices rests with trading networks and platform connections, although their relative influence varies based on the NFT's auction price.

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1 Introduction

Non-Fungible Tokens (NFTs) have recently surged in popularity, commanding prices that sometimes reach into the millions of dollars (Kireyev and Evans, 2021). Within the realm of NFTs, a notable category is that of crypto art, which empowers artists to bypass traditional intermediaries typically found in conventional art auctions. Transactions occur on a platform where users can access information, engage in auctions, or offer their artwork for sale. These platforms also function as information hubs, facilitating users in accessing details regarding artworks, artists, and additional sources of information, such as social media accounts. This capability enables users to collect information about past transactions and the popularity of others, information not typically available in traditional auctions.

NFTs allow for the development of a decentralized network whose impact on information diffusion can be fundamentally distinct from that of traditional art markets where dealers, as market makers, play a central role in shaping market outcomes. De Silva et al. (2022a) studied information transmission through trading networks in a traditional art market using a historical dataset of auctions taking place in London in a span of a century and a half. By examining the development of networks of art dealers and their subsequent influence on artwork prices, this research examined factors such as network size and the depth of interactions among bidders and dealers. The findings suggest that a larger and more interconnected dealer network intensifies informational imbalances among buyers to the benefit of informed dealers.

However, in the context of the decentralized digital market for NFTs, in addition to trading networks, factors such as platform connections and social media presence take on new dimensions of importance. The survey paper by Grover et al. (2022) on the evolution of social media influence underscores the limited exploration in the literature of topics such as information diffusion, and competitive influence in a market context. Etter et al. (2019) and Rapp et al. (2013) established that social media facilitates individuals in building public perception for increasing their reputation in the market. Within these digital connections, users amass social capital, which can be effectively leveraged for the purposes of disseminating information and exerting influence over others. The distinctive features of NFT platforms, their reliance on digital connections and the interdependence among auction participants offer an opportunity to examine how information diffusion and competitive influence affect market outcomes.

Our investigation reveals that in the NFT market, the dynamics of information diffusion through various network connections play a pivotal role in shaping prices. Our basic modeling structure allows us to explore the differential impact of trading networks and social media presence on prices, particularly at the tails of the distribution. We incorporate three types of network measures: (i) the network of past transactions, which gauges the trading experience and reputation of both buyers and sellers; (ii) platform-based networks, measuring popularity; and (iii) indicators of social media presence, which assess the potential for gathering additional information.

The NFT market has witnessed significant fluctuations in the valuation of digital art, experiencing both rapid growth and subsequent decline. The market we analyze is characterized by a widespread price distribution, with values ranging from an average of \$51 (10 least expensive NFTs) to \$1.15 million (10 most expensive NFTs). While it is possible to use standard regression to investigate the effects of networks on prices (as in, e.g., Vasan et al. 2022), mean regression analysis might not be informative if effects vary across the distribution. For instance, the prestige of the seller, the popularity of the buyer, and/or their social media connections can have heterogeneous impacts on auction prices. To investigate this possibility, we employ regression methods that allow us to obtain point estimates at different price points or quantiles of the distribution (Chernozhukov et al., 2023; Lamarche and Parker, 2023). Furthermore our approach enables us to account for latent dependencies, which is another prevalent feature of the NFT market, as participants often transition between the roles of buyers and sellers. By deviating from mean regressions, we gain a more comprehensive understanding of how various factors differentially affect prices.

Our analysis indicates that while trading networks of sellers and buyers remain critically important, their impact on highly priced NFTs is diminished. Platform followers are not as crucial for buyers, but for sellers, they serve as a channel for popularity, and explain more of the price difference in the upper tail of the distribution. The decisive influence of social media presence (Twitter and Instagram), evident in our descriptive regressions, diminishes when we control for latent connections and group dependencies. Even within decentralized markets, our findings underscore that trading networks wield significant influence over both sellers and buyers for low priced NFTs.

Our contribution to the empirical literature on networks and decision making lies in our study of factors that influence price formation across the distribution. We focus on NFTs for digital art, extending the foundations laid by previous studies, to go beyond the investigation of data pattern using aggregate statistics, hedonic regressions, visualization and machine learning techniques (e.g., Nadini et al. 2021, Vasan et al. 2022 and Alizadeh et al. 2023). Instead, we engage in distributional regression analysis, uncovering systematic effects in the data while overcoming estimation challenges that are pervasive in the NFT market. By leveraging recent advancements in econometric techniques, originating in the work of Chernozhukov et al. (2023) and Lamarche and Parker (2023), we can effectively tackle the issues of participant interdependencies, endogeneity, and potential estimation bias. Our work threads together two strands of literature on traditional art auctions (e.g., Ashenfelter and Graddy 2003, Beggs and Graddy 2009, Botelho and Gertsberg 2022, De Silva et al. 2022a and De Silva et al. 2022b) and the influence of platforms and social media on market outcomes (e.g., Etter et al. 2019 and Grover et al. 2022), by introducing a network dimension into bidding decisions and ultimately the price determination process. Finally, our paper complements the work by Oh et al. (2022), which assesses investor performance in the NFT market with an emphasis on experience. While a broad network often suggests substantial experience, our research focuses on understanding the distinct effects of the network structure and platform reputation across the entire range of prices.

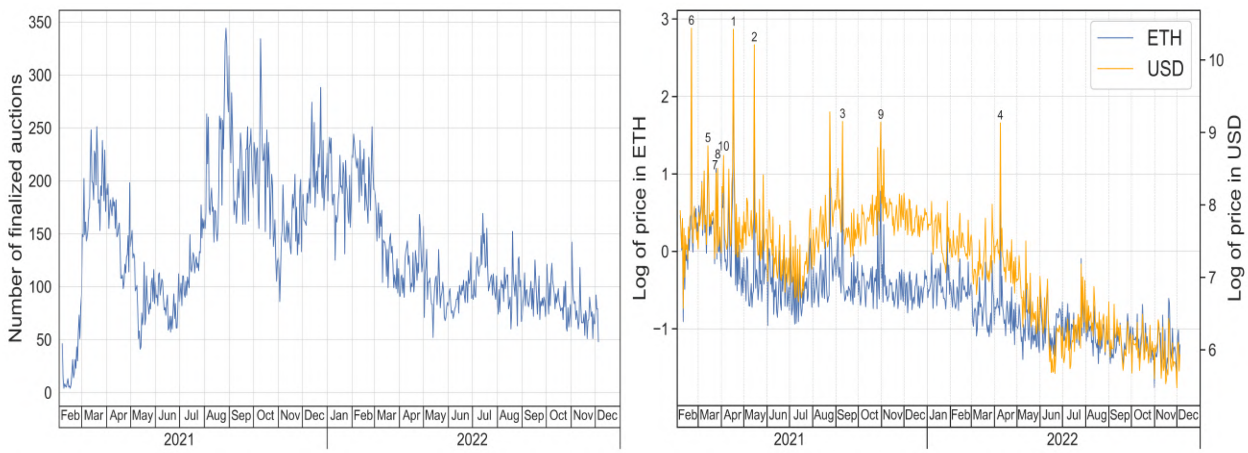
The remainder of the paper is organized as follows. In Section 2, we present information on CryptoArt and the Foundation Platform. Section 3 describes the auction data on the Blockchain. Section 4 conducts an empirical analysis, detailing network formation and bidding implications without accounting for bidder interdependences and potential bias in estimation. In Section 5, we explore theoretical predictions. Section 6 investigates the impact of buyer and seller networks on prices, through distributional and panel quantile regressions. Finally, in Section 7, we conclude our study, summarizing findings and discussing implications for the digital art market.

2 CryptoArt and the Foundation Platform

During the initial stages of blockchain technology, value transfer primarily relied on fungible tokens (FT), like Bitcoin and Ethereum. These tokens possess traits of homogeneity, interchangeability, divisibility, and replaceability. Blockchain users later found new applications for the technology to verify digital assets. Digital assets are distinct entities that are non-interchangeable. This led to the emergence of non-fungible tokens (NFT) to address the requirement for recording singular, verifiable, and non-interchangeable assets on the blockchain.

NFTs encompass various categories, including Collectibles, Gaming, Metaverses, Utilities, and Cryptoart. Cryptoart provides artists with an alternative avenue to sell their creations, facilitated by specialized art platforms that support various transaction formats, including auctions. Owning such an NFT is akin to possessing a digital certificate of authenticity for the associated artwork, making it valuable as a verifiable and tradable good (Oh et al., 2022). Although cryptoart operates on the Ethereum blockchain, its market dynamics are not solely tethered to the value of Ether (ETH) (Dowling, 2022). Figure 1 aggregates information from all transactions of cryptoart available on the Foundation.app platform from February 5, 2021 to December 5, 2022 and illustrates that the transaction values are closely correlated in both USD and ETH, with exceptions during the period of steady cryptocurrency market decline that started at the end of 2021.[1]

Figure 1: Number of NFT auctions and prices over time



Notes: The figure on the left presents the daily total number of auctions. The figure on the right shows the daily average transaction prices in Ethereum and their corresponding value in USD. It also identifies the timing of sales for the top ten most expensive NFTs, with additional information delegated to Table A.1.

Several marketplaces, including SuperRare and OpenSea, offer platforms for cryptoart. However, the Foundation.app distinguishes itself as a platform solely dedicated to the sales of cryptoart, setting it apart from others that cater to a broader spectrum of categories. The Foundation has an invitation-based model which allows any user with an invitation to join the market, eliminating the need for evaluation by a select group. Launched in February 2021, the Foundation remains a prominent platform in the cryptoart domain. Like most markets, it experienced an initial surge in daily auctions but later stabilized at around 100 daily auctions, as depicted in Figure 1.

Upon joining the marketplace, users can mint new NFTs, enabling them to sell their creations directly to interested buyers. Buyers mint NFTs by sending cryptocurrency to the

[1] In November 2022, FTX, a prominent exchange with a total value of $32 billion, declared bankruptcy following a cryptocurrency market scenario similar to a bank run. This event had a ripple effect across the entire cryptocurrency market, leading to a 75% decline in the value of Bitcoin, the largest cryptocurrency, from its 2021 peak. This incident differed from other cryptocurrency crashes in 2022, like those of LUNA and TerraUSD, as it significantly eroded market security and trust (Yaffe-Bellany, 2022).

smart contract, which creates and transfers the NFT to the buyer's wallet.[2] The ERC-721 standard on Ethereum outlines the separation of NFT object data and proof of ownership. Each wallet is equipped with a public address, which is accessible to anyone, and a private key that remains exclusive to the wallet's owner. The key is necessary for executing cryptocurrency transactions. The minting process involves choosing a marketplace, creating a crypto wallet, inputting metadata, and listing the NFT for sale, rendering it a decentralized process devoid of intermediaries. Ownership is recorded on the blockchain's distributed ledger but does not grant copyright or intellectual property rights to the underlying content. Whenever the NFT changes hands within the platform, the seller pays a percentage of subsequent sales (royalties) to the original creator.

An NFT can be listed for sale when the owner specifies a 'Buy Now' value for immediate purchase or sets a reserve price for auction. The auction starts when a bidder submits a bid at the reservation price and concludes 24 hours subsequent to the initial bid.[3] The owner of the NFT holds the authority to modify the reservation price only before the first bid is submitted. Upon the conclusion of the auction, the highest bidders, who becomes the auction winner, transfers a sum matching their bid to the seller's wallet and the NFT is transferred.[4] A listed NFT cannot be transferred to a different account or burned.[5]

The Foundation also functions as a social network, permitting users to follow profiles of their choice. Over time, creators can build reputations through the sale of art pieces that appreciate in value, while collectors can form networks based on their prior acquisitions. As

[2]"A smart contract is simply a program that runs on the Ethereum blockchain. It's a collection of code (its functions) and data (its state) that resides at a specific address on the Ethereum blockchain." See Ethereum Development Documentation for more details.

[3]At any given time, an auction can be in one of four possible states. An open auction refers to an ongoing auction that has not been canceled or finalized yet. Such an auction may be either active and still accepting bids or pending finalization. On the other hand, a canceled auction indicates that it was terminated before reaching the reserve price. An invalidated auction is one that has been rendered invalid due to another action, such as a Buy Now option being exercised. Finally, a finalized auction signifies that the auction process has been completed, and the NFT has been successfully transferred to the winning bidder.

[4]Over time, Foundation.app has introduced various alternative methods for selling NFTs. In addition to auctions, these methods include Buy Now, Offers, Drops, Editions, Worlds, and Batch Listing. For more detailed information on these alternative selling methods, please refer to the Foundation Help Center.

[5]Burning is the irreversible destruction of an NFT by sending it to a designated burn address. This action renders the NFT unusable and is commonly used to decrease the total number of tokens available.

the user base and artwork sales increase, the network's structure changes.

As a new market, Foundation underwent significant transformations. During its rise, which stretched from February 2021 to September 2021, the market saw rapid growth characterized by numerous daily auctions and high volatility, as shown in Figure 1. However, from September 2021 to April 2022, the increase in the number of auctions plateaued, indicating the end of rapid growth in numbers and the attainment of maturity. This phase coincided with the peak of Ethereum exchange rates. Subsequently, from April 2022 to December 2022, a period that aligned with the cryptocurrency market crash, the number of auctions experienced a decline and eventually stabilized with reduced volatility.

As implied by the right panel of Figure 1, the price of some NFTs reached into millions of dollars. This is more precisely documented in Table A.1, which presents prices of the ten most expensive NFTs in the sample. Leading this list is "Stay Free," which sold for \$5.1 million, surpassing the sale prices of notable artworks like Claude Monet's "Vernon Soleil," which sold for \$4.7 million at Sotheby's in June of this year, and "Paysage, environs du Havre," which fetched \$402 thousand in March 2021, around the time of the NFT's sale. "Stay Free" sold for nearly five times the price of Pablo Picasso's "Tête de femme," which recently sold at the same auction house. Despite the digital nature of cryptoart, which is widely accessible to anyone with internet access, their prices often reach levels typically associated with works by the most renowned painters.

3 Auction Data on the Blockchain

Our primary data source consists of the auctions conducted on the Foundation.app platform from February 5, 2021, to December 5, 2022. Foundation.app utilizes Ethereum as its native currency, and all transactions are recorded using smart contracts on the Ethereum blockchain. An important feature of this dataset is that due to the comprehensive ledger maintained on the blockchain, we can access not only the details of an auction and its corresponding NFT but also the past activities of all participants. This includes other sales by the sellers and purchases by the buyers. Additionally, the unique identification of users through distinct addresses allows us to trace their social interactions within the Foundation platform.

To obtain the relevant data, we accessed the subgraph hosted by the Foundation platform on thegraph.com; thegraph.com is a decentralized protocol specifically designed for indexing and querying blockchain data. We selected the finalized auctions, to focus on completed transactions. The auction information includes the time that the auction is created, the reservation price, the history of reservation price changes if applicable, and information about bidders and the amount of their bid. After eliminating auctions involving participants banned or suspended from the platform due to terms of service violations, the remaining count totals 89,385 auctions.[6] We also excluded resales, a category distinct from auctions initiated by creators and currently less prevalent on the Foundation platform, resulting in a final count of 86,989 auctions.

Panel A of Table 1 provides auction summary statistics for the period of analysis. The average winning bid in auctions stands at 0.70 ETH, with a median of 0.30 ETH. The average duration between listing and final sale is roughly 28 days; however it is worth noting that half of the NFTs in our data set found a buyer within just four days of their initial listing. This listing-to-sale duration provides a more realistic assessment of the time it took for the seller to successfully organize a sale of an NFT compared to the 24-hour auction duration, particularly in cases of pre-sale auctions or auctions where the owner changed the reservation price.[7]

One attribute shared by participants in the Foundation's auctions with those in online marketplaces and the stock exchange, is their capacity to assume multiple roles. In contrast,

[6] Penalties for any form of misrepresentation on the platform include account termination and referral to law enforcement.

[7] Pre-sale auctions are relatively infrequent. Some *Fixed Pricing Drops* may have a pre-sale phase, exclusively accessible to chosen collectors as designated by the seller. For more information, please refer to the Foundation Help Center.

Table 1: Descriptive Statistics

Variable	Mean	Deviation Standard	Min	Max	Number of Observations
		A. Auction Characteristics			
Winning Bid Amount	0.703	8.618	0.050	2224.000	86989
Listing-to-Sale duration (Hours)	675.797	1359.979	23.013	14226.608	86989
Reservation Price Change	0.220	0.414	0.000	1.000	86989
		B. Participants Type in Auctions			
No. of Bidders Never Won	0.125	0.633	0.000	24.000	86989
No. of Artist and Seller	1.048	1.104	0.000	15.000	86989
No. of Artist and Collector	1.665	1.921	0.000	39.000	86989
No. of Collector	2.566	2.216	0.000	34.000	86989
Seller is DAO	0.003	0.057	0.000	1.000	86989
Buyer is DAO	0.004	0.065	0.000	1.000	86989
		C. NFT characteristics			
Length of NFT's Description	232.975	228.232	0.000	1000.000	86988
Still Image	0.653	0.476	0.000	1.000	86989
Animated	0.340	0.474	0.000	1.000	86989
3D Format	0.007	0.082	0.000	1.000	86989
		D. Network and Social Media			
Centrality Seller	0.012	0.055	0.000	1.000	85579
Centrality Buyer	0.077	0.214	0.000	1.000	82101
Centrality 2nd Highest Bidder	0.042	0.129	0.000	1.000	20540
Number of Followers Seller	704.268	1024.362	0.000	14100.000	86987
Number of Following Seller	375.387	2283.088	0.000	161000.000	86987
Number of Followers Buyer	1818.031	2657.301	0.000	14000.000	86979
Number of Following Buyer	233.959	815.123	0.000	101100.000	86979
Seller Has Twitter	0.957	0.202	0.000	1.000	86987
Seller Has Instagram	0.746	0.435	0.000	1.000	86987
Buyer Has Twitter	0.672	0.470	0.000	1.000	86979
Buyer Has Instagram	0.303	0.460	0.000	1.000	86979

Notes: DAO stands for Decentralized Autonomous Organization, and the computation of Katz centrality follows the method outlined in Section 4.1. The participant types in Panel B are determined based on the categories illustrated in Figure 2.

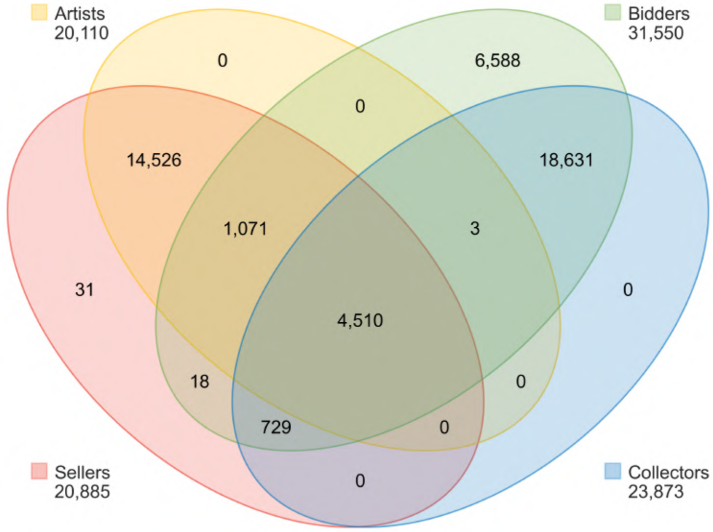
traditional art auctions mostly involve a one-directional flow of primary sales, where artists create pieces subsequently sold by auction houses and acquired by collectors, often by art dealers (De Silva et al., 2022a), with very limited overlap between the groups of buyers and sellers. This one-way transactional feature is also shared by government procurement auctions (Hortaçsu and Perrigne, 2021). However, due to the decentralized nature of NFTs, the accessibility of information, simplified transactions, and the absence of intermediaries like art dealers, creators have ample opportunities to participate in auctions as bidders.

Therefore, we categorize users into four groups based on their past activities within the platform's auctions. A seller refers to a user who has successfully sold an NFT, while a collector denotes a user who was the winner in an auction. An artist represents a creator who has minted an NFT, and a bidder includes users who have participated in auctions by placing bids, irrespective of whether they were winners.

Our sample is restricted to primary auction sales on the Foundation platform excluding resale opportunities, that resulted in 46,195 unique users. It is important to note that a user can assume multiple roles on the platform. For instance, approximately 28 percent of the NFT creators within our sample engaged as bidders in auctions, and roughly 19 percent of collectors have minted and sold their own NFTs. About 10% of all unique users have had experiences in all listed categories, while all but three artists sold their own work directly in the market. These categories and their sizes are visually illustrated in Figure 2 and summary statistics detailing the participant types in auctions are presented in Panel B of Table 1.

In addition, we identified Decentralized Autonomous Organizations (DAO) in our data. DAOs are blockchain-based entities that operate without centralized control or management. They are designed to be autonomous and self-governing, relying on smart contracts and code to execute decisions and manage resources. DAOs can curate and manage collections of digital art and have the ability to pool funds from members to collectively purchase high-value NFTs, enabling broader ownership or shared access. Overall, we observed 48 DAOs in our data with participation in 381 auctions, which represents less than 1 percent of the total

Figure 2: Type of participants in Auctions



Note: This Venn type diagram shows the number of participants in the auctions by type. An artist is a participant who creates NFTs. Sellers are defined as participants who sell NFTs. Bidders are participants who placed bids in an auction, and collectors (or buyers) are the participants who won at least one auction.

number of NFT auctions.

We also obtain accompanying information for each NFT, including details such as the creator's unique identifier on the blockchain, the mint date, and the IPFS path which allows us to locate the NFT's metadata.[8] Subsequently, using the previously acquired addresses, we retrieve the metadata for each individual NFT from ipfs.tech. This metadata contains information on the NFTs such as name, description, and the link to the stored file. We utilize the link to extract both the file name and its corresponding extension, which in turn allows us to identify the specific file type.

To categorize the file types, we classify them into three distinct groups. Files with extensions ".jpg," ".png," and ".svg" are classified as static, indicating non-animated or still images. Files with extensions ".gif," ".mov," and ".mp4" are categorized as animated. Additionally, 3D images are identified by file formats such as ".glb" or ".gltf". Creators can also add more details to NFTs by writing descriptions, which consist of around 229

[8]InterPlanetary File System (IPFS) is a decentralized file storage protocol employed for storing NFT-related data. For further information, please visit ipfs.tech.

characters on average. More specific characteristics of the NFTs are listed in Panel C of Table 1.

We employ users' unique blockchain identification to access their profiles on the Foundation website. User-related information for all participants in auctions is directly obtained from the Foundation.app website. On this platform, users can follow other accounts of interest, allowing us to observe the number of followers and accounts they follow. Buyers tend to have more followers and follow fewer users compared to sellers. On average, buyers have around 2,112 followers, which is 2.7 times higher than sellers. They also follow approximately 247 accounts, which is 0.62 times the number followed by sellers.

Users can personalize their accounts by linking external websites and integrating social media platforms. Although users can connect any social media or external website, the Foundation platform primarily showcases Twitter and Instagram accounts. The majority of creators (95 percent) have linked their Twitter accounts to the platform, while a substantial portion (74 percent) have linked their Instagram accounts. In contrast, fewer buyers have linked their Twitter accounts (68 percent), and even fewer have connected their Instagram accounts (30 percent). The specifics of user social media activities are provided in Panel D of Table 1.

Users create the network through their prior transactions. Using the methodology detailed in section 4.1, we calculate Katz centrality for all users, providing a measure of the relative importance of each user trading in past auctions. Summary statistics for these values in our auction data can be found in Panel D of Table 1.

Lastly, we obtain the exchange rate of Ethereum (ETH) to USD from etherscan.io, a widely-used source for tracking the Ethereum-to-US-dollar exchange rate.

4 Network Measures and Descriptive Evidence

This section presents regression results from estimating a model of winning bids that includes different trading network measures. Before we introduce the empirical evidence, we describe the construction of the network variables.

4.1 Network Measures

We construct the network based on past transactions where nodes in the network represent users involved in NFT sales or purchases (Kranton and Minehart, 2001). An edge in the network represents a connection from the seller to the buyer and is weighted by the winning bid. The weight of each edge corresponds to the value of transactions in ETH. We use Katz centrality to measure the centrality of each node k at time t using the following formula:

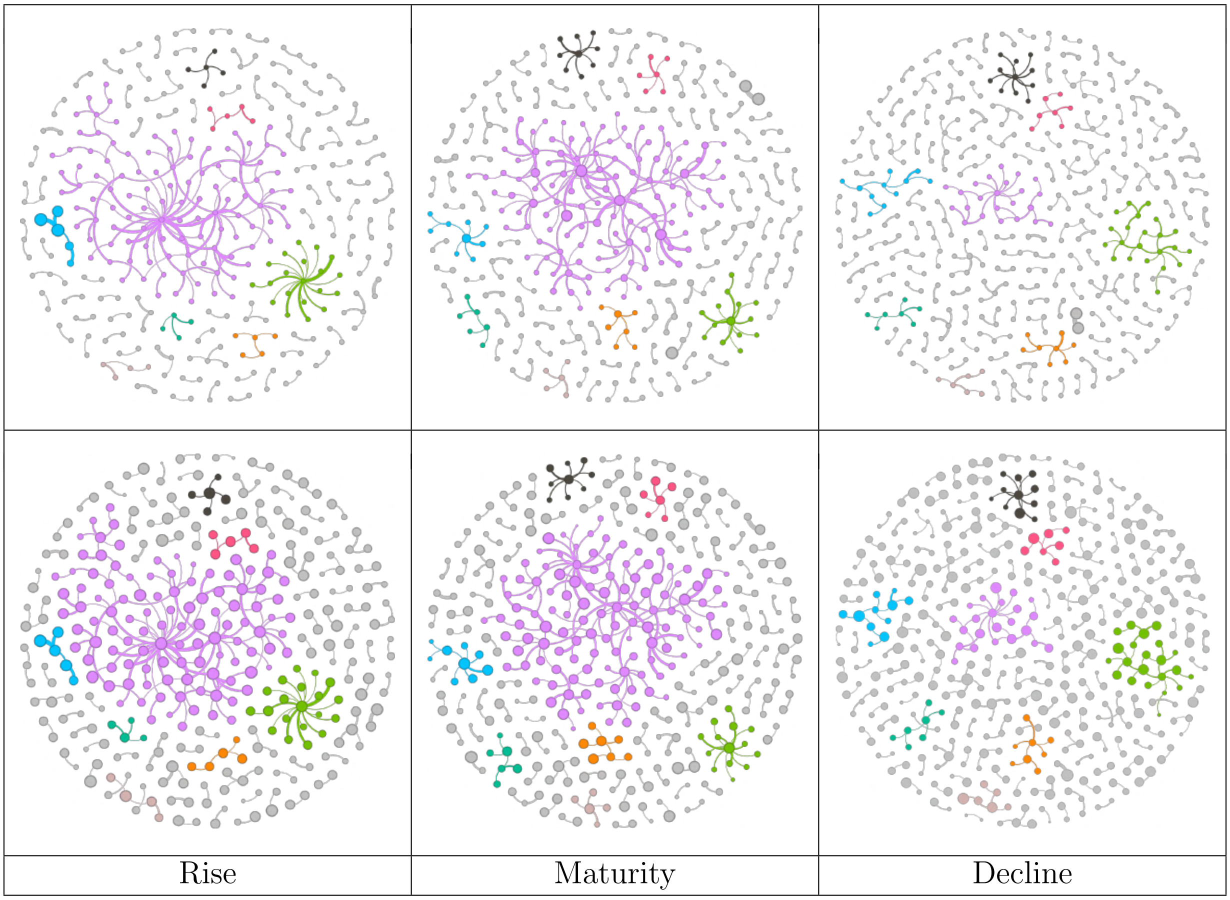
$$kc_{k,t}(N_t) = \sum_{l} \sum_{j} \delta^l \mathbf{A}^l_{t,k,j}, \tag{1}$$

where N_t represents the network of sellers and buyers spanning transactions from the last 30 days, but excluding those at t, with $\mathbf{A}_t$ representing its corresponding adjacency matrix. A non-zero value of $\mathbf{A}_{t,k,j}$ indicates the presence of an edge between node k and j during the time frame before t, while a zero value of $\mathbf{A}_{t,k,j}$ signifies the absence of such an edge within the same time frame. 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 $\mathbf{A}_t$.[9] Katz centrality allows us to assess the importance of nodes within a trading network. It extends the concept of eigenvector centrality and takes into account not only a node's direct connections but also its indirect connections through other nodes in

[9]To ensure convergence, for all t, δ need to satisfy $\delta < \lambda_t^{-1}$, where λ_t is the largest eigenvalue of N_t. We computed the largest eigenvalue for each t, with the maximum of these values being $2,280$. We selected δ corresponding to a larger eigenvalue of approximately 2,500. We later employed min-max normalization to ensure comparability across different days, accounting for the growing number of network nodes over time.

the network.

Figure 3: The top 300 highest-value transactions



Notes: The "Rise" period spans from February 5, 2021, to September 1, 2021, while the "Maturity" phase extends from September 1, 2021, to April 1, 2022. The "Decline" period is from April 1, 2022, to December 5, 2022. The thickness of edges denotes the transaction value in ETH. In the top row, node size corresponds to Katz centrality, while in the bottom row, node size indicates the number of followers. Connected components are highlighted.

Figure 3 provides a way to visualize trading networks of sellers and buyers of NFTs. It illustrates the 300 highest-value transactions per period, during three distinct phases of the market: the rise, maturity, and decline. This sample represents approximately 1% of the transactions per period, a size large enough to provide a clear visualization of the network structure but not too large to obstruct visual clarity. In these network graphs, the nodes represent participants identified as sellers or buyers, and the edges are links whose thickness varies by the value of user transactions. In the top row, node size signifies Katz centrality for the specified period as in equation (1), capturing the relative importance of nodes within the NFT trading network. In the bottom row, node size reflects the number of followers. Connected components are highlighted, showing the auction participants who are linked through some transaction.

In the first phase, the top 300 highest-value transactions were primarily concentrated within a large connected component featuring a small number of highly central nodes. However, dominant nodes and transactions gradually lost their prominence as the market transitioned from the phase of maturity to the decline. In the right panels, we see that participants involved in the most expensive transactions are not all interconnected, while their transactions become less central to the network's structure. The figure also reveals that for the most expensive NFTs, follower connections are more prominent than the trading network. Conversely, the relative importance of the trading network increases for the lowest priced NFTs.[10]

4.2 Regression Results

This section presents a series of descriptive regressions aimed at exploring the impact of trading and social networks, as a conduit of information, on prices. We estimate the following equation:

$$y_{iast} = \boldsymbol{N}'_{iast}\boldsymbol{\delta}_1 + \boldsymbol{F}'_{iast}\boldsymbol{\delta}_2 + \boldsymbol{S}'_{iast}\boldsymbol{\delta}_3 + \boldsymbol{B}'_{it}\boldsymbol{\theta} + \boldsymbol{X}'_{i}\boldsymbol{\beta} + f_d(D_{it}) + f_e(E_t) + \mu_t + u_{iast}, \quad (2)$$

where y_{iast} denotes a winning bid in an NFT auction i bought by buyer a, and sold by seller s at time t. The vector $\boldsymbol{N}_{iast}$ denotes network variables, $\boldsymbol{F}_{iast}$ includes the number of accounts in the Foundation following buyers and sellers, and the number of accounts the buyer or the seller follows, $\boldsymbol{S}_{iast}$ includes indicators for social media presence (i.e, the buyer has a Twitter or Instagram account connected to the Foundation platform), $\boldsymbol{B}_{it}$ are auction

[10]These figures are available by the authors upon request.

specific controls, $\boldsymbol{X}_i$ are NFT related controls, μ_t are time dummies and u_{iast} is an error term. The model also includes two unknown functions in terms of the listing-to-sale duration of the auction D_{it} and the exchange rate E_t. A detailed description of all the variables used in our analysis is provided in Table A.2 in the appendix.

Auction participants can access information regarding the NFT's value in three distinct ways. First, they can utilize past connections ($\boldsymbol{N}$), quantified by the Katz centrality of the seller, the buyer and the second highest bidder. This metric allows us to gauge experience and reputation; a higher centrality score for the seller indicates a strong network connection within the platform, implying extensive trading experience and a strong reputation through associations with important users. Similarly, a high centrality score for a buyer suggests robust trading network connections.[11] Second, participants can assess the popularity of sellers and buyers by examining the number of followers and profiles they follow within the Foundation platform ($\boldsymbol{F}$). We transform the variables and consider the logarithm of the number of followers and number of profiles followed. Foundation allows for asymmetric relationships, where a user can follow a profile without requiring confirmation from the profile being followed. In such relationships, a user's decision to follow another profile typically signifies an interest in obtaining information about that profile's activities. The number of followers serves as a measure of influence on the platform, indicating that others seek information from those they follow. Users with a higher number of followers on platforms are generally considered more popular, as more users express interest in obtaining information by following their accounts, a concept well-documented in the literature (Grover et al., 2022; Kane et al., 2014). Finally, participants can gather information from external social media platforms ($\boldsymbol{S}$), including Twitter and Instagram. In contrast to the Foundation platform, we lack direct data on the number of followers and accounts followed on Twitter and Instagram. We view these platforms as supplementary sources of information for participants. Since users have

[11] Alizadeh et al. (2023) employ NFT data from the Moralis platform and presents an analysis of networks, shedding light on their structural characteristics, evolution, and interactions. The study reveals that a select group of buyers and sellers frequently engage in NFT sales and purchases, while the majority participate in a more limited number of transactions.

the option to link their social media accounts to their profiles on the Foundation platform, they introduce an additional channel for gathering information. Instagram is known for its visual content, offering creators a platform to showcase their upcoming work, while Twitter, primarily text-based, is commonly used for announcements. Nevertheless, both platforms offer versatility, accommodating various types of content and providing participants with additional means of information acquisition.

The vector $\boldsymbol{B}$ comprises auction-related controls, including bidder type and an indicator denoting changes in the reservation price. NFT-specific characteristics ($\boldsymbol{X}$) include the type of NFTs auctioned off and the length of their description. We also use month and year dummies to control for time-specific effects. Lastly, we control for f_e, a cubic B-spline function with five knots, to smooth the exchange rate of Ethereum to USD at the time of minting. Similarly, f_d represents a cubic B-spline function of listing-to-sale duration with five knots.

The first column of Table 2 presents results from estimating equation (2) by Ordinary Least Squares (OLS). The OLS approach has its limitations in capturing the extent to which the effect of different predictors on prices can vary across the distribution. To investigate the impact of network and platform connections across the entire range of NFT prices, spanning from the least to the most expensive, we employ quantile regression and present results using the other columns of Table 2. We report the results of the effect of the main independent variables at the median (i.e., 0.5 quantiles), and at the lower and upper tails of the conditional price distribution (0.1 and 0.9 quantiles).

As expected, the results in the first column show that the network connections of the seller positively impact the winning bid, and the effect is similar across quantiles. The influence of the second highest bid, as a measure of competitive pressures, varies by quantile, although the effects are not significantly different. In contrast, the effect of followers increases across the quantiles of the price distribution. It is interesting to see that while a higher number of followers positively influences the winning bid, a greater number of accounts followed has a

Table 2: Descriptive regressions for the logarithm of winning bid

	Mean	Quantiles				
	OLS	0.1	0.25	0.5	0.75	0.9
Centrality Seller	0.964***	1.087***	1.199***	0.841***	0.933***	1.021***
	(0.071)	(0.208)	(0.069)	(0.087)	(0.154)	(0.215)
Centrality Buyer	0.377***	0.282***	0.393***	0.393***	0.429***	0.347***
	(0.041)	(0.061)	(0.059)	(0.051)	(0.063)	(0.075)
Centrality 2nd Highest Bidder	0.590***	0.657***	0.593***	0.599***	0.546***	0.440***
	(0.043)	(0.042)	(0.048)	(0.051)	(0.063)	(0.068)
Number of Followers Seller	0.288***	0.123***	0.194***	0.294***	0.367***	0.410***
	(0.006)	(0.009)	(0.008)	(0.009)	(0.011)	(0.013)
Number of Following Seller	−0.142***	−0.065***	−0.102***	−0.138***	−0.180***	−0.214***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)
Number of Followers Buyer	0.194***	0.121***	0.161***	0.194***	0.212***	0.236***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.011)
Number of Following Buyer	−0.097***	−0.043***	−0.068***	−0.094***	−0.123***	−0.143***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.009)
Seller Has Twitter	0.048*	0.054*	0.090**	0.050	0.026	0.051
	(0.029)	(0.029)	(0.038)	(0.035)	(0.045)	(0.065)
Seller Has Instagram	−0.001	0.038**	0.016	−0.005	−0.010	−0.032
	(0.013)	(0.015)	(0.016)	(0.015)	(0.017)	(0.021)
Buyer Has Twitter	−0.117***	−0.052***	−0.092***	−0.114***	−0.121***	−0.111***
	(0.014)	(0.018)	(0.018)	(0.018)	(0.020)	(0.026)
Buyer Has Instagram	−0.109***	−0.062***	−0.106***	−0.108***	−0.108***	−0.111***
	(0.013)	(0.015)	(0.016)	(0.016)	(0.019)	(0.023)
Auction 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
Observations	18,103	18,103	18,103	18,103	18,103	18,103

Notes: The dependent variable is the logarithm of the winning bid in Ethereum for an NFT auction (i) sold by seller (s) and won by buyer (a) at time (t). 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.

negative impact.[12].

The results for social media are mixed. Twitter account connections have a positive effect for sellers among low-priced NFTs and a negative effect for buyers among low- and high-priced NFTs. Having an Instagram account has a significant positive effect for the seller only at the 0.10 quantile. The implication is that sellers with an Instragram account sell low-priced NFTs higher than sellers without an Instagram account connected to the Platform.

The results presented so far indicate that trading networks, the platform, and social media have a differential impact across the distribution of NFT prices. These estimated effects, however, are obtained without controlling for network and group dependencies that are latent and possibly correlated to the network variables. In the next section, we outline the theoretical predictions offered in the literature, and in Section 6, we provide distributional regression and quantile regression estimates that are designed to address issues associated with latent connections and interdependence of participants in the auctions.

5 Conceptual Framework

This section offers a conceptual framework that sets the stage for the expectations concerning the subsequent empirical analysis. In any time period t, n individuals are actively participating in an NFT auction. The expected value of the NFT i for a buyer a depends on various factors, including a privately observed signal, NFT characteristics, the seller's identity and reputation, the network of buyer a at time $t-1$, the number of followers and users followed on the Foundation platform, information flow through connections in social media, and information revealed through the auction process. Let the vector of variables $\boldsymbol{w}_{ait}$ include all those characteristics with the NFT value estimate for bidder a represented

[12]Previous work by Vasan et al. (2022) in the NFT-driven crypto art marketplace reveals that artists' success is influenced by perceived reputation and a follower base, leading to the formation of clusters driven by homophily that affect individual artists' achievements. Successful artists tend to attract repeated investments from a select group of collectors, highlighting the significance of artist-collector relationships in the digital art space.

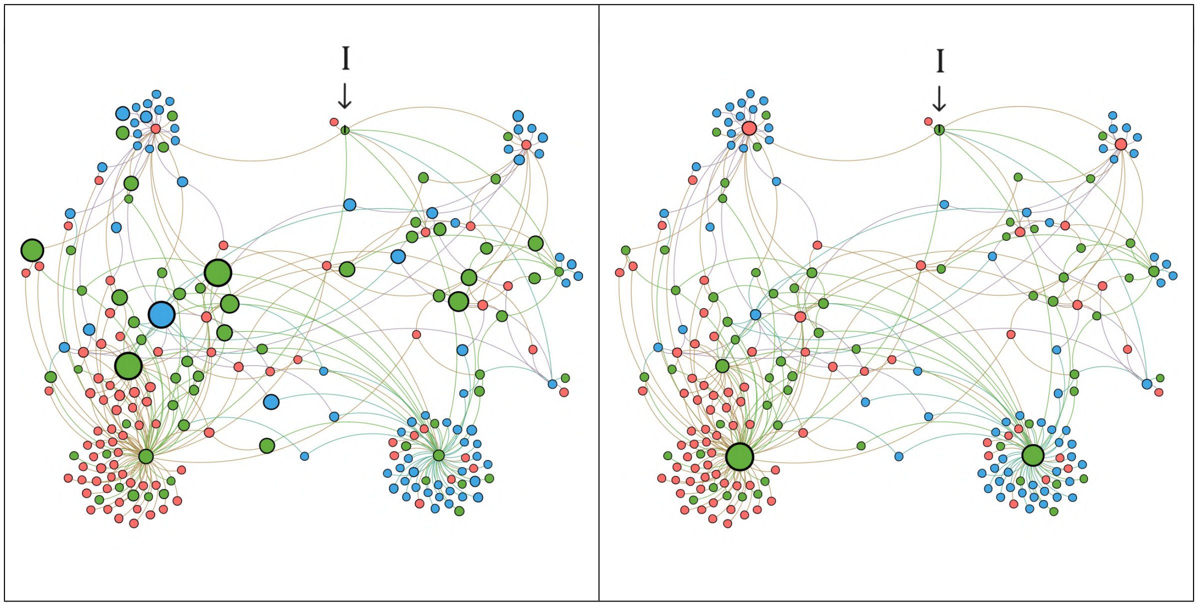
by $Z_{ait} = f(\boldsymbol{w}_{ait})$. The auction format employed by the Foundation is an asymmetric variant of the auction framework described by Milgrom and Weber (1982). The asymmetric version was introduced by Wilson (1998) and subsequently generalized by Hong and Shum (2003) to encompass both common and private value frameworks. Assuming that the expected value of an NFT is strictly increasing in the value estimates of individual bidders (a typical assumption made in the literature) then the theory predicts that equilibrium prices will also experience an increase as a direct consequence of the bidders' estimates.

Let $Y_{(k)it}$ represent the k-th order statistic of all value estimates Z_{jit}, for $j = 1, \ldots, n$ and $Y^{-a}_{(k)it}$ be the corresponding order statistic for all but buyer a. Based on the theory, the expected price paid by buyer a is $E(V_{it}|Z_{ait} = Y^{-a}_{(1)it})$, which is increasing in the value estimates. Note that, connections through networks, platforms, and social media lead to asymmetric information among bidders. Following the principles outlined in Engelbrecht-Wiggans et al. (1983) and Hendricks and Porter (1988), the bidder with superior information enjoys higher profit margins and lower prices compared to others.[13] The strength of a network creates asymmetries in the same vein as in Maskin and Riley (2000) where "strong" bidders (in this case, the ones with a large network, a large number of followers, a strong reputation, and clout) have higher average expected value and induce more aggressive bidding behavior at auctions.

While the theory underscores the critical impact of asymmetries on market outcomes, a practical question arises regarding the prevalence of "strong" bidders who can influence bidding behavior in NFT auctions. Figure 4 sheds light on this issue by showing a snapshot of the trading network structure for a representative auction participant from our sample, labeled I. In this figure, red nodes represent sellers, blue nodes represent buyers, and green nodes represent auction participants who engaged both in buying and selling. The size of

[13] Note that Hong and Shum (2003) provide an example of a parametric family of distributions where the equilibrium bidding functions have closed-form solutions. In this example, bidder valuations follow a log-normal distribution, and more information leads to higher information rents in a common value context. In the context of our empirical framework, a bidder with more platform connections is expected to be more informed relative to their competitors, resulting in higher profit margins and lower prices. Likewise, sharing information creates advantages for the followers leading to lower profit margins and higher prices.

Figure 4: Network structures with interdependence



Notes: The network structure of a representative auction participant, denoted as I, over our sample period, featuring a walk of length 2. Nodes shaded in green depict users who engaged both in buying and selling activities. Red nodes represent sellers, while blue nodes represent buyers. In the figure to the right, the size of each node is proportional to its Katz centrality and in the figure to the left it is proportional to the number of followers on the platform.

the node is proportional to the number of trading connections (left panel) or the number of followers on the platform (right panel).

Judging by the size of each node, the figure reveals that while participant I may not be a strong player, she is facing some competitors with denser trading networks or larger number of followers who in turn are competing against well-connected bidders. Moreover, the evidence brings out an additional layer of complexity. Individuals involved in transactions, particularly those transitioning from buyers to sellers and vice versa, can create interdependence across networks. For instance, a popular buyer could sell a NFT whose high price might not be determined by her trading network but instead her popularity as a buyer. This naturally affects bidding behavior and could potentially introduce estimation biases if these latent dependencies are not controlled for. We tackle this challenge in the next section.

6 Networks and Platforms Influence on NFT Prices

How do trading networks, platform and social media connections affect low-priced and high-priced NFTs? In this section, we employ distributional regression and quantile regression approaches to estimate the impact of these factors on prices. We extend the descriptive quantile regression analysis introduced in section 4.2 to account for latent dependencies. These dependencies are a pervasive feature of the NFT market, as participants often transition between the role of buyer and seller as shown in Figure 4, maintaining interdependencies that can introduce bias into our estimation. Section 6.1 presents a parametric estimator for a model with a large number of buyer and seller effects, and Section 6.2 presents an estimator that is computationally more attractive for a similar model. Both approaches offer complementary evidence to investigate the effect of networks on the winning bid in NFT auctions.[14]

Our empirical analysis offers several important findings. While trading networks remain critically important, their impact decreases across the distribution of NFT prices. Moreover, platform followers for sellers, possibly capturing popularity, help explain price differences among the highest NFT prices. Lastly, the influence of social media on prices, which was immediately apparent in our descriptive regressions, dissipates when we consider latent network and group dependencies in the NFT market.

Before we present the first estimation approach in the next section, it is convenient to introduce additional notation. Let the observed data be represented by $\{(y_{sa}, \boldsymbol{w}'_{sa}) : (s, a) \in \mathcal{D}\}$, where s denote seller and a denotes buyer. The variable winning bid $y \in \mathcal{Y} \subseteq R$ is also indexed by auction i and time t as in equation (2), but we omit these indexes to simplify the notation. As above, let the vector of variables $\boldsymbol{w}$ includes the vector of network variables, the number of accounts in the Foundation following buyers and those following

[14] Koenker et al. (2013) compares distributional regression to quantile regression, offering several theoretical results for cross-sectional models. The literature on panel data offers less clear theoretical conclusions, although in our case, quantile regression offered a superior and more efficient computational performance in Section 6.3 when we estimate models with a large number of seller effects (6449) and buyer effects (6603).

sellers and the number of accounts the buyer or the seller follow, the indicator variables for social media presence, the auction specific controls, and the NFT related controls. All the models estimated below include controls for the listing-to-sale duration of the auction and the exchange rate, as well as individual time effects. Finally, let $P(\boldsymbol{w})$ denote a dictionary of transformations of $\boldsymbol{w}$ that includes B-splines functions for the listing-to-sale duration of the auction and the exchange rate as in equation (2).

6.1 Distributional Regressions

Recent work by Chernozhukov et al. (2023) allows us to control for network and group dependencies that are latent and possibly correlated to the network variables. This approach can be valuable in addressing network effects due to latent linkages in our data, where buyers and sellers can assume multiple roles. For instance, the same pair of market participants, when their roles are reversed from seller to buyer and vice versa, may exhibit interdependence. Let $\alpha(v_s, y)$ and $\mu(v_a, y)$ denote seller and buyer latent heterogeneity, where v_s captures private information available to seller s. The variable v_a is defined similarly.

In the case of NFT data, the set $\mathcal{D}$ contains all pairs (s, a) corresponding to observed connections, which is a subset of all possible pairs. Since we do not observe trading with s when $a = s$ and y is the winning bid, the number of observations is the cardinality of $\mathcal{D} = \{(s, a) : s = 1, \ldots, n_s, a = 1, \ldots, n_a\} \setminus \{(s, s) : s = 1, \ldots, n_s\}$. We specify the conditional model as,

$$G_{y_{sa}}(y|\boldsymbol{w}_{sa}, v_s, v_a) = \Lambda_y \left(P\left(\boldsymbol{w}_{sa}\right)' \boldsymbol{\gamma}(y) + \alpha(v_s, y) + \mu(v_a, y) \right), \tag{3}$$

where $\Lambda_y(\cdot)$ is the logistic distribution and $\boldsymbol{\gamma}(y)$ is an unknown parameter that varies with the winning bid $y \in \mathcal{Y}$. Since $G_{y_{sa}}(y|\boldsymbol{w}_{sa}, v_s, v_a)$ is a conditional CDF, the model's parameters are related to the derivatives of the quantiles of the conditional winning bid distribution through the following expression:

$$\frac{\partial}{\partial w_{sa}^{j}} P\left(\boldsymbol{w}_{sa}\right)' \boldsymbol{\gamma}(y) = \gamma_j(y) \propto -\frac{\partial}{\partial w_{sa}^{j}} Q_{y_{sa}}(\tau|\boldsymbol{w}_{sa}, v_s, v_a), \tag{4}$$

where $Q_{y_{sa}}(\tau|\boldsymbol{w}_{sa}, v_s, v_a)$ is the conditional quantile function. If the quantile function is linear as in equation (6) in Section 6.3, the sign of the effect in the quantile model is the opposite to the sign of the distributional regression parameter.

The estimation of the parameters in equation (3) follows closely Chernozhukov et al. (2023). The vector $\boldsymbol{\theta}(y) := (\boldsymbol{\gamma}(y)', \alpha_1(y), \ldots, \alpha_{n_s}(y), \mu_1(y), \ldots, \mu_{n_a}(y))'$ can be estimated, for each $y \in \mathcal{Y}$, by maximizing

$$\ell(\boldsymbol{\theta}, y) = \sum_{(s,a)\in\mathcal{D}} d_{sa} \log(G_{y_{sa}}(y|\boldsymbol{w}_{sa}, v_s, v_a)) + (1 - d_{sa})(1 - \log(G_{y_{sa}}(y|\boldsymbol{w}_{sa}, v_s, v_a)), \tag{5}$$

where the indicator variable $d_{sa} := 1\{y_{sa} \leq y\}$. The Maximum Likelihood (ML) estimator with fixed effects is then defined as $\hat{\boldsymbol{\theta}}(y) := \text{argmax}_{\theta\in\Theta}\{\ell(\boldsymbol{\theta}, y)\}$.

The method is implemented considering a grid of values for the winning bid that includes the sample quantiles of y_{sa}. Moreover, as fixed effects in nonlinear models can lead to bias due to incidental parameters, it is advised to implement bias corrections in finite samples. The results presented in Section 6.3 are obtained by adopting the correction proposed by Fernández-Val and Weidner (2016).

6.2 Panel Quantile Regression

Since y is continuous, the model stated in equation (3) is related to conditional panel quantile functions with individual intercepts. If we set $u_{sa} = G_{y_{sa}}(y|\boldsymbol{w}_{sa}, v_s, v_a)$, where $u_{sa}|\boldsymbol{w}_{sa}, v_s, v_a \sim \mathcal{U}(0, 1)$, the τ-th quantile of y_{sa} conditional on $\boldsymbol{w}_{sa}$ is

$$Q_y(\tau|\boldsymbol{w}_{sa}) = \boldsymbol{w}_{as}'\boldsymbol{\gamma}(\tau) + \alpha_s(\tau) + \mu_a(\tau), \tag{6}$$

where $\tau \in (0,1)$ and $Q_y(\tau|\boldsymbol{w}_{sa})$ is the τ-th quantile of the conditional distribution of the winning bid y_{sa}, α_s is the seller effect, and μ_a denotes the buyer effect. Let the parameter vector be $\boldsymbol{\theta}(\tau) = (\boldsymbol{\gamma}(\tau)', \boldsymbol{\alpha}(\tau)', \boldsymbol{\mu}(\tau))' \in \boldsymbol{\Theta} \subseteq R^{p+n_a+n_s}$, where $\boldsymbol{\alpha}(\tau) = (\alpha_1(\tau), ..., \alpha_{n_s}(\tau))'$, and $\boldsymbol{\mu}(\tau) = (\mu_1(\tau), ..., \mu_{n_a}(\tau))'$. The following estimator is an extension of a one-way panel quantile estimator considered by Koenker (2004) and Lamarche (2010):

$$\hat{\boldsymbol{\theta}}(\tau) = \underset{\boldsymbol{\theta} \in \boldsymbol{\Theta}}{\operatorname{argmin}} \sum_{(s,a) \in \mathcal{D}} \rho_\tau(y_{sa} - \boldsymbol{w}_{sa}'\boldsymbol{\gamma} - \alpha_s - \mu_a) + \lambda_1 \|\boldsymbol{\alpha}\|_1 + \lambda_2 \|\boldsymbol{\mu}\|_1, \tag{7}$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ is the quantile regression loss function and $\|\cdot\|_1$ denotes the ℓ_1 norm. The last two terms represent Lasso-type penalties with tuning parameters $(\lambda_1, \lambda_2) \geq 0$. These tuning parameters and the standard error of the estimator $\hat{\boldsymbol{\theta}}(\tau)$ are obtained following Lamarche and Parker (2023).[15]

If $\lambda_1 = \lambda_2 = 0$ in (7), the estimator is a quantile regression estimator with seller and buyer effects, which can be biased due to the estimation of individual parameters, an issue similar to the one discussed for the estimator defined in (5). Rather than using a bias correction formula to reduce the potential bias due to incidental parameters, the penalty terms in (7) help reducing the noise in the estimation of individual intercepts, and consequently, the penalized estimator can reduce the bias of the fixed effects estimator. The idea is related to Bester and Hansen (2009) who propose an approach to bias reduction in nonlinear models with fixed effects using a penalty function.[16]

6.3 Main Results

Table 3 presents a comparison of estimates of panel quantile regressions and distributional regressions for the network variables. Consistent with the auction framework discussed

[15] Lamarche and Parker (2023) propose a wild residual bootstrap for statistical inference and establish its consistency. The tuning parameters are selected by cross-validation adopted iteratively over a grid of values for the λs.

[16] Koenker (2004) and Harding and Lamarche (2019) document reductions in the bias of the fixed effects estimator when a penalized estimator similar to the one defined in equation (7) is considered.

Table 3: Results for Network Effects in Models with Seller Effects

	Quantile Regression		Distributional Regression		
	QR	PQR	DR	DR	BC
	(1)	(2)	(3)	(4)	(5)
			0.1 Quantile		
Centrality Seller	1.087***	0.482***	−2.468***	−3.675***	−2.451
	(0.208)	(0.126)	(0.685)	(1.407)	
Centrality Buyer	0.282***	0.380***	−0.332	−1.190*	−0.534
	(0.061)	(0.066)	(0.309)	(0.639)	
Centrality 2nd Highest Bidder	0.657***	0.296***	−2.029***	−1.926***	−1.254
	(0.042)	(0.039)	(0.321)	(0.638)	
			0.5 Quantile		
Centrality Seller	0.841***	0.492***	−5.063***	−3.075***	−2.394
	(0.087)	(0.101)	(0.436)	(1.083)	
Centrality Buyer	0.393***	0.329***	−0.422***	−1.619***	−0.918
	(0.051)	(0.054)	(0.151)	(0.323)	
Centrality 2nd Highest Bidder	0.599***	0.297***	−1.395***	−2.155***	−1.482
	(0.051)	(0.054)	(0.150)	(0.299)	
			0.9 Quantile		
Centrality Seller	1.021***	0.351***	−4.965***	−1.835***	−1.274
	(0.215)	(0.100)	(0.294)	(0.570)	
Centrality Buyer	0.347***	0.438***	−0.442**	−1.867***	−0.896
	(0.075)	(0.048)	(0.184)	(0.400)	
Centrality 2nd Highest Bidder	0.440***	0.228***	−0.841***	−2.127***	−1.399
	(0.068)	(0.044)	(0.212)	(0.458)	
Foundation/Social Media Variables	Yes	Yes	Yes	Yes	Yes
Auction Controls	Yes	Yes	Yes	Yes	Yes
NFT Controls	Yes	Yes	Yes	Yes	Yes
Semiparametric Functions	Yes	Yes	Yes	Yes	Yes
Monthly and Year Dummies	Yes	Yes	Yes	Yes	Yes
Seller Effects	No	Yes	No	Yes	Yes
Observations	18,103	18,103	18,103	18,103	18,103

Notes: The dependent variable is the logarithm of the winning bid in Ethereum for an NFT auction (i) sold by seller (s) and won by buyer (a) at time (t). QR is quantile regression, PQR stands for panel quantile regression, DR for distributional regression, and BC for bias-corrected DR. Standard errors are in parentheses. 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.

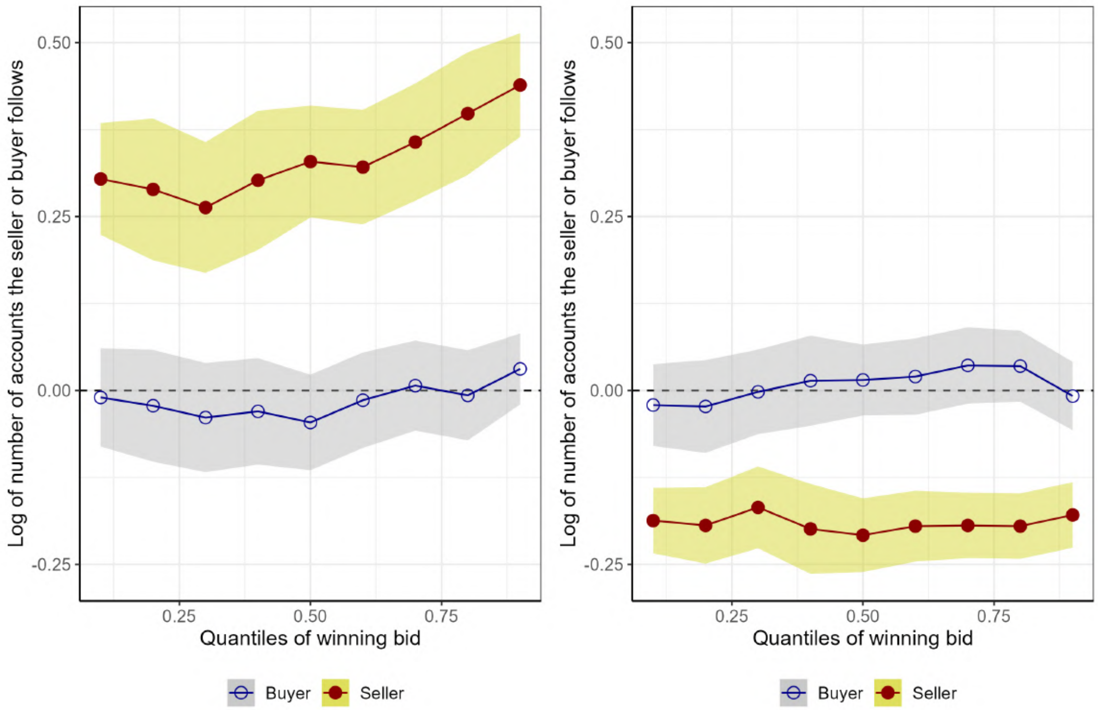
above, we begin by estimating a model with seller effects, as they appear to be the most important latent drivers of winning bids in the NFT auctions. This is also convenient for the computational performance of the ML estimator, due to the demanding memory usage in models with a large number of sellers and buyers. Nevertheless, we demonstrate that the results from the bias-corrected distributional regression with seller fixed effects closely align with those obtained through panel quantile regression. The model also includes Foundation variables and social media variables as in equation (2), but, due to the inclusion of seller effects, the effects are not always identified.

The first two columns of Table 3 present results obtained by quantile regression methods, and the other columns show results obtained by employing several distributional regression estimators. The last column shows the results of the bias-corrected distributional regression. A direct comparison of the estimates can be made using equation (4), noting that the signs of the coefficients in the distributional regression are opposite to those in the panel quantile regression. The table presents three panels with results, and each panel provides estimates across quantiles. In the case of quantile regression, $\tau = \{0.1, 0.5, 0.9\}$ and in the case of distributional regression, we use the empirical quantiles of y corresponding to $\{0.1, 0.5, 0.9\}$ to initiate the procedure.

The results in the first two columns are consistent with expectations. Seller's centrality positively impacts winning bids, suggesting that trading networks provide significant informational advantages to sellers. Moreover, these quantile regression results reveal the importance of controlling for seller's effects. For instance, while the sign and significance do not change from column (1) to column (2) at the 0.1 quantile, the estimated effect is significantly smaller in column (2). We also note that the effect increases across quantiles in column (1) while slightly decreases in column (2).

The results also suggest that trading networks provide greater informational advantages to sellers who sell at relatively lower prices, in comparison to those who sell at higher prices. While the point estimates do not show a sharp decline across quantiles, they do suggest that

Figure 5: The effect of platform connections on winning bids



the seller's trading network may not remain the dominant driver of higher trading values of NFTs confirming the evidence provided in Figure 3. Based on the estimates, the results in column (2) indicate a decrease in the seller's centrality as we move from the 0.1 to the 0.9 quantile. In contrast, the distributional regression results presented in column (3) shows an increasing effect for the seller's centrality. These latter estimates, which do not include seller fixed effects, yield biased results. After the inclusion of seller fixed effects, we observe outcomes similar to those of panel quantile regressions, confirming a decreasing effect of the centrality measure of the seller across quantiles. The final column presents the bias-corrected estimator of the distributional regression with seller fixed effects, and these results closely align with those of the panel quantile regression across quantiles.

We now focus our attention on estimating models with both seller and buyer effects. We report panel quantile regression estimates, since the model can be efficiently estimated with a total of 13,052 seller and buyer effects and we expect distributional regressions and quantile regressions to deliver similar qualitative conclusions as shown in Table 3. Due to the estimation of more than 13,000 parameters in our application, the algorithm for ML with fixed effects encountered convergence issues. In the next steps of this analysis, we are using Figure 5, Figure 6, and Figure 7, to present results for the main effects of interest included in the winning bid equation (6).

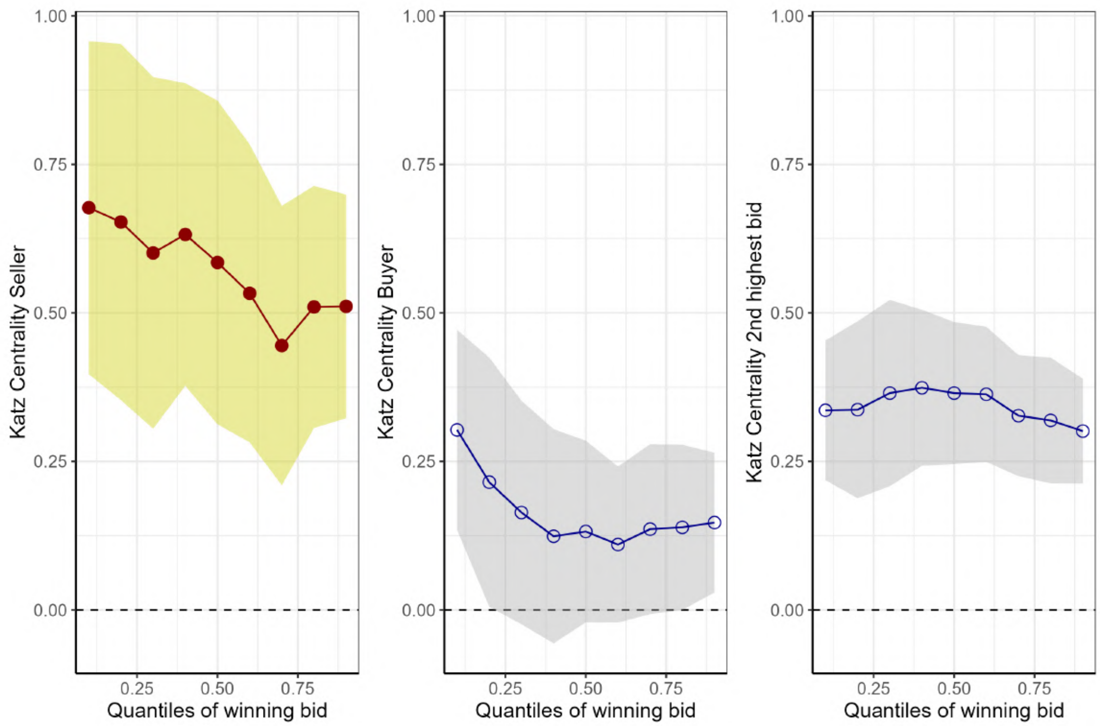
Figure 5 displays the estimated effects of the logarithm of seller and buyer followers and the number of accounts followed as a function of the quantile τ of the conditional distribution of winning bids. The dotted line corresponds to the point estimate, while the shaded region represents a 95 percent point-wise confidence interval for these estimates. Buyers are depicted in blue, while sellers in red. The results in the left panel reveal that, once we account for potential group dependencies, the impact of the number of followers of the buyers becomes consistently muted across quantiles. In contrast, the estimated effect of the number of followers of the seller is positive and increasing, suggesting that platform connectivity provides a channel through which influence and visibility might help explain conditionally high NFT prices.

The right panel of Figure 5 continues to show negligible and insignificant effects for the buyers, this time considering the number of accounts they follow. In contrast, the impact of the number of accounts followed by sellers is negative and constant across quantiles. The evidence seems to suggest that high trading prices might be associated with popular sellers who tends to lead and not follow other participants on the platform.

Figure 6 presents point estimates and 95 percent point-wise confidence intervals for the effect of trading networks across quantiles of the conditional distribution of winning bid. The left panel show results for the Katz centrality of the seller, and the middle panel show results for the same measure constructed for the buyer. The panel on the right shows the estimated impact of the network of the bidder with the second highest bid.

It is interesting to see that trading networks do not seem to be as impactful at the highest trading prices. This is evident in the declining effect of seller centrality when moving across quantiles. While the seller's centrality is associated with higher prices at the upper tail of

Figure 6: The effect of trading networks on winning bids

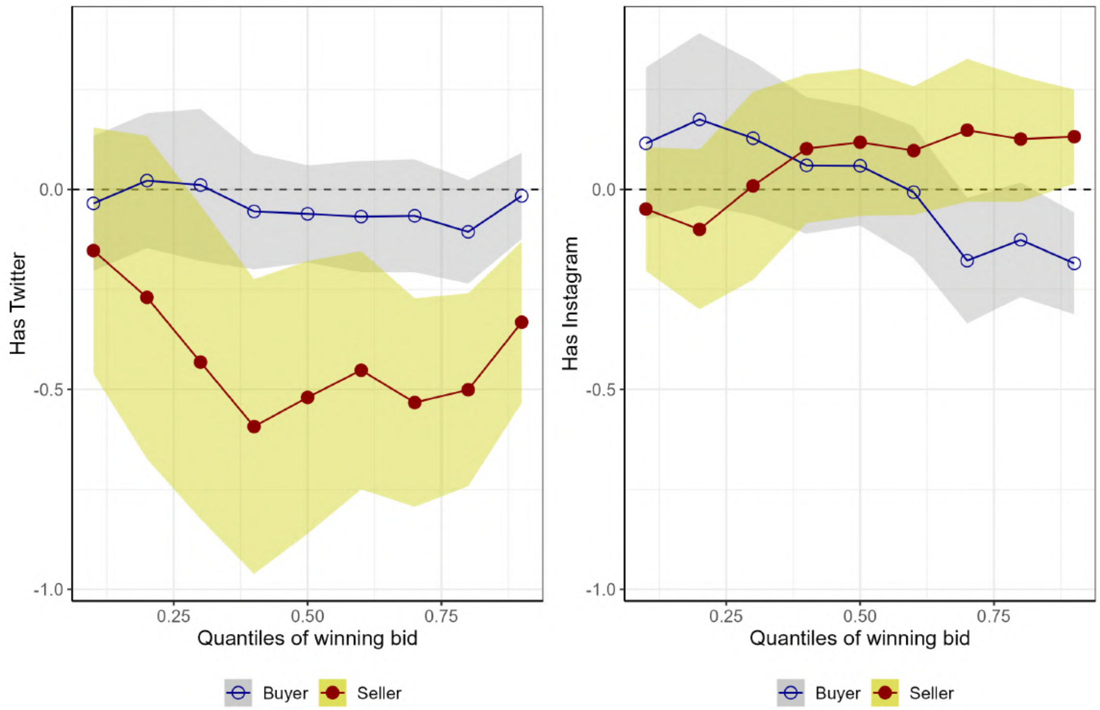


the distribution, they have a higher marginal impact at the lowest conditional quantiles.[17] Additionally, we observe a higher effect for the buyer's centrality in the lower tail, possibly implying that buyers with more trading connections in the past pay relatively more for low-priced NFTs. The effect of competition in the auctions, which is measured by the centrality of the second highest bid, is positive and constant, consistent, once again, with expectations.

Finally, Figure 7 presents estimates and point-wise confidence intervals for Twitter and Instagram as a function of τ. These effects can be identified because social media usage varies across auctions, although the variation is rather limited. As before, the blue (red) dotted line corresponds to results of the effect of the variables for the buyer (seller). The evidence of the impact on the winning bid of social media accounts connected to the Foundation platform is mixed. For instance, connecting a Twitter account to the platform has a negative effect on winning bids at the 0.9 quantile, while connecting an Instagram account has a 0 positive effect. Linking a Twitter or Instagram account to the platform does not seem to affect buyers.

[17] As suggested by the figure, the slope coefficient is not significantly different acrosss quantiles.

Figure 7: The effects of social media on winning bids



Social media links, while providing access to supplementary information that can prove useful in assessing the value of an NFT, they may also offer a window to other personality traits that can adversely affect some traders.

These figures also show the importance of group dependencies. For instance, in the descriptive regressions shown in Table 2, we observe that the number of followers for both buyers and sellers exhibited an increasing effect on winning bids, and the number of accounts followed had an increasing negative effect. However, after controlling for seller and buyer effects, these patterns continue to hold only for followers of the seller. While the number of accounts followed by the seller now has a constant negative effect across quantiles, the buyers' links have no effect on prices. Furthermore, Table 2 indicates a constant effect for the seller's Katz centrality and an increasing effect for the buyer's Katz centrality. However, when dependencies are taken into account, we now observe a declining effect for the seller and a non-increasing effect for the buyer.

In summary, the results of this section suggest that controlling for latent interdependencies in the network is critical for consistently estimating price effects. We find that trading networks are relatively more important the less expensive the NFTs are. However, popular sellers can earn higher profits in high-priced NFTs, even in the absence of experience and well-established reputation through past transactions. Among sellers, while social media connections seem to be of third order importance and take a back seat in this digital marketplace, platform connections affect the overall distribution of prices and, in particular, higher-priced items.

7 Conclusion

This research aims to shed light on the evolving dynamics of NFT markets, where traditional market structures are being reshaped by decentralized networks and digital connections. Our analysis shows that informational disparities stemming from trading networks have more direct effects on sellers and buyers than the information distributed through the platform, even in the absence of powerful market makers. Nonetheless, a combination of a substantial follower count and a limited number of connections made by following others on the platform, can still lead to significant price increases for popular sellers. Trading network effects for sellers are dominant for low valued NFTs, while the dynamics shift, and popularity gains importance for high-valued NFTs. On the other hand, buyers may see larger trading networks as validation for higher bids, but their involvement in the Foundation community or their social media interactions do not appear to impact NFT prices.

Our research offers valuable insights that extend beyond the realm of NFTs for digital art. Our contribution to the empirical literature on networks and decision making, particularly through distributional regression analysis, can have broader applications in the study of online marketplaces. Our approach, which allows us to overcome estimation challenges and accounts for participant interdependencies, endogeneity, and potential estimation bias, can be applied to real estate sales, the market for financial securities, and e-commerce, to study factors that influence price formation across the distribution.

While our analysis allows us to control for Foundation connections we do not have detailed information on the structure of those connections. Future analysis could focus on an in-depth exploration of how the structure of the Foundation connections vis-a-vis the trading networks influence prices within the NFT market. This structure could also help us understand the relative influence on prices of individuals with followers versus those who follow others on the platform. Further research could also center on sentiment analysis, exploring the impact of positive or negative attitudes and emotions toward NFT assets thus adding an insight into additional forces that might shape market outcomes.

A Appendix

Table A.1: The top 10 NFTs based on their USD value at the time of purchase.

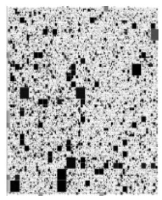
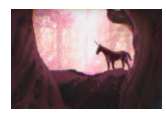
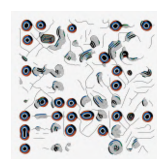
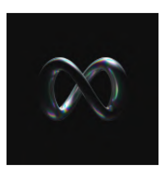
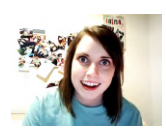
Price Ranking	Details	Price Ranking	Details
1	Stay Free (Edward Snowden, 2021) $ 5,155,254 4/17/2021	6	Nyan Cat $ 574,536 2/20/2021 
2	Dreaming at Dusk $ 1,822,020 5/15/2021 	7	The New York Times x NFT $ 555,919 3/25/2021 
3	Yield by Stani x Sven Eberwein $ 1,123,294 9/10/2021 	8	x*y=k $ 531,321 3/27/2021 
4	Coffin Dance (Dancing Pallbearers) $ 1,065,896 4/9/2022 	9	K-Meanearest Neighbors $ 506,232 10/31/2021 
5	Finite. $ 820,818 3/14/2021 	10	Overly Attached Girlfriend $ 415,324 4/4/2021 

Table A.2: 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.
	Centrality 2nd Highest Bidder	Measures the Katz centrality of the second highest bidder 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.
$\boldsymbol{B}_{it}$	Seller is DAO	An indicator variable denoting whether the seller is a DAO.
	Buyer is DAO	An indicator variable denoting whether the buyer is a DAO.
	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).

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