Why There is the Imbalance Income Distribution in the NFT Markets? An Evolutionary Game Study

Hemiao Gao[1*]

[1] Business School, Shandong Normal University, Jinan Shandong 250014, China
*ghemiao@163.com

Abstract. Imbalance income distribution is the important problem disturbing NFT markets, this paper applies an evolutionary game model and network externality theory to discuss why there is the huge differentiation of price and demand between NFTs. By constructing the three-sided model, this paper conducts the simulation analysis, then gives the explanation for the imbalance distribution. Firstly, the network externality increases the utility of the earlier and famous NFTs, and buyers have limited attention on the NFTs' value, so the buyers prefer the earlier and famous NFTs rather than non-famous or new NFTs. Secondly, network externality increases the buyers' demand for earlier and famous NFTs, so they can keep a high price. Thirdly, Expansion of market size makes the non-famous and new NFTs keep a low price. this paper makes several contributions: firstly, it explores the unequal distribution in NFTs markets, filling a gap in existing research, which focuses on copyright-related problems. Secondly, it applies the theory of network externality and evolutionary game model, providing a new idea to explore the distribution of profits in NFT markets.

Keywords: Non-fungible tokens; Network externality; Platform economy

1 Introduction

Non-Fungible Tokens (NFTs) are the encrypted digital assets. They are widely applied in blockchain technology and are usually used to represent unique, irreplaceable digital assets or collectibles. Unlike fungible tokens in cryptocurrencies (such as Bitcoin and Ethereum's ETH), each NFT has the unique properties and value [1]. NFTs foster the interoperable commercialization of both digital and physical assets [2], promote the development and application of the Metaverse and Web 3.0 [3],[4], provide a trading market for intangible assets such as power, influence, and status [5], and increase the groups income of some industries such as the art industry [3],[6],[7].

However, with the development of NFT, the problems behind it are gradually exposed. A typical problem is the unbalanced distribution of economic benefits, a few early NFTs designers obtained most of the profits, resulting in NFT failing to increase the income of industry groups. This problem can be divided into the two subquestions, first is the buyers' demand is concentrated in a few NFTs. Just like the famous "CRYPTO PUNKS" series of digital artworks, released in 2017, their current lowest

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price is as high as \$80,000, but they are only 10,000 pixel images generated by algorithms [9]. Second is the few NFTs focused by buyers can keep a high price in the long time, while other NFTs only have a lower price. One study showed that nearly 80% of NFTs sold for less than \$500, while 1.8% of NFTs cost more than \$894 [10].

This paper aims to explore the reasons why a few NFTs designers obtained most of the profits.In comparison to previous studies, this paper makes several contributions: firstly, it finds the reasons why there is the unequal distribution in NFTs markets, filling a gap in existing research. Secondly, it applies the theory of network externality to study the NFTs markets, this theory is seldom used in prior NFT research, but it is suitable for studying Internet and platform economy. Thirdly, the evolutionary game model has been applied by a few NFT studies, this method is a useful tool to discuss the distribution of profits.

2 Methodology

Assumption 1: In the game, there are three players, the existing designer, new designer and buyer. Existing and new designer mint NFTs. The NFTs minted by Existing designer enter the market earlier and are more well-known. The NFTs minted by new designer enter later and are less famous, but have the higher value. Buyer will purchase the NFTs from the both designers, but he has a preference for NFTs of one designer. When buying NFTs, he will buy the preferred NFTs first, after meeting the demand for preferred NFTs, he will buy another NFTs.

Assumption 2: The strategies set of the existing designer is (low price, high price), when choosing low price, existing designer can maintain the price of NFTs at a low level, when choosing high price, he can maintain at a high level. The probability of the existing designer choosing low price is x, the probability of the old designer choosing low price is y. The strategies set of the buyer is (existing-preference, new-preference), when choosing existing-preference, he will buy the NFTs of existing designer first, when choosing new-preference, he will buy the NFTs of new designer first. The probability of the existing designer choosing existing-preference is z.

Assumption 3: The existing and new designer's cost of minting NFTs are C_1 and C_2, where $C_1 < C_2$, because new designer's NFTs have the higher value. Based on the transaction rules of NFTs' platforms, existing designer and new designer can free set the price of NFTs, we assume they can set the low or high price P_{low} and P_{high}, where $P_{low} < P_{high}$. When one designer chooses the high price strategy, his price of NFTs is P_{high}, on the contrary, the price of NFTs is P_{low}.

Based on assumptions, the payoff matrix of the game can be listed as in Table 1, where (1,1,0) means that the old designer chooses the low price strategy, the new designer chooses the low price strategy, and the buyer chooses the existing-preferred strategy, other strategy combinations can be understood in the same way.

Table 1. Payoff matrix.

Combination	Payoff
(1,1,0)	$(P_{low} - C_1) * (1+\alpha) * Q_{low}$ $(P_{low} - C_2) * (Q - (1+\alpha) * Q_{low})$ $((1+\alpha) * U_1 - P_{low}) * (1+\alpha) * Q_{low} + (U_2 - P_{low}) * (Q - (1+\alpha) * Q_{low})$
(1,1,1)	$(P_{low} - C_1) * (Q - Q_{low})$ $(P_{low} - C_2) * Q_{low}$ $(U_2 - P_{low}) * Q_{low} + ((1+\alpha) * U_1 - P_{low}) * (Q - Q_{low})$
(1,0,0)	$(P_{low} - C_1) * (1+\alpha) * Q_{low}$ $(P_{high} - C_2) * Q_{low} * (1 + e_d * \Delta P)$ $((1+\alpha) * U_1 - P_{low}) * (1+\alpha) * Q_{low} + (U_2 - P_{high}) * Q_{low} * (1 + e_d * \Delta P)$
(1,0,1)	$(P_{low} - C_1) * (Q - Q_{low} * (1 + e_d * \Delta P))$ $(P_{high} - C_2) * (Q - Q_{low} * (1 + e_d * \Delta P))$ $(U_2 - P_{high}) * Q_{low} * (1 + e_d * \Delta P) + ((1+\alpha) * U_1 - P_{low}) * (Q - Q_{low} * (1 + e_d * \Delta P))$
(0,1,0)	$(P_{high} - C_1) * (1+\alpha) * (Q_{low} * (1 + e_d * \Delta P))$ $(P_{low} - C_2) * (Q - Q_{low} * (1 + e_d * \Delta P))$ $((1+\alpha) * U_1 - P_{high}) * (1+\alpha) * Q_{low} * (1 + e_d * \Delta P) + (U_2 - P_{low}) * (Q - Q_{low} * (1 + e_d * \Delta P))$
(0,1,1)	$(P_{high} - C_1) * (1+\alpha) * (Q_{low} * (1 + e_d * \Delta P))$ $(P_{low} - C_2) * Q_{low}$ $(U_2 - P_{low}) * Q_{low} + ((1+\alpha) * U_1 - P_{high}) * (1+\alpha) * Q_{low} * (1 + e_d * \Delta P)$
(0,0,0)	$(P_{high} - C_1) * (1+\alpha) * (Q_{low} * (1 + e_d * \Delta P))$ $(P_{high} - C_2) * (Q_{low} * (1 + e_d * \Delta P))$ $((1+\alpha) * U_1 - P_{high}) * (1+\alpha) * Q_{low} * (1 + e_d * \Delta P) + (U_2 - P_{high}) * Q_{low} * (1 + e_d * \Delta P)$
(0,0,1)	$(P_{high} - C_1) * (1+\alpha) * Q_{low} * (1 + e_d * \Delta P)$ $(P_{high} - C_2) * Q_{low} * (1 + e_d * \Delta P)$ $(U_2 - P_{high}) * Q_{low} * (1 + e_d * \Delta P) + ((1+\alpha) * U_1 - P_{high}) * (1+\alpha) * Q_{low} * (1 + e_d * \Delta P)$

Based on payoff matrix, the expected return functions of the old designer choosing low price U_x, choosing high price U_{1-x} can be written as in equations (1) and (2) :

$$U_x = y * \left(Payoffy, (1,1,0) + Payoffy, (1,1,1)\right) + (1-y) * \left(Payoffy, (1,0,0)\right) + Payoffy, (1,0,1) + z * (Payoffz, (1,1,1) + Payoffz, (1,0,1) + (1-z) * (Pay\,offz, (1,0,0) + Payoffz, (1,1,0) \quad (1)$$

$$U_{1-x} = y * (Payoffy, (0,1,0) + Payoffy, (0,1,1)) + (1-y) * (Payoffy, (0,0,0) + Payoffy, (0,0,1)) + z * (Payoffz, (0,1,1) + Payoffz, (0,0,1)) + (1-z) * (Payoffz, (0,0,0) + Payoffz, (0,1,0)) \quad (2)$$

Where $Payoffy, (1,1,0)$ means the new designer's payoff choosing low price strategy when strategic combination is (low price, high price, existing-preference), The meanings of other items are deduced in the same way.

The expected return functions of the new designer choosing low price V_y, choosing high price V_{1-y}can be written as in equations (3) and (4) :

$$V_y = x * (Payoffx,(1,1,0) + Payoffx,(1,1,1)) + (1-x) * (Payoffx,(0,1,0) + Payoffx,(0,1,1)) + z * (Payoffz,(1,1,1) + Payoffz,(0,1,1)) + (1-z) * (Payoffz,(1,1,0) + Payoffz,(0,1,0)) \tag{3}$$

$$V_{1-y} = x * (Payoffx,(1,0,0) + Payoffx,(1,0,1)) + (1-x) * (Payoffx,(0,1,0) + Payoffx,(0,1,1)) + z * (Payoffz,(1,1,1) + Payoffz,(0,1,1)) + (1-z) * (Payoffz,(0,0,0) + Payoffz,(1,0,0)) \tag{4}$$

The expected return functions of the buyer choosing old-preference W_z, choosing high price W_{1-z}can be written as in equations (5) and (6) :

$$W_z = x * (Payoffx,(1,0,1) + Payoffx,(1,1,1)) + (1-x) * (Payoffx,(0,1,1) + Payoffx,(0,0,1)) + y * (Payoffy,(1,1,1) + Payoffy,(0,1,1)) + (1-y) * (Payoffy,(1,0,1) + Payoffz,(0,0,1)) \tag{5}$$

$$W_{1-z} = x * (Payoffx,(1,0,0) + Payoffx,(1,1,0)) + (1-x) * (Payoffx,(0,1,0) + Payoffx,(0,0,0)) + y * (Payoffy,(1,1,0) + Payoffy,(0,1,0)) + (1-y) * (P\,ayoffy,(0,0,0) + Payoffy,(1,0,0)) \tag{6}$$

3 Numerical Simulation

The simulation is carried out through MATLAB software. The main work of the simulation is to program the replication dynamics equations and solve them through the MATLAB. The solutions to the equations are the evolve stable strategies maked by the players. The initial values of all variables are listed as follows, where $\boldsymbol{\alpha}$ =5, $\boldsymbol{Q}$ =5, $\boldsymbol{P_{low}}$ =2.8, $\boldsymbol{P_{high}}$ =3, $\boldsymbol{e_d}$ =-1.1, $\boldsymbol{C_1}$ =0.5, $\boldsymbol{C_2}$ =1, $\boldsymbol{U_1}$ =2, $\boldsymbol{U_2}$ =6, $\boldsymbol{Q_{low}}$=0.5, $\boldsymbol{\Delta P}$=0.5, $\boldsymbol{x}$=0.5, $\boldsymbol{y = 0.5}$. In Fig 1, we explore the strategic evolution of buyer under the influence of variables for exploring the reasons why the buyers' demand concentrates on the part of NFTs.

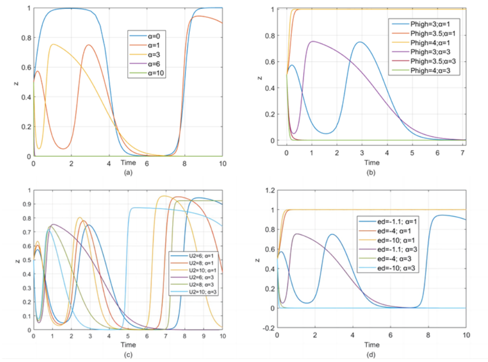

Fig. 1. Strategic evolution of buyer.

Fig 1(a) reflects the dynamic evolution of the buyer's strategy under the influence of network externality α, we find the stronger the network externality, the lower the buyer's willingness to buy the new NFTs z. Specifically, when subsidy $\alpha = 0$, as shown by the blue curve, the curve is in a shocking state. That is, the buyer's strategy cannot reach a stable state, his preference for NFTs is not obvious. However, with the values' increase of α, the shoking state gradually evolute to the stable state. Fig 1(b) reflects the influence of NFTs' price P_{high} on buyer's strategy, we find when there are the lower values of network externality, the higher the price, the higher the willingness to buy the new NFTs. When there are the higher values of network externality, higher price will lead to the lower willingness. Fig 1(c) reflects the influence of new NFTs' utility U_2 on dynamic evolution of the buyer's strategy, we find new NFTs' utility can exert a few influences on buyer under the different values of network externality. Fig 1(d) reflects the influence of demand elasticity on the buyer's strategy, we find when there are the lower values of network externality, the higher demand elasticity (absolute value) will lead to the higher willingness buying the new NFTs. On the contrary, higher demand elasticity will lead to the lower willingness.

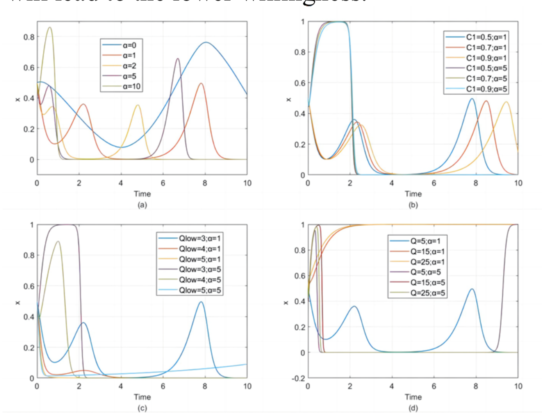

Fig. 2. Strategic evolution of existing designer.

Fig 2(a) reflects the dynamic evolution of the existing designer's strategy under the influence of network externality α, we can find the stronger the network externality, the stronger the existing designer's willingness to keep a high price $1 - x$. when $\alpha = 0$, as shown by the blue curve, the curve is in a shocking state. However, with the values' increase of α, the shoking state gradually evolutes to the stable state. Fig 2(b) reflects the influence of minting NFTs' cost of existing designer C_1 on dynamic evolution of the existing designer's strategy, we find NFTs' cost and existing designer's willingness keeping a high price of NFTs $1 - x$ are almost irrelevant. Fig 2(c) reflects the influence of buyer's demand for preferred NFTs Q_{low} on dynamic evolution of the existing designer's strategy, we find the demand and the existing designer's willingness keeping a high price are negative related. Fig 2(d) reflects the influence of total demand Q on dynamic evolution of the existing designer's strategy, we find the total demand and the existing designer's willingness keeping a low price are positive related when there is the higher network externality.

4 Conclusions

Based on the simulation results, this paper gives the explanation for the imbalance distribution. Firstly, the network externality increases the utility of the earlier and famous NFTs and buyers have limited attention on the NFTs' value, so the NFTs' buyers prefer the earlier and famous NFTs rather than non-famous or newly minted NFTs. Secondly, network externality increases the buyers' demand for earlier and famous NFTs, so they can keep at a high price. Thirdly, Expansion of NFTs' market size makes the non-famous and newly minted NFTs keep a low price.

According to the conclusions, we know that buyers with low demand elasticity still have a certain preference for New NFTs. Therefore, by promoting NFTs market segmentation, it may be beneficial to the transactions of New NFTs. For example, based on the users' history of transaction and browsing records, the decision makers like NFT platforms can collaborate with other social media to recommend new NFTs to non-price-sensitive buyers. In addition, given that buyers have limited attention to the value of NFTs, the price strategy is the useful competitive strategy for new designers. Specifically, they should initially sell NFTs at a lower price, even if the value of their NFTs is higher. As buyers pay more attention on them, these designers can start raising prices to achieve higher revenue.

References

1. Schwiderowski, J., Pedersen, A. B., Jensen, J. K., & Beck, R. (2023). Value creation and capture in decentralized finance markets: Non-fungible tokens as a class of digital assets. Electronic Markets, 33(1), 45.
2. Idelberger, F., & Mezei, P. (2022). Non-fungible tokens. Internet Policy Review, 11(2).
3. Hartwich, E., Ollig, P., Fridgen, G., & Rieger, A. (2023). Probably something: A multi-layer taxonomy of non-fungible tokens. Internet Research, Forthcoming.
4. Kshetri, N. (2022). Web 3.0 and the Metaverse Shaping Organizations' Brand and Product Strategies. IT Professional, 24(2), 11-15.
5. Kraizberg, E. (2023). Non-fungible tokens: A bubble or the end of an era of intellectual property rights. Financial Innovation, 9(1), 32.
6. Fairfield, J. A. T. (2022). Tokenized: The law of non-fungible tokens and unique digital property. Indiana Law Journal, 97(4), 1261–1313.
7. Pawelzik, L., & Thies, F. (2022). Selling digital art for millions—A qualitative analysis of NFT art marketplaces. ECIS 2022 Research Papers. European Conference on Information Systems, Timisoara, Romania.
8. Taherdoost, H. (2023). Non-Fungible Tokens (NFT): A Systematic Review. Information, 14(1), 26.
9. CryptoPunks. Available online: https://cryptopunks.app/cryptopunks/topsales(accessed on 2 November 2023).
10. Parker, K. Most Artists Are not Making Money off NFTs and Here Are Some Graphs to Prove It. Available online: https://thatkimparker.medium.com/most-artists-are-not-making-money-off-nfts-and-here-are-some-graphs-to-prove-it-c65718d4a1b8 (accessed on 22 October 2023).