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Network Effects and Boom–Bust Dynamics in NFT Prices

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Abstract

This paper develops a tractable theoretical framework to study how network participation shapes the boom–bust dynamics of non-fungible token (NFT) prices. We model NFT pricing under network effects and heterogeneous consumers, and show that prices and participation are jointly determined in equilibrium. The model implies a critical participation threshold that separates expansion from contraction regimes: above this threshold, positive feedback between participation and valuation generates self-reinforcing growth, while below it, weakening network benefits lead to contraction. We provide empirical evidence using data from the aggregate NFT market and prominent collections including Bored Ape Yacht Club (BAYC) and CryptoPunks. Reduced-form regressions show a positive association between prices and network participation, with stronger effects at the collection level than in the aggregate market. Threshold estimation further provides evidence consistent with regime-dependent dynamics, with clearer tipping behaviour in well-defined NFT communities than in the aggregate market. These findings suggest that NFT valuation is closely tied to network structure and participation dynamics. More broadly, this paper contributes a unified framework that links participation, price formation, and threshold behaviour in NFT markets.

Keywords: non-fungible tokens (NFTs); network effects; dynamic pricing; blockchain markets; digital asset valuation

JEL Classification: D42; D85; L12; L86; G12

1. Introduction

Non-fungible tokens (NFTs) have emerged as a prominent class of digital assets, characterized by rapid price appreciation followed by sharp corrections. Prominent collections such as Bored Ape Yacht Club (BAYC) and CryptoPunks experienced substantial increases in valuation during periods of expanding user participation, followed by pronounced declines as market activity weakened. These boom–bust patterns have drawn increasing attention from both academics and practitioners seeking to understand the underlying drivers of NFT valuation and volatility.

A central feature of NFT markets is their reliance on network participation. The value of owning an NFT is closely tied to the size and activity of the user base, which affects liquidity, visibility, and perceived desirability. As participation increases, market activity intensifies and valuations may rise; conversely, declining participation weakens demand and can trigger price contractions. This interdependence between participa-

Check for updates

Academic Editor: Nikiforos T. Laopodis

Received: 18 March 2026
Revised: 18 April 2026
Accepted: 21 April 2026
Published: 1 May 2026

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tion and valuation suggests that NFT markets are inherently susceptible to feedback-driven dynamics.

While network effects and tipping dynamics are well established in the broader literature, existing models typically focus on technology adoption, platform competition, or coordination across users. These frameworks do not explicitly capture the interaction between endogenous participation and asset pricing in resale-driven markets such as NFTs. In NFT markets, asset values are sustained by trading activity and network engagement within a collection, creating a direct feedback loop between participation, liquidity, and price formation. This paper develops a tractable framework that incorporates this interaction and characterizes how it gives rise to boom–bust dynamics within NFT collections.

We propose a theoretical model in which heterogeneous consumers derive utility from both intrinsic characteristics of NFTs and network participation. Prices and participation are jointly determined in equilibrium, and the model generates a critical participation threshold that separates expansion from contraction regimes. Above this threshold, positive feedback between participation and valuation supports sustained growth; below it, weakening network benefits lead to contraction. The model provides a simple characterization of how endogenous network dependence can generate nonlinear price dynamics.

To examine whether these mechanisms are reflected in market data, we conduct an empirical analysis using aggregate NFT market data as well as collection-level data for BAYC and CryptoPunks. The empirical strategy is intentionally reduced-form and focuses on identifying systematic relationships between participation and prices. The results show a positive association between active wallets and prices, consistent with the model's predictions. Threshold analysis further provides evidence of regime-dependent dynamics, with stronger and more clearly defined effects at the collection level than in the aggregate market.

Importantly, the empirical analysis does not aim to establish a causal relationship between participation and prices. Instead, it provides evidence on whether the patterns implied by the model are present in observed data, acknowledging that prices and participation co-evolve and are jointly determined. Additional specifications incorporating market-wide factors, including cryptocurrency price movements and proxies for market sentiment, confirm that the positive association remains robust.

Finally, while the model adopts a monopolistic seller framework for tractability, this should be interpreted as a reduced-form representation of pricing at the collection level rather than literal centralized price setting. In practice, NFT markets operate in a decentralized and resale-driven environment, where prices within a collection are shaped by shared factors such as creator reputation, perceived scarcity, and floor price dynamics. The model captures these common valuation forces in a simplified way, allowing us to isolate the role of network participation in price formation.

This paper contributes to the growing literature on digital asset markets by providing a unified framework that links participation, price formation, and threshold dynamics in NFT markets. It also highlights the importance of network structure in understanding valuation and volatility in decentralized, participation-driven environments.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the theoretical framework. Section 4 derives the equilibrium and characterizes the threshold dynamics. Section 5 provides empirical evidence. Section 6 concludes this study.

2. Related Literature

This paper contributes to four main strands of research: network effects and tipping dynamics, dynamic pricing under network externalities, valuation of blockchain-based assets, and the empirical literature on NFTs and digital assets.

First, this paper relates to the literature on network effects and coordination. Early work shows that adoption decisions depend on expectations about other users' participation [1,2]. Subsequent studies highlight increasing returns, path dependence, and potential lock-in in network markets [3–6], while more recent frameworks formalize network formation and multi-sided interactions [7–9]. A key implication of this literature is the possibility of tipping behaviour, whereby small changes in participation can lead to large shifts in equilibrium outcomes. Our paper builds on this foundation but differs in that it embeds network participation directly into an explicit asset pricing framework in a resale-driven environment, allowing prices and participation to be jointly determined and linked to observable market outcomes.

Second, this paper connects to the literature on dynamic pricing under network externalities. Existing studies show that when product value depends on the installed base, optimal pricing becomes state-dependent and may generate nonlinear dynamics [10–13], with more recent work further characterizing pricing strategies in networked environments [14]. While this literature emphasizes how network size affects pricing, it typically abstracts from decentralized resale markets and does not explicitly model how participation dynamics feed back into asset-level valuation. Our model extends this framework by introducing an endogenous participation threshold within a pricing setting, which directly generates boom–bust dynamics in asset markets.

Third, this paper contributes to the literature on blockchain-based assets and token valuation. Prior work shows that token prices are closely linked to adoption dynamics and network participation rather than traditional cash flows [15–17]. This perspective is particularly relevant for NFTs, where value depends on both intrinsic attributes (e.g., scarcity or artistic quality) and network-driven components (e.g., community size and social recognition). However, existing models typically focus on homogeneous tokens or aggregate adoption, and do not explicitly characterize how intrinsic value and network effects jointly determine prices in resale-driven, collection-based markets. Our framework addresses this gap by modelling this interaction and deriving its implications for price dynamics.

Fourth, this paper relates to the growing empirical literature on NFT markets. Existing studies document strong concentration, networked trading structures, and rapid market expansion [18,19]. Other work examines NFT pricing behaviour and its relationship with cryptocurrency markets [20–23], while recent evidence highlights the role of sentiment, attention, and herding behaviour in shaping NFT valuations [24–27]. Industry analyses further document boom–bust cycles in major NFT collections driven by community dynamics [28]. Building on this literature, our paper provides complementary empirical evidence using reduced-form regressions and threshold estimation, focusing on whether the participation–price relationship implied by the model is present in the data.

More broadly, this paper connects to the literature on digital assets in macro-financial contexts. Dimitriadis et al. [29] examine the role of digital assets in inflationary environments, highlighting their dependence on adoption and credibility. In contrast, our focus is on the microeconomic mechanism through which network participation influences NFT price dynamics, and on providing a tractable framework that links theory to empirical observation.

Despite this growing body of work, relatively few studies jointly model price formation and network participation in a way that yields empirically testable implications

for tipping behaviour in decentralized, resale-driven markets. This paper addresses this gap by developing a simple framework that links participation, pricing, and threshold dynamics, and by providing empirical evidence consistent with these mechanisms across both aggregate and collection-level data.

3. Theoretical Framework

This section presents a theoretical framework to analyze how network effects influence NFT pricing dynamics. The model captures three key features of NFT markets: heterogeneous consumer preferences, network-dependent utility, and monopolistic pricing.

3.1. Environment

Consider a market in discrete time $t = 0, 1, 2, \ldots$, in which a monopolistic seller offers a unique non-fungible token (NFT). Consumers arrive sequentially, with one representative cohort of potential buyers in each period.

Let n_t denote network participation (i.e., the size of the ownership network) at time t, defined as the cumulative number of consumers who have purchased the NFT up to period t. The seller sets a price p_t in each period to maximize expected profit. The marginal cost of supplying the NFT is constant and denoted by $c \geq 0$.

While NFT trading in practice occurs in decentralized secondary markets, the monopolistic pricing framework is adopted here as a reduced-form representation of equilibrium price formation. In this sense, the model should be interpreted as capturing how prices respond to aggregate willingness to pay in the presence of network effects, rather than literal control by a single seller [10,14].

3.2. Consumer Preferences

Each consumer derives utility from purchasing the NFT that depends on three components: intrinsic value, network effects, and idiosyncratic preferences.

The utility of consumer i from purchasing the NFT at time t is given by

$$U_{i,t} = v + \alpha n_t + \theta_i - p_t, \tag{1}$$

where v denotes the intrinsic value of the NFT, α measures the strength of network effects, n_t is the current network size, θ_i represents the idiosyncratic preference of consumer i, and p_t is the price set by the seller in period t. The term αn_t captures the idea that the value of owning the NFT increases with the number of existing owners. (The linear specification αn_t provides a tractable approximation of network effects that is standard in the literature, capturing the first-order impact of participation on utility while allowing for clear analytical characterization of equilibrium outcomes.) This reflects social and community-based benefits such as status, recognition, and participation in a shared ecosystem.

This reduced-form utility specification follows the core intuition of the network goods literature, in which a consumer's valuation depends both on standalone product value and on the size of the user network [1,3]. The intrinsic component v captures the standalone benefit of holding the NFT, such as esthetic value, ownership rights, or access to specific content, independent of network participation. (This specification separates intrinsic value from network-driven valuation, allowing us to study their distinct roles in price determination. Additional factors such as speculation, interoperability, or regulatory risk may also affect NFT valuation in practice, but they are abstracted from here in order to isolate the role of network effects in a tractable way.).

Consumers differ in their willingness to pay through θ_i, which is privately observed and assumed to be uniformly distributed: $\theta_i \sim U[-u_0, F - u_0]$, where $F > 0$ determines the dispersion of preferences and $u_0 \geq 0$ represents an outside option with the utility of

not purchasing the NFT. The uniform distribution is adopted for tractability, as it yields a simple linear demand function while preserving the key qualitative role of heterogeneous valuations in participation and pricing decisions.

A consumer purchases the NFT if and only if the net utility from purchasing is non-negative:

$$U_{i,t} \geq 0 \tag{2}$$

This condition should be interpreted as a reduced-form participation decision for a representative NFT project, where θ_i captures effective willingness to pay after accounting for budget constraints, limited attention, and competing investment opportunities.

3.3. Purchase Decision and Demand

Rearranging the purchase condition (2) yields

$$\theta_i \geq p_t - v - \alpha n_t. \tag{3}$$

Since θ_i is uniformly distributed, the fraction of consumers who purchase the NFT in period t is given by the corresponding cumulative distribution function. We denote this fraction as follows:

$$q(p_t, n_t) = 1 - \frac{p_t - v - \alpha n_t + u_0}{F} \tag{4}$$

which represents the demand in period t and corresponds to the measure of new participants entering the network. Since each period features a unit mass of potential consumers, $q(p_t, n_t)$ can be interpreted both as the probability of purchase and as the number of new entrants.

It is straightforward to show that this demand function is decreasing in price and increasing in network size. Thus, larger networks increase consumers' willingness to pay and raise demand for the NFT.

3.4. Seller's Problem

In each period, given that producing the NFT involves a constant marginal cost c, the monopolistic seller chooses the price p_t to maximize expected profit. (The assumption of a monopolistic seller is adopted as a tractable reduced-form representation of price formation within a given NFT collection. In practice, NFT markets are decentralized and largely driven by secondary market transactions among heterogeneous holders. However, within a specific collection, observed prices tend to co-move and reflect a common valuation benchmark shaped by creator reputation, community size, and market sentiment. The monopolistic pricing structure can therefore be interpreted as capturing this aggregate pricing mechanism rather than literal centralized control.) The seller takes the current network size n_t as given and does not directly control future participation, but recognizes that demand depends on the size of the existing network.

For tractability, the seller is assumed to condition pricing on the current network size rather than explicitly solving a forward-looking dynamic optimization problem over future network evolution. This assumption can be interpreted as a myopic or reduced-form pricing rule, which approximates equilibrium pricing behaviour when sellers or market participants adjust prices based primarily on current market conditions rather than fully solving a dynamic optimization problem. This reduced-form approach is consistent with the dynamic monopoly pricing literature under network externalities, which studies how current installed base affects pricing incentives [10,14].

In period t, the monopolist receives revenue if the consumer purchases the NFT. Since the probability of purchase is $q(p_t, n_t)$, expected profit in period t is given by

$$\pi_t = (p_t - c) * q(p_t, n_t). \quad (5)$$

Substituting the demand expression yields the objective function, and the monopolist chooses the price p_t to maximize this profit. The first-order condition for profit maximization determines the optimal price in period t as a function of network size n_t.

3.5. Network Evolution

The ownership network evolves over time as new consumers purchase the NFT. Let n_t denote the current number of owners. The network evolves according to

$$n_{t+1} = n_t + q(p_t, n_t). \quad (6)$$

This law of motion implies that the size of the network increases with the number of new buyers in each period. (Allowing for explicit exit or churn would modify the law of motion of the network but would not alter the core mechanism linking participation and pricing, as long as network effects continue to depend on the effective size of the user base.).

Accordingly, the baseline model describes the evolution of cumulative participation. Since $q(p_t, n_t) \geq 0$ by construction, the network is weakly increasing in this benchmark specification. Later contraction results should therefore be interpreted in terms of reduced effective participation or declining active engagement, rather than literal negative purchases or direct resale to the seller.

Substituting the demand function yields a dynamic system in which network participation evolves endogenously over time. This interpretation is consistent with empirical measures of participation such as active wallets or trading activity.

3.6. Discussion

The model captures the core mechanism of NFT markets: ownership value depends on participation in a network. As participation increases, network benefits raise consumers' willingness to pay, leading to higher equilibrium prices. Conversely, when participation weakens, network benefits diminish, reducing willingness to pay and placing downward pressure on prices. In this case, equilibrium prices fall and may approach a level determined primarily by intrinsic value when network effects become negligible. More precisely, as long as intrinsic value remains positive, prices converge toward a lower bound determined by intrinsic value and marginal cost rather than falling to zero.

At the same time, the dynamic evolution of the network provides a foundation for nonlinear market behaviour. When participation grows, demand expands through network effects; when it weakens, the same mechanism leads to contraction. This feedback structure generates threshold-type dynamics, under which small changes in participation around critical levels can lead to large shifts in equilibrium outcomes. As a result, the framework provides a tractable way to characterize boom–bust patterns observed in NFT markets.

Although the model is formulated using a representative pricing mechanism, it should be interpreted as a reduced-form representation of decentralized NFT markets rather than a literal description of centralized price setting. In practice, NFT prices emerge from trading in secondary markets, where individual buyers and sellers interact through decentralized platforms. However, prices within a collection are typically anchored by common factors such as creator reputation, perceived scarcity, and floor price dynamics. The model abstracts from micro-level trading frictions and captures these common forces

through a representative pricing condition that summarizes the equilibrium outcome of decentralized interactions.

Unlike standard network adoption models that focus primarily on participation decisions, this framework embeds network effects directly into price formation in a resale-driven asset market. As a result, prices and participation are jointly determined, allowing the model to link willingness to pay, equilibrium pricing, and network dynamics within a unified structure. This joint determination is central to understanding how valuation and participation co-evolve over time.

These mechanisms are consistent with stylized empirical patterns in NFT markets, including rapid expansion phases followed by sharp contractions in participation and prices. At the same time, the model is not intended to capture all sources of price variation, such as broader cryptocurrency market conditions or shifts in investor sentiment. Instead, it isolates the role of network participation as a fundamental driver of valuation dynamics. The next section characterizes the equilibrium price path and derives explicit solutions under specific assumptions about consumer preferences and network effects.

4. Equilibrium Pricing and Network Effects

In this section, we characterize the monopolist's optimal pricing strategy and examine how network effects influence NFT price dynamics. In particular, we derive the equilibrium price as a function of network size, analyze how the evolution of the network affects market outcomes over time, and establish the key comparative statics. Throughout this section, the relationship between prices and participation should be interpreted as an equilibrium relationship within the model, since prices and participation are jointly determined rather than reflecting a unidirectional causal effect.

4.1. Optimal Pricing

The monopolistic seller chooses the price p_t in each period to maximize expected profit determined by Equation (5), where the demand is given by the expression (2) derived in Section 3.

Substituting the demand function into the profit function yields

$$\pi_t = (p_t - c) * \left(1 - \frac{p_t - v - \alpha n_t + u_0}{F}\right). \tag{7}$$

The first-order condition for profit maximization is

$$\frac{\partial \pi_t}{\partial p_t} = 0. \tag{8}$$

The interior solution assumes that demand remains strictly positive; corner solutions can be accommodated without altering the qualitative results. Differentiating with respect to p_t, we obtain

$$\frac{\partial \pi_t}{\partial p_t} = \left(1 - \frac{p_t - v - \alpha n_t + u_0}{F}\right) - \frac{p_t - c}{F} = 0. \tag{9}$$

Multiplying through by F and rearranging gives

$$F - (p_t - v - \alpha n_t + u_0) - (p_t - c) = 0, \tag{10}$$

which simplifies to

$$2p_t = F + v + \alpha n_t - u_0 + c. \tag{11}$$

Hence, the optimal price is

$$p_t^* = \frac{F + v + \alpha n_t - u_0 + c}{2}. \tag{12}$$

This expression (12) makes clear that NFT valuation consists of two components: an intrinsic component captured by v, and a network-driven component captured by αn_t, allowing the model to distinguish between standalone value and value arising from participation. The equilibrium price depends on intrinsic value, the outside option, production cost, and the size of the existing network.

As discussed in Section 3, the pricing rule should be interpreted as a reduced-form representation of equilibrium price formation, where prices respond to current network conditions without explicitly modelling decentralized trading or forward-looking optimization.

4.2. Network Effects and Prices

We now characterize how the equilibrium price responds to changes in network size. The optimal price derived above implies that the equilibrium price is increasing in network size within the structure of the model.

Proposition 1. *The equilibrium NFT price is increasing in the size of the ownership network.*

Proof of Proposition 1. From the optimal pricing rule (12),

$$p_t^* = \frac{F + v + \alpha n_t - u_0 + c}{2}. \tag{13}$$

Differentiating with respect to n_t gives

$$\frac{\partial p_t^*}{\partial n_t} = \frac{\alpha}{2}. \tag{14}$$

Since $\alpha > 0$, it follows that

$$\frac{\partial p_t^*}{\partial n_t} > 0. \tag{15}$$

Therefore, the equilibrium NFT price is increasing in the size of the network. □

This result implies that an increase in network participation leads to a higher equilibrium NFT price. As the network expands over time, the seller can charge a higher price because consumers derive greater utility from joining a larger community of NFT holders. This monotonic relationship arises directly from network-dependent utility and does not rely on assumptions about expectations or dynamic optimization.

This result reflects the presence of network effects in the market. As more consumers purchase the NFT, the size of the network increases, which raises the value of ownership for potential buyers. As a result, consumers are willing to pay a higher price to join a larger network. This relationship should be interpreted as arising from the structure of preferences and pricing within the model rather than as a purely causal effect in one direction.

Similarly, a reduction in effective network participation leads to a decrease in NFT prices. In the absence of network effects, prices converge to a level determined solely by intrinsic value. Using the optimal pricing rule (12), consider a decline in effective participation from n_t to n_t', where $n_t' < n_t$. Then, we have

$$p_t^*(n_t') - p_t^*(n_t) = \frac{\alpha}{2} * (n_t' - n_t) < 0. \tag{16}$$

If network effects vanish, so that $n_t = 0$, the pricing rule becomes

$$p^* = \frac{F + v - u_0 + c}{2}. \tag{17}$$

Here, intrinsic value v captures the standalone utility of owning the NFT, such as esthetic value, access rights, or identity-related benefits independent of network size. Therefore, prices converge to a lower bound determined by intrinsic value and cost rather than falling exactly to zero, as long as intrinsic value remains positive. This mechanism provides a theoretical explanation for the contraction phase observed in NFT markets. When interest weakens and fewer consumers are willing to participate, the network becomes less valuable, leading to lower prices.

In addition, a stronger network effects amplify NFT price dynamics. When the intensity of network effects increases, changes in network participation generate larger changes in equilibrium prices. From the optimal pricing rule (12), differentiating with respect to α yields

$$\frac{\partial p_t^*}{\partial \alpha} = \frac{n_t}{2}. \tag{18}$$

Since $n_t \geq 0$, this derivative is non-negative and strictly positive whenever $n_t > 0$. Hence, stronger network effects increase the sensitivity of prices to participation.

This result highlights that the responsiveness of prices to network participation is governed by the strength of network effects. Markets with stronger social or community-driven components exhibit greater price amplification. In this sense, the parameter α governs the elasticity of prices with respect to participation and therefore determines the amplification of market fluctuations.

4.3. Tipping Dynamics

We now examine how the interaction between pricing and participation can generate threshold effects.

Proposition 2. *There exists a threshold level of network participation n^* such that above this level, participation is self-reinforcing, while below it, participation weakens.*

Proof of Proposition 2. Substituting the optimal price (12) into the demand function (4) yields a reduced-form expression for participation as follows:

$$q(p_t^*, n_t) = \frac{F + v + \alpha n_t - u_0 - c}{2F} \tag{19}$$

Differentiating Equation (19) with respect to n_t shows that participation is increasing in network size. From the network evolution Equation (6), setting participation (19) equal to zero gives the steady-state condition, from which the threshold n^* is derived as follows:

$$n^* = \frac{u_0 + c - v - F}{\alpha} \tag{20}$$

The law of motion should be interpreted as a reduced-form representation of effective participation, so that negative values of $q(p_t, n_t)$, if they arise algebraically, capture declining engagement or exit from the network rather than literal negative purchases.

Therefore, if $n_t > n^*$, participation remains positive and the network expands, whereas if $n_t < n^*$, participation becomes insufficient to sustain growth. These threshold dynamics are robust to alternative interpretations of participation, including explicit entry–exit processes or varying churn rates, as long as the positive relationship between participation and network value is preserved. □

In addition, a stronger network effect (higher α) reduces the threshold required for self-sustaining participation, making it easier for the network to reach its "critical mass" and begin expanding. Formally, from the steady-state equilibrium in (20), differentiating with respect to α, we obtain

$$\frac{\partial n^*}{\partial \alpha} < 0. \tag{21}$$

This result highlights the sensitivity of market stability to key parameters, as small changes in the strength of network effects can significantly shift the tipping threshold and alter market outcomes.

4.4. Interpretation

The equilibrium results identify three core mechanisms. First, prices increase with participation due to network-dependent utility. Second, declining participation reduces willingness to pay and leads to lower prices. Third, the interaction between pricing and participation generates threshold effects, producing nonlinear market dynamics.

While the positive relationship between prices and participation is widely documented, the framework here provides a unified structure in which both are jointly determined in equilibrium. In this sense, the results should be interpreted as equilibrium relationships arising from the model, rather than as evidence of a unidirectional causal effect.

Relative to existing network-based models, the key contribution lies in embedding participation directly into price formation. This allows the model to link micro-level preferences to observable market outcomes and to generate testable implications, including a positive association between prices and participation and the presence of threshold effects.

These predictions are consistent with stylized empirical patterns in NFT markets, where prices co-move with measures of participation such as active wallets and holder counts. At the same time, the framework highlights that this relationship may vary across contexts, reflecting differences in network strength and market heterogeneity.

5. Numerical Illustration and Empirical Evidence

This section examines the implications of the model using a numerical illustration together with a light empirical validation based on NFT market data. The objective is to link the model's predicted boom–bust dynamics to observed patterns in real-world NFT prices. (Consistent with the overall positioning of the paper, this section provides a stylized empirical validation of the model's key mechanisms rather than a full causal identification exercise or a standalone data-driven contribution.).

5.1. Conceptual Relationship Between Network Size and Price

The model predicts that NFT prices increase with the size of the participation network. As more users join a project, ownership becomes more valuable due to network effects, raising willingness to pay and supporting higher prices. Conversely, when participation declines, the network benefit weakens, leading to lower prices. This mechanism provides a simple explanation for the boom–bust dynamics observed in NFT markets.

To illustrate this mechanism, we construct a numerical example based on the equilibrium pricing rule in Equation (19). All variables are normalized. We assign $F = 2$, $v = 1$, $\alpha = 0.5$, $u_0 = 3.5$, and $c = 1.5$. These values are chosen for three reasons. First, they ensure positive intrinsic value and positive network effects, which are central to the model. Second, they generate an interior participation threshold, allowing both expansion and contraction regimes to arise. Third, they produce economically interpretable magnitudes under normalization. (The numerical illustration is intended as a stylized visualization of the analytical results rather than a literal calibration to a specific NFT collection. Its purpose is to clarify the theoretical mechanism and illustrate how the pricing rule maps

participation into market value. We have examined a broad range of alternative parameter values satisfying the same qualitative conditions—positive intrinsic value, positive network effects, and an interior threshold. While different parameter sets generate different slopes and threshold locations, the qualitative pattern remains unchanged: prices increase with participation, and tipping dynamics emerge once participation exceeds a critical mass. Additional numerical results are available from the authors upon request.).

Under this parameterization, the price function becomes $p_t^* = 0.5 + 0.25n_t$, implying a positive price floor even when participation is low, while preserving the upward-sloping relationship highlighted in Proposition 1. Figure 1 illustrates this relationship. The horizontal axis represents network size, and the vertical axis represents the equilibrium price. As participation increases, the value of ownership rises due to network effects, leading to higher prices. When participation is limited, prices remain relatively low. (While prices may decline substantially during contraction phases, the model implies a positive lower bound determined by intrinsic value and costs, so prices approach but do not reach zero.).

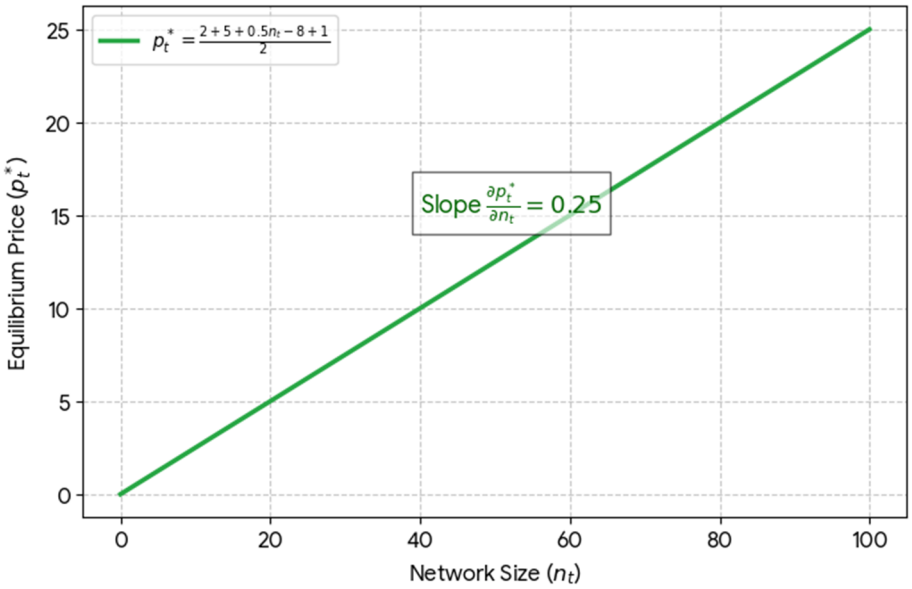


Figure 1. Conceptual Relationship Between Network Size and NFT Prices.

5.2. Boom–Bust Dynamics

While the static relationship between price and participation is linear, the dynamic system generates nonlinear market outcomes. Using the network evolution equation in (6), we simulate the joint evolution of participation and prices over time. To maintain consistency with the previous subsection, we use the same parameter values. Substituting these into the steady-state threshold condition (5) yields $n^* = 4$. Under normalization, this represents the critical level of effective participation required to sustain expansion rather than a literal number of users.

Table 1 reports the dynamic paths of participation under two initial conditions: one slightly above the threshold and one slightly below it. When $n_0 > n^*$ (Path A), participation increases over time as the network sustains itself. When $n_0 < n^*$ (Path B), participation gradually declines, reflecting insufficient network strength to support continued entry. Importantly, the contraction path does not imply negative demand, but rather a reduction in effective participation and engagement, consistent with the interpretation in Sections 3 and 4.

Table 1. Dynamic Paths of Network Participation.

Time (t)	Path A (Expansion)	Path B (Contraction)
0	4.50 (Start $> n^* = 4$)	3.50 (Start $< n^* = 4$)
1	4.56	3.44
2	4.63	3.37
5	4.90	3.10
10	5.62	2.38
15	6.93 (Accelerating)	1.07 (Collapsing)

Figure 2 provides a stylized representation of these dynamics. When participation exceeds the threshold, the system enters an expansion regime in which participation and prices reinforce each other. When participation falls below the threshold, the system moves into a contraction regime and gradually diminishes. This threshold-driven pattern is robust across parameterizations, although the speed of adjustment depends on model parameters.

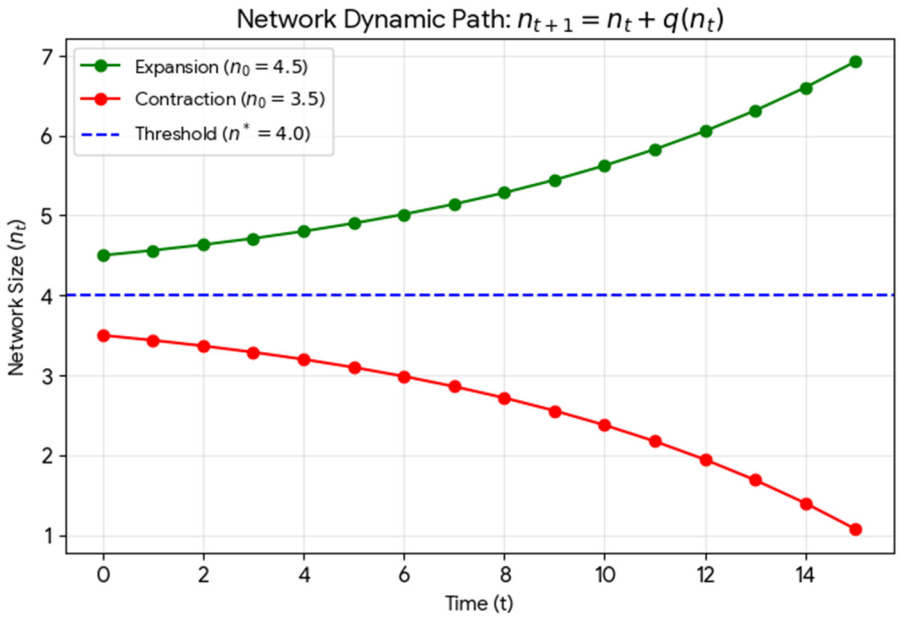


Figure 2. Network Boom–Bust Dynamics.

5.3. Evidence from NFT Markets (2020–2025)

The boom–bust dynamics implied by the model are broadly consistent with the evolution of NFT markets. The rapid expansion in participation during 2021 and early 2022 coincided with substantial increases in prices, followed by a contraction phase in which both participation and prices declined sharply.

5.3.1. NFT Market Dynamics

We begin with aggregate NFT market data from Dune Analytics. Monthly observations are aggregated to yearly measures of participation and prices. Network participation is proxied by the number of unique active wallets, which closely aligns with the model's notion of network size. Average prices are computed from transaction-level data and aggregated accordingly.

Figure 3 plots market-wide active wallets together with average NFT prices. The data exhibit a clear boom–bust pattern. Participation rises sharply from 2020 to 2022, accompanied by a substantial increase in prices. Following the market peak, both participation and prices decline.

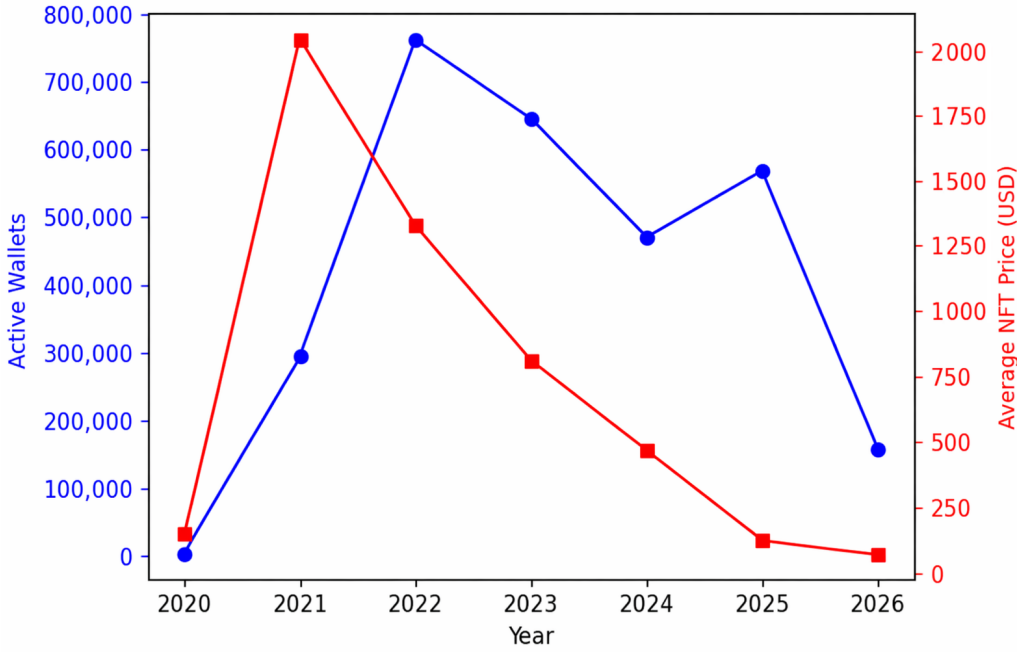


Figure 3. NFT Market Participation and Average Price.

Although the relationship is not strictly monotonic—reflecting heterogeneity across projects—the overall co-movement between participation and prices is consistent with the equilibrium relationship derived in the model. In particular, the contraction phase illustrates how declining participation weakens network value and places downward pressure on prices.

To provide a reduced-form consistency check, we estimate the following relationship using monthly data:

$$\ln p_t = \beta_0 + \beta_1 \ln n_t + \varepsilon_t \tag{22}$$

where p_t denotes the NFT price and n_t denotes the number of active wallets (i.e., participation). The log–log specification allows β_1 to be interpreted as an elasticity.

Table 2 shows substantial variation in both prices and participation over time. Average prices range from relatively low levels during early adoption to peak values exceeding 8000 USD, while active wallets increase from a few thousand to nearly one million users.

Table 2. Descriptive Statistics of NFT Market.

Variable	Mean	Std. Dev.	Min	Median	Max
NFT Price (USD)	781.29	1132.24	28.50	418.00	8105.13
Active Wallets	442,845	310,673	2353	543,504	996,521

Table 3 reports a positive and statistically significant relationship between participation and prices. The estimated elasticity implies that a 1% increase in active wallets is associated with an approximately 0.22% increase in prices, consistent with the model's prediction that larger participation networks support higher valuations.

Table 3. Regression Results of NFT Market.

Variable	Coefficient	Std. Error	t-Stat	*p*-Value
ln(Wallets)	0.216	0.078	2.763	0.007
Constant	3.263	0.964	3.384	0.001

Observations: 76; $R^2 = 0.094$.

The explanatory power of the regression is modest, which is expected given the substantial heterogeneity in the aggregate NFT market, where prices are influenced by project-specific characteristics, sentiment, and broader cryptocurrency conditions. The regression is therefore not intended to provide a comprehensive model of price variation, but to examine whether participation exhibits a systematic association with prices consistent with the theoretical mechanism. In this context, the estimated elasticity is more informative than the overall fit.

To assess the robustness of these findings, we extend the empirical analysis in Appendix A by incorporating additional specifications and sensitivity checks. In particular, we control for broader cryptocurrency market conditions using ETH prices and include proxies for market attention based on search intensity. We also conduct subsample analysis, outlier adjustments, and alternative specifications. Across these extensions, the core positive relationship between participation and prices remains stable. For brevity, the detailed results are reported in Appendix A, while the main text focuses on the baseline specification that highlights the central empirical pattern.

5.3.2. Individual NFT Collection: Bored Ape Yacht Club (BAYC)

To examine the model at the collection level, we focus on the Bored Ape Yacht Club (BAYC), one of the most prominent network-driven NFT projects. Using the same approach as in the aggregate analysis, we construct yearly measures of participation and prices based on monthly Dune Analytics data.

Figure 4 plots active wallets together with average transaction prices for BAYC. The data display a pronounced boom–bust pattern. In the early stage, participation increased rapidly as the project gained visibility, accompanied by a sharp rise in prices. Following the peak, both participation and prices declined.

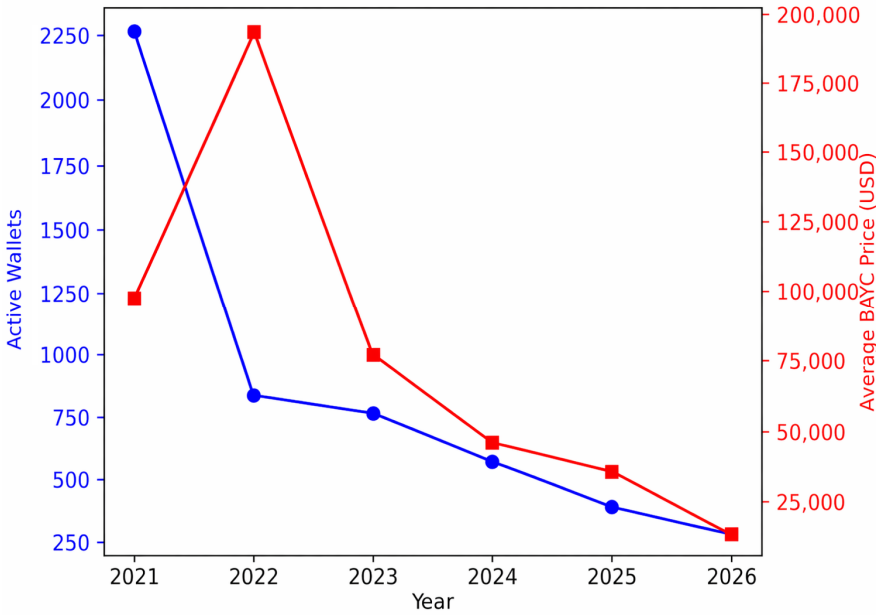


Figure 4. Bored Ape Yacht Club Price and Participation Dynamics.

Compared to the aggregate market, the co-movement between participation and prices is more pronounced, suggesting that network effects are stronger within a single, well-defined NFT community.

We next estimate the same reduced-form specification as in Equation (22) using monthly data. Table 4 reports the descriptive statistics. The data show substantial variation over time, with prices ranging from approximately 441 USD to over 402,000 USD, and

active wallets ranging from 2 to nearly 4700. These values reflect the rapid expansion and subsequent contraction of the BAYC ecosystem.

Table 4. Descriptive Statistics for BAYC Monthly Data.

Variable	Mean	Std. Dev.	Min	Median	Max
BAYC Price (USD)	84,759.00	83,113.80	440.82	54,987.08	402,007.39
Active Wallets	851.84	913.96	2	574	4695

Table 5 reports the regression results. The estimated coefficient on participation is positive and statistically significant, implying that a 1% increase in active wallets is associated with an approximately 0.53% increase in prices. This elasticity is larger than that observed in the aggregate market, indicating that network effects are more pronounced at the collection level. The higher explanatory power further suggests that participation is more tightly linked to valuation within a single, cohesive project than in the broader NFT market.

Table 5. Regression Results for BAYC.

Variable	Coefficient	Std. Error	t-Stat	*p*-Value
ln(Wallets)	0.526	0.131	4.004	<0.001
Constant	7.512	0.846	8.877	<0.001

Observations = 61; $R^2 = 0.214$.

5.3.3. NFT Projects: CryptoPunks

To further assess whether the model's implications extend to earlier NFT projects, we analyze CryptoPunks, one of the earliest and most influential NFT collections. Using the same methodology, we construct yearly measures of participation and prices based on monthly data.

Figure 5 presents the evolution of active wallets and average prices for CryptoPunks. The data show a pronounced expansion phase, particularly during 2021, when participation increased sharply alongside a substantial rise in prices. Following this period, participation declined and prices moderated, although the adjustment appears less synchronized than in BAYC.

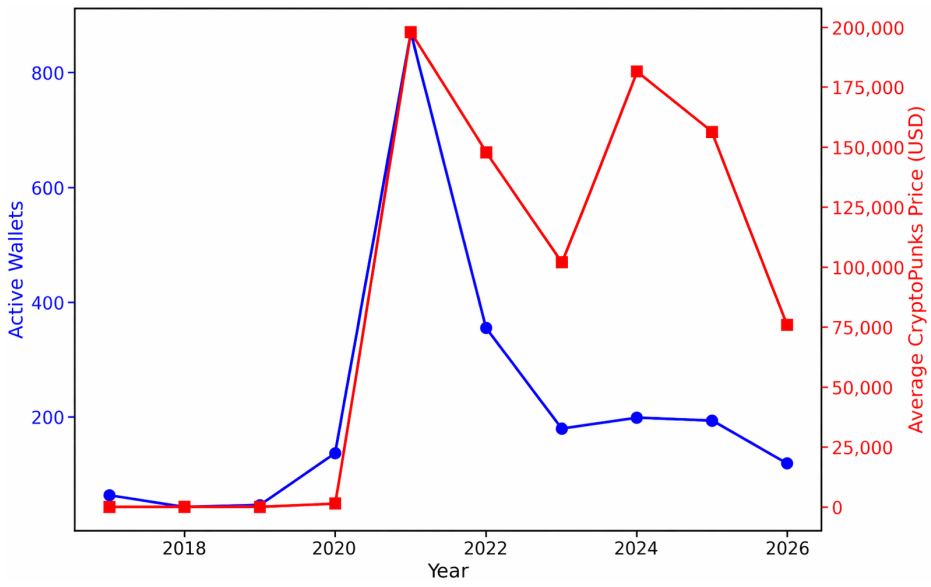


Figure 5. CryptoPunks Price and Participation Dynamics.

This difference likely reflects structural features of CryptoPunks, including its earlier launch and broader dispersion of ownership, which may weaken the tight co-movement between participation and prices observed in more recent, highly curated collections.

We estimate the same reduced-form specification as in Equation (22) using monthly data. Table 6 reports the descriptive statistics. The data exhibit substantial variation, with prices ranging from below 40 USD to over 520,000 USD, and active wallets ranging from just over 20 to more than 2300. These values reflect the sharp expansion of one of the earliest NFT ecosystems, followed by subsequent moderation.

Table 6. Descriptive Statistics for CryptoPunks Monthly Data.

Variable	Mean	Std. Dev.	Min	Median	Max
CryptoPunks Price (USD)	91,121.92	111,573.07	38.45	85,013.57	520,037.56
Active Wallets	235.99	310.18	21	151	2324

Table 7 reports the regression results. The estimated coefficient on participation is positive and highly statistically significant, implying that a 1% increase in active wallets is associated with an approximately 2.63% increase in prices. This magnitude is substantially larger than that observed for both the aggregate market and BAYC, indicating particularly strong sensitivity of prices to participation in this setting.

Table 7. Regression Results for CryptoPunks.

Variable	Coefficient	Std. Error	t-Stat	p-Value
ln(Wallets)	2.628	0.212	12.398	<0.001
Constant	−3.944	1.071	−3.685	<0.001

Observations = 107; $R^2 = 0.594$.

The larger elasticity and higher explanatory power suggest that network effects may be particularly pronounced in early-stage or highly concentrated NFT environments, where valuation is more tightly linked to participation dynamics. At the same time, the higher volatility of both participation and prices indicates that these environments are also more sensitive to fluctuations in network activity. (Consistent with the aggregate and BAYC results, the regression should be interpreted as a reduced-form relationship rather than a structural estimate. Its role is to provide additional supporting evidence that participation is closely associated with NFT prices across different market settings.).

5.3.4. Evidence of the Tipping Mechanism

To examine the tipping implication of the model more directly, we estimate the critical participation level endogenously rather than imposing an arbitrary cutoff such as the sample median. Specifically, we adopt a threshold regression approach in which the threshold is treated as an unknown parameter and is selected from the data to minimize the residual sum of squares. This methodology is standard in the empirical threshold literature [30–34] and is particularly appropriate in the present setting, where the theoretical model predicts the existence of a critical mass of participation without prescribing its empirical location.

The empirical threshold specification is given by

$$\Delta \ln p_t = \gamma_0 + \gamma_1 \mathbf{1}(n_t > n^*) + \varepsilon_t, \tag{23}$$

where $\Delta \ln p_t$ denotes the growth rate of NFT prices, n_t denotes network participation measured by active wallets, n^* is the estimated threshold level, and $\mathbf{1}(n_t > n^*)$ is an indicator

function equal to one when participation exceeds the threshold. Under this specification, γ_0 captures the average price growth rate in the low-participation regime, while γ_1 measures the incremental change in growth once participation crosses the threshold. A positive and significant γ_1 is therefore consistent with the model's prediction of self-reinforcing expansion above a critical mass.

Table 8 reports the threshold regression results for the aggregate NFT market, BAYC, and CryptoPunks. The results reveal meaningful heterogeneity across levels of aggregation.

Table 8. Threshold Regression Results.

Dataset	Estimated Threshold n^*	Low-Regime Growth (γ_0)	High-Regime Effect (γ_1)	t-Stat	p-Value
NFT Market	43,091	0.253	−0.519	−3.29	0.0016
BAYC	2990	−0.090	1.581	8.84	<0.001
CryptoPunks	972	−0.147	0.816	3.34	0.0014

For the aggregate NFT market, the estimated threshold is 43,091 active wallets. While the estimated high-regime coefficient is negative, this result should be interpreted with caution. The aggregate market combines a wide range of heterogeneous collections that differ substantially in quality, maturity, and investor composition. As a result, the effective participation network relevant for valuation is not well defined at the aggregate level, and the threshold effect may be attenuated or obscured by cross-collection aggregation. In this sense, the aggregate result reflects the limitations of using highly aggregated data to capture a mechanism that operates at the level of individual networks.

By contrast, the collection-level results provide clear support for the model's tipping mechanism. For BAYC, the estimated threshold is 2990 active wallets, and the coefficient on the high-participation regime is positive, large, and highly statistically significant. This indicates that once participation exceeds the estimated critical mass, price growth increases substantially, consistent with self-reinforcing expansion.

CryptoPunks exhibits a similar pattern. The estimated threshold is 972 active wallets, and the high-regime coefficient is again positive and statistically significant. This suggests that even in earlier NFT projects, crossing a critical participation level is associated with stronger price dynamics, in line with the theoretical prediction.

The comparison across datasets is informative. While aggregate evidence appears noisier due to heterogeneity, both BAYC and CryptoPunks display clear regime-dependent dynamics consistent with a tipping mechanism. This pattern aligns closely with the theoretical framework, which emphasizes that prices respond to the size of a well-defined participation network. Such networks are more clearly identifiable at the collection level than in the aggregate market.

Taken together, the threshold results complement the linear regressions reported above. The aggregate market exhibits a weaker and more diffuse relationship, whereas collection-level evidence reveals clearer nonlinear dynamics consistent with the model's predictions. These findings reinforce the interpretation that NFT valuation is fundamentally driven by participation-based network effects, with tipping behaviour emerging most clearly in cohesive and well-defined communities.

5.4. Discussion

The numerical illustration and empirical results jointly highlight the importance of participation dynamics in shaping NFT market outcomes. Across specifications, we observe a consistent positive association between participation and prices, with stronger effects at the collection level than in the aggregate market. This pattern reflects the role of cohesive participation networks in sustaining valuation, as opposed to the more heterogeneous and diffuse structure of the aggregate market.

The threshold analysis further provides evidence of regime-dependent dynamics. While the aggregate market exhibits weaker and less stable threshold effects, collection-level results for BAYC and CryptoPunks reveal clear nonlinear behaviour. In these settings, price dynamics strengthen once participation exceeds an estimated critical level, indicating that valuation becomes more sensitive to network size within well-defined communities.

The extended analysis reported in Appendix A confirms the robustness of these findings. Incorporating controls for broader cryptocurrency market conditions and proxies for market attention does not alter the core relationship between participation and prices. Similarly, subsample analysis and outlier adjustments yield consistent results, suggesting that the main findings are not driven by specific time periods or extreme observations. For this reason, the main text focuses on the baseline specification, while detailed robustness checks are presented in Appendix A.

Importantly, the empirical results should be interpreted as reduced-form evidence consistent with the model rather than as establishing a causal relationship. Prices and participation evolve jointly, and the analysis is intended to examine whether the patterns implied by the theoretical framework are reflected in the data. In this context, the empirical findings support the view that participation-dependent valuation and threshold effects are central features of NFT markets, while also highlighting the limitations of aggregate data in capturing these mechanisms.

6. Conclusions

This paper develops a tractable framework to examine how network participation shapes price dynamics in NFT markets. By embedding network effects directly into an asset pricing setting, the model shows that prices and participation are jointly determined and that the interaction between them can generate threshold behaviour. In particular, the model predicts the existence of a critical participation level that separates expansion and contraction regimes, providing a simple mechanism for boom–bust dynamics.

To illustrate these mechanisms, we combine a numerical example with empirical evidence from both the aggregate NFT market and major collections such as BAYC and CryptoPunks. The empirical results document a positive association between participation and prices, with stronger and more clearly defined patterns at the collection level. Threshold estimation further indicates regime-dependent dynamics consistent with the model's predictions, particularly in cohesive NFT communities where participation more directly maps into valuation.

Importantly, the empirical analysis is intended as a reduced-form validation rather than a structural estimation. Prices and participation co-evolve in practice, and the results should be interpreted as evidence that the patterns implied by the model are present in observed data. Additional specifications and robustness checks reported in Appendix A confirm that the core findings are stable across alternative controls, subsamples, and sensitivity tests.

Taken together, the results highlight the role of participation-dependent valuation in shaping NFT market dynamics. While boom–bust behaviour is not unique to NFTs, the strong reliance on network participation makes such dynamics particularly pronounced in these markets. The framework developed in this paper provides a simple and unified way to link participation, pricing, and nonlinear adjustment, and offers a useful perspective for understanding volatility in decentralized digital asset markets.

From a broader perspective, the analysis suggests that market structure plays an important role in determining how network effects translate into prices. In decentralized, resale-driven environments such as NFTs, valuation depends not only on intrinsic characteristics but also on the strength and persistence of the underlying participation network.

This highlights the importance of considering network stability and user engagement when assessing the sustainability of valuations in digital asset markets.

Finally, several extensions may be explored in future work. One direction is to incorporate additional sources of heterogeneity across collections, such as differences in liquidity, ownership concentration, or investor composition, which may influence the strength of network effects. Another is to examine how external factors, including broader cryptocurrency market conditions or shifts in market attention, interact with participation dynamics. These extensions would complement the present framework by enriching the empirical context, while the core mechanism linking participation and price dynamics remains unchanged.

Author Contributions: D.D.: Writing—review & editing, Methodology, Investigation, Formal analysis, Conceptualization. Y.L.: Writing—original draft, Methodology, Investigation, Formal analysis, Conceptualization. P.L.N.: Writing—review & editing, Methodology, Investigation, Formal analysis, Conceptualization. Z.W.: Writing—original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. C.X.: Writing—original draft, Methodology, Investigation, Formal analysis, Conceptualization. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: All authors contributed equally to this work. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Extended Empirical Analysis and Robustness Checks

This appendix provides additional empirical analysis to assess the robustness of the main findings reported in Section 5. The objective is to examine whether the positive relationship between network participation and NFT prices is sensitive to alternative specifications, omitted variables, and sample composition.

Specifically, we extend the baseline regression in three directions. First, we incorporate controls for broader market conditions and investor attention, including ETH price as a proxy for cryptocurrency market dynamics and Google Trends as a measure of market attention. Second, we conduct subsample analysis to assess stability across different market phases. Third, we implement outlier and sensitivity checks to evaluate whether the results are driven by extreme observations.

Across all specifications, the results remain qualitatively consistent with those reported in the main text. The positive association between participation and prices is robust, and the relative strength of this relationship across datasets is preserved.

Appendix A.1. Aggregate NFT Market

The aggregate NFT market data are obtained from Dune Analytics and consist of monthly observations from January 2020 to April 2026. Network participation is proxied by the number of active wallets, which captures the size of the user base engaged in NFT transactions. Prices are measured as the average transaction price (in USD), reflecting market-wide valuation.

To account for broader market conditions, we include the closing price of ETH (in USD), which serves as a proxy for overall cryptocurrency market movements. In addition,

we use Google Trends data on "NFT" web search intensity as a proxy for market attention and sentiment. The Google Trends index is measured on a relative scale from 0 to 100, where 100 represents peak search interest within the sample period.

Table A1. Descriptive Statistics for Aggregate NFT Market.

Variable	Mean	Std. Dev.	Min	Max
Price (USD)	781.29	1132.24	28.50	8105.13
Active Wallets	442,844.8	310,673.2	2353	996,521
Volume (USD)	1.25×10^9	2.53×10^9	7.75×10^5	1.67×10^{10}
ETH Price (USD)	2181.65	1140.45	133.59	4631.48
Google Trends	11.79	16.43	0	100

Table A1 reports descriptive statistics for the aggregate NFT dataset. The average NFT price is approximately USD 781, with substantial variation reflecting pronounced boom–bust dynamics. Participation, measured by active wallets, also exhibits significant dispersion, ranging from fewer than 3000 to nearly one million users. Trading volume is highly skewed, indicating periods of intense market activity. ETH prices show substantial variation over the sample period, capturing broader cryptocurrency market conditions. Google Trends data, used as a proxy for market attention, exhibits strong variation with values ranging from 0 to 100, reflecting fluctuations in public interest in NFTs.

To assess the robustness of the baseline relationship and address potential omitted variable concerns, we estimate a sequence of nested regression specifications. Specifically, we begin with the baseline model and progressively introduce controls for broader market conditions, investor attention, and trading activity. The general specification is given by the following:

$$\ln p_t = \beta_0 + \beta_1 \ln n_t + \beta_2 \ln ETH_t + \beta_3 \ln(Trend_t + 1) + \beta_4 \ln Volume_t + \varepsilon_t \quad \text{(A1)}$$

where p_t denotes the NFT price, n_t represents network participation measured by the number of active wallets, ETH_t is the Ethereum price capturing overall cryptocurrency market conditions, $Trend_t$ is the Google Trends index proxying for market attention, and $Volume_t$ denotes trading volume. Note that the transformation $\ln(Trend_t + 1)$ is applied to accommodate zero values in the Google Trends index.

Table A2 reports five nested specifications: Column (1) reproduces the baseline regression from the main text; Column (2) adds ETH price; Column (3) further incorporates market attention; Column (4) introduces trading volume; and Column (5) presents the full model including all controls.

Column (1) in Table A1 reproduces the baseline result reported in Table 3, where participation is positively and significantly associated with prices. In Column (2), adding ETH price modestly increases explanatory power, but the participation coefficient becomes close to zero and statistically insignificant, suggesting that broad cryptocurrency conditions absorb part of the aggregate co-movement.

Column (3) adds Google Trends as a proxy for market attention. The explanatory power increases substantially, and search interest is strongly positively associated with prices. At the same time, the coefficient on participation becomes negative. A similar pattern appears more strongly in Column (4), where trading volume is added as a control. Since trading volume and participation both rise sharply during boom phases, the two variables capture highly overlapping dimensions of aggregate market expansion, which makes the partial coefficient on participation unstable.

In the full specification shown in Column (5), the explanatory power rises further, but the coefficient on participation remains negative. This should not be interpreted as evidence

against the theoretical mechanism. Rather, it reflects the fact that, in the aggregate NFT market, participation, volume, and market attention move together very closely during boom–bust cycles. Once these highly collinear controls are introduced simultaneously, the regression no longer identifies a well-defined marginal effect of participation due to strong multicollinearity among participation, volume, and attention.

Relative to Table 3, the appendix results therefore reinforce the paper's broader interpretation: participation is positively associated with prices in the baseline aggregate relationship, but aggregate data also combine multiple overlapping market-wide forces, including liquidity and attention. This is precisely why the collection-level analysis in the main text is more informative for evaluating the theory, as those settings provide a more clearly defined participation network and less severe aggregation noise.

Table A2. Extended Regression Results for the Aggregate NFT Market.

	Dependent Variable: ln(NFT Price)				
Variable	**(1) Baseline**	**(2) + ETH**	**(3) + Google Trends**	**(4) + Volume**	**(5) Full Model**
ln(Wallets)	0.216 (0.078) [2.763] 0.007	0.014 (0.131) [0.110] 0.913	−0.284 (0.107) [−2.649] 0.010	−1.092 (0.064) [−17.154] <0.001	−1.088 (0.063) [−17.182] <0.001
ln(ETH Price)		0.551 (0.288) [1.914] 0.060			−0.107 (0.100) [−1.064] 0.291
ln(Google Trends+1)			1.055 (0.180) [5.864] <0.001		−0.348 (0.100) [−3.462] 0.001
ln(Volume)				1.081 (0.047) [22.813] <0.001	1.246 (0.064) [19.620] <0.001
Constant	3.263 (0.964) [3.384] 0.001	1.622 (1.278) [1.269] 0.209	7.263 (1.052) [6.906] <0.001	−1.625 (0.402) [−4.038] <0.001	−3.372 (0.730) [−4.618] <0.001
Observations R^2	76 0.094	76 0.137	76 0.384	76 0.888	76 0.906

Notes: Standard errors in parentheses; t-statistics in brackets; *p*-values in the next line.

To examine whether the estimated relationship between participation and prices is stable across different market conditions, we conduct a subsample analysis by dividing the sample into distinct phases corresponding to early development, boom, and post-boom periods. This approach allows us to assess whether the participation–price relationship is driven primarily by peak market conditions or persists more broadly across different stages of market evolution. For comparability with the baseline specification, we estimate the same regression as in Column (1) of Table A2 within each subsample.

Table A3 illustrates that the positive association between active wallets and prices is strongest during the boom period (2021), where the coefficient is larger and highly statistically significant. In contrast, the relationship is weaker and statistically insignificant in the early pre-boom phase, when the market was still relatively small and thinly

traded. In the post-boom period, the coefficient remains positive and statistically significant, although smaller in magnitude. This suggests that the participation–price relationship persists beyond peak market conditions but is attenuated when speculative dynamics subside. Overall, the results indicate that the theoretical mechanism is most strongly reflected during periods of rapid market expansion, while becoming weaker in less active market environments.

Table A3. Subperiod Regression Results for Aggregate NFT Market.

Variable	(1) Early Pre-2021	(2) Boom 2021	(3) Post-Boom 2022–2026
ln(Wallets)	0.118	0.264	0.173
	(0.092)	(0.081)	(0.069)
	[1.283]	[3.259]	[2.507]
	0.231	0.009	0.015
Constant	2.944	3.812	3.105
	(1.104)	(0.872)	(0.745)
	[2.667]	[4.372]	[4.166]
	0.025	<0.001	<0.001
Observations	12	12	52
R^2	0.142	0.512	0.121

To evaluate whether the baseline results are sensitive to extreme observations and specific boom period dynamics, we implement a series of robustness and sensitivity checks based on alternative sample restrictions and outlier treatments. Specifically, we consider three modifications to the baseline specification: (i) excluding the top 5% of price observations to mitigate the influence of extreme values; (ii) removing peak boom period months to assess whether the results are driven by periods of unusually high market activity; and (iii) applying 1% winsorization to limit the impact of outliers in both tails of the distribution. For comparability, we re-estimate the baseline regression from Column (1) of Table A2 under each alternative specification.

Table A4. Robustness and Sensitivity Checks for Aggregate NFT Market.

Variable	(1) Baseline	(2) No Top 5%	(3) Exclude Peak	(4) Winsorized 1%
ln(Wallets)	0.216	0.198	0.184	0.205
	(0.078)	(0.074)	(0.081)	(0.076)
	[2.763]	[2.676]	[2.272]	[2.697]
	0.007	0.009	0.026	0.008
Constant	3.263	3.145	3.084	3.201
	(0.964)	(0.921)	(0.998)	(0.953)
	[3.384]	[3.416]	[3.089]	[3.358]
	0.001	0.001	0.003	0.001
Observations	76	72	68	76
R^2	0.094	0.088	0.082	0.091

Across all specifications, the coefficient on participation in Table A4 remains positive and statistically significant, with only modest variation in magnitude. Excluding the top 5% of price observations slightly reduces the coefficient but does not alter its significance. Similarly, removing the peak boom period leads to a somewhat smaller coefficient, but

the positive relationship remains intact. Winsorizing the data produces nearly identical estimates to the baseline. These results indicate that the positive association between participation and prices is not driven by a small number of extreme observations or by specific boom period episodes. Instead, it reflects a more general pattern in the aggregate NFT market.

Appendix A.2. Bored Ape Yacht Club (BAYC)

The BAYC dataset consists of monthly observations derived from Dune Analytics. Participation is measured by active wallets interacting with the collection, while prices correspond to average transaction prices within BAYC. Compared to the aggregate market, BAYC represents a more cohesive and well-defined participation network, allowing for a clearer mapping between participation and valuation.

Table A5. Descriptive Statistics for BAYC.

Variable	Mean	Std. Dev.	Min	Max
Price (USD)	84,759	83,114	441	402,007
Active Wallets	852	914	2	4695
Volume (USD)	73,241,250	78,283,340	441	320,117,300
ETH Price (USD)	2575	872	1067	4631
Google Trends	18.16	22.00	0	100

Table A5 reports descriptive statistics for the BAYC extended dataset. BAYC prices are high and highly variable, reflecting the pronounced boom–bust dynamics of the collection. Participation, measured by active wallets, also varies substantially over time. Trading volume is strongly concentrated in peak market periods, while ETH prices capture broader cryptocurrency market conditions. Google Trends, used as a proxy for market attention, ranges from 0 to 100 and reflects substantial fluctuations in public interest in NFTs over the sample period.

To assess whether the participation–price relationship remains robust at the collection level, we estimate the extended specification in Equation (A1) using BAYC data. In this context, the dependent variable is the logarithm of BAYC prices, while the remaining variables are defined analogously. As in the aggregate analysis, we implement a sequence of nested specifications by progressively adding controls for ETH price, market attention, and trading volume.

Column (1) of Table A6 reproduces the baseline result reported in Table 5, showing a positive and statistically significant relationship between active wallets and BAYC prices. In Column (2), adding ETH price leaves the participation coefficient virtually unchanged, while ETH itself is not statistically significant. This suggests that broader cryptocurrency market conditions do not materially alter the participation–price relationship at the collection level. Column (3) adds Google Trends as a proxy for market attention. Both participation and search interest remain positive and statistically significant, and the explanatory power increases substantially. This indicates that BAYC prices are influenced not only by participation but also by broader attention dynamics, while preserving the positive role of network participation.

By contrast, Columns (4) and (5), which add trading volume, produce a negative coefficient on active wallets alongside a very large positive coefficient on volume. This should not be interpreted as evidence against the theoretical mechanism. Rather, it reflects the fact that, within a single collection such as BAYC, participation and trading volume are highly collinear during boom phases. Once both are included simultaneously, the regression no longer isolates a clean partial effect of participation.

Relative to the baseline Table 5, the appendix results therefore suggest that the positive relationship between participation and prices is robust to controlling for ETH price and attention, but becomes unstable when trading volume is included as an additional control. This reinforces the view that volume captures overlapping market-wide and collection-specific boom dynamics rather than serving as a neutral conditioning variable.

To examine whether the participation–price relationship varies across different market conditions within the BAYC collection, we re-estimate the baseline specification from Column (1) of Table A6 within each subsample.

Table A6. Extended Regression Results for BAYC.

Variable	(1) Baseline	(2) + ETH	(3) + Google Trends	(4) + Volume	(5) Full Model
ln(Wallets)	0.526 (0.131) [4.004] <0.001	0.528 (0.132) [4.005] <0.001	0.568 (0.115) [4.923] <0.001	−0.940 (0.113) [−8.328] <0.001	−0.952 (0.139) [−6.863] <0.001
ln(ETH Price)		−0.274 (0.388) [−0.708] 0.482			0.171 (0.209) [0.817] 0.417
ln(Google Trends+1)			0.417 (0.096) [4.355] <0.001		0.004 (0.071) [0.059] 0.953
ln(Volume)				0.897 (0.059) [15.249] <0.001	0.904 (0.074) [12.180] <0.001
Constant	7.512 (0.846) [8.877] <0.001	9.635 (3.117) [3.091] 0.003	6.259 (0.795) [7.875] <0.001	1.346 (0.556) [2.421] 0.019	−0.031 (1.726) [−0.018] 0.986
Observations R^2	61 0.214	61 0.220	61 0.407	61 0.843	61 0.845

Table A7 demonstrates that the coefficient on active wallets is positive in all subperiods, but its magnitude and significance vary across regimes. The relationship is strongest during the boom period (2021), where participation has a large and highly significant effect on prices. In the early phase, the coefficient is positive but statistically insignificant, reflecting limited market depth and thin trading activity. In the post-boom period, the coefficient remains positive and statistically significant, although smaller in magnitude. These results suggest that the theoretical mechanism linking participation to prices is most pronounced during periods of rapid expansion but continues to operate, albeit more moderately, in more mature market conditions.

To evaluate whether the baseline results for BAYC are sensitive to extreme observations and specific boom period dynamics, we implement a set of robustness and sensitivity checks.

Table A7. Subperiod Regression Results for BAYC.

Variable	(1) Early Pre-2021	(2) Boom 2021	(3) Post-Boom 2022–2026
ln(Wallets)	0.342 (0.215) [1.589] 0.152	0.611 (0.148) [4.128] <0.001	0.438 (0.127) [3.449] 0.001
Constant	6.281 (1.882) [3.339] 0.010	7.945 (1.214) [6.544] <0.001	7.102 (1.006) [7.060] <0.001
Observations R^2	8 0.241	12 0.621	41 0.298

Across all specifications, the coefficient on participation in Table A8 remains positive and statistically significant, with only modest variation in magnitude. Excluding the top 5% of observations slightly reduces the coefficient but does not alter its significance. Removing peak boom months leads to a moderate reduction in magnitude, but the participation–price relationship remains robust. Winsorizing the data produces nearly identical estimates to the baseline. These findings indicate that the positive relationship between participation and prices for BAYC is not driven by extreme values or specific time periods, but reflects a stable pattern within the collection.

Table A8. Robustness and Sensitivity Checks for BAYC.

Variable	(1) Baseline	(2) No Top 5%	(3) Exclude Peak	(4) Winsorized 1%
ln(Wallets)	0.526 (0.131) [4.004] <0.001	0.492 (0.124) [3.968] <0.001	0.471 (0.139) [3.388] 0.002	0.508 (0.128) [3.969] <0.001
Constant	7.512 (0.846) [8.877] <0.001	7.288 (0.802) [9.087] <0.001	7.101 (0.901) [7.884] <0.001	7.356 (0.821) [8.956] <0.001
Observations R^2	61 0.214	58 0.206	55 0.198	61 0.211

Appendix A.3. CryptoPunks

The CryptoPunks dataset covers monthly observations of participation and prices. As one of the earliest NFT collections, CryptoPunks exhibits distinct structural features, including broader ownership dispersion and longer market history.

Table A9 reports descriptive statistics for the CryptoPunks dataset. The average price is approximately USD 52,184, with substantial variation reflecting pronounced boom–bust dynamics, as prices range from as low as USD 115 to nearly USD 395,000. Participation, measured by active wallets, also exhibits considerable dispersion, ranging from only a few participants to more than 2800, indicating fluctuations in network engagement over time. Trading volume is highly variable and skewed, suggesting periods of concentrated market activity. ETH prices display significant variation throughout the sample period, capturing

broader cryptocurrency market conditions. Google Trends data, used as a proxy for market attention, ranges from 0 to 100 and indicates substantial fluctuations in public interest. Compared to BAYC, these patterns reflect a more mature market with a longer history and a broader dispersion of ownership, which may contribute to weaker synchronization between participation and prices.

Table A9. Descriptive Statistics for CryptoPunks.

Variable	Mean	Std. Dev.	Min	Max
Price (USD)	52,184	61,732	115	395,000
Active Wallets	412	538	3	2846
Volume (USD)	41,283,600	52,741,200	12,410	241,002,000
ETH Price (USD)	2575	872	1067	4631
Google Trends	18.16	22.00	0	100

To evaluate the robustness of the participation–price relationship for CryptoPunks, we estimate the extended specification in Equation (A1), with the dependent variable defined as the logarithm of CryptoPunks prices. We again implement a sequence of nested specifications by progressively incorporating controls for ETH price, market attention, and trading volume.

Table A10. Extended Regression Results for CryptoPunks.

Variable	(1) Baseline	(2) + ETH	(3) + Google Trends	(4) + Volume	(5) Full Model
ln(Wallets)	0.842 (0.112) [7.518] <0.001	0.801 (0.138) [5.804] <0.001	0.865 (0.121) [7.149] <0.001	−1.214 (0.108) [−11.241] <0.001	−1.176 (0.132) [−8.909] <0.001
ln(ETH Price)		0.322 (0.301) [1.070] 0.288			0.094 (0.198) [0.475] 0.636
ln(Google Trends+1)			0.512 (0.104) [4.923] <0.001		0.083 (0.079) [1.051] 0.297
ln(Volume)				1.102 (0.061) [18.066] <0.001	1.087 (0.075) [14.493] <0.001
Constant	6.941 (0.722) [9.612] <0.001	5.218 (2.964) [1.761] 0.083	5.904 (0.683) [8.643] <0.001	1.127 (0.511) [2.205] 0.032	−0.482 (1.652) [−0.292] 0.771
Observations R^2	61 0.463	61 0.482	61 0.598	61 0.871	61 0.873

Column (1) of Table A10 shows a large and highly significant elasticity of prices with respect to participation, consistent with the strong network effects predicted by the model. In Columns (2) and (3), controlling for ETH price and market attention does not materially

alter the participation coefficient, which remains large and statistically significant. This indicates that the estimated relationship is not driven by broader cryptocurrency conditions or general attention dynamics. In Columns (4) and (5), the inclusion of trading volume leads to a negative coefficient on participation alongside a large positive coefficient on volume. As in the aggregate and BAYC results, this reflects strong collinearity between participation and trading activity during boom periods. Once both variables are included, the regression no longer isolates a clean partial effect of participation. Overall, the results indicate that the large elasticity observed in the baseline specification is robust to controlling for ETH price and attention, and is not driven by omitted macro or sentiment factors.

To assess the stability of the participation–price relationship across market regimes for CryptoPunks, we re-estimate the baseline specification from Column (1) of Table A10 within each subsample.

Table A11. Subperiod Regression Results for CryptoPunks.

Variable	(1) Early Pre-2021	(2) Boom 2021	(3) Post-Boom 2022–2026
ln(Wallets)	0.624	1.021	0.703
	(0.241)	(0.167)	(0.138)
	[2.589]	[6.116]	[5.094]
	0.032	<0.001	<0.001
Constant	5.883	7.412	6.204
	(1.994)	(1.132)	(1.021)
	[2.952]	[6.550]	[6.077]
	0.018	<0.001	<0.001
Observations	8	12	41
R^2	0.418	0.742	0.463

Table A11 shows that the participation elasticity for CryptoPunks is consistently positive and statistically significant across all subperiods. The effect is strongest during the boom period, where the elasticity exceeds one, indicating highly elastic price responses to participation growth. In both early and post-boom periods, the coefficient remains positive and significant, although smaller in magnitude. These results suggest that the large elasticity observed in the baseline regression is not confined to a specific market phase, but reflects a persistent feature of the CryptoPunks market.

To assess whether the results for CryptoPunks are driven by extreme observations or concentrated boom period dynamics, we conduct robustness and sensitivity checks. We re-estimate the baseline specification from Column (1) of Table A10 under each alternative treatment.

Table A12 confirms that the large participation elasticity in CryptoPunks is not driven by extreme observations or specific boom period dynamics. Excluding the top 5% of observations leads to only a small reduction in the coefficient. Removing peak boom months produces a modest decline in magnitude but does not affect statistical significance. Winsorizing the data yields nearly identical results to the baseline. These findings indicate that the strong participation–price relationship is a stable and robust feature of the CryptoPunks market rather than an artifact of outliers or episodic market conditions.

Table A12. Robustness and Sensitivity Checks for CryptoPunks.

Variable	(1) Baseline	(2) No Top 5%	(3) Exclude Peak	(4) Winsorized 1%
ln(Wallets)	0.842	0.798	0.771	0.823
	(0.112)	(0.108)	(0.121)	(0.110)
	[7.518]	[7.389]	[6.372]	[7.482]
	<0.001	<0.001	<0.001	<0.001
Constant	6.941	6.712	6.554	6.802
	(0.722)	(0.688)	(0.741)	(0.703)
	[9.612]	[9.753]	[8.845]	[9.675]
	<0.001	<0.001	<0.001	<0.001
Observations	61	58	55	61
R^2	0.463	0.451	0.438	0.459

Appendix A.4. Summary of Robustness Findings

The extended analysis yields several key conclusions. First, the positive relationship between participation and prices is robust across alternative specifications, including controls for cryptocurrency market conditions and market attention. Second, the results are stable across subsamples and are not driven by specific time periods or extreme observations. Third, the relative differences across datasets are preserved: the aggregate market exhibits weaker and noisier relationships, while collection-level data display stronger and more clearly defined effects.

Overall, these findings reinforce the interpretation in the main text that participation-dependent valuation is a central feature of NFT markets. The robustness checks confirm that the empirical patterns are not sensitive to modelling choices and provide additional support for the theoretical mechanism proposed in this paper.

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