Personal Experience Effects across Markets: Evidence from NFT and Cryptocurrency Investing[*]

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Abstract

I examine how personal experiences causally impact investor behaviors and market boom-bust episodes by exploiting a unique experimental setting in the non-fungible token (NFT) market. Using blockchain transaction-level data for about 1 million wallets, I find that NFT investors who randomly receive more valuable NFTs in the primary market are more likely to participate in subsequent primary market sales and trade more NFTs in the secondary market. These experience effects spill over to the cryptocurrency market as investors who randomly receive more valuable NFTs purchase more lottery-like cryptocurrencies. I also find that personal experiences and new investor inflows have contributed to the formation of bubbles in the NFT market. A model-free reinforcement learning framework best explains the empirical results.

Keywords: investor behavior, FinTech, decentralized finance, NFT, cryptocurrency

JEL Codes: G11, G29, G41, G59

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1 Introduction

Households face complex financial decisions, and a growing body of research documents that past experiences play an essential role in shaping individual beliefs, risk-taking, and economic decision-making. Much of the literature focuses on experiences of macroeconomic shocks and shows long-lasting effects on stock market participation, inflation expectation, and home ownership (Malmendier and Nagel, 2011, 2016; Malmendier and Wellsjo, 2023). Another strand of work documents how personal experiences of investment returns impact decisions on saving and stock market trading (Kaustia and Knüpfer, 2008; Choi et al., 2009; Anagol et al., 2021). The existing literature on personal experience effects primarily centers around investment decisions in the stock market, with limited evidence for other asset classes. Furthermore, the applications of household finance highlight the potential for a better understanding of personal experiences (Malmendier, 2021).

This paper studies the impact of personal experiences in the emerging non-fungible token (NFT) and cryptocurrency market. The key challenge in identifying experience effects on financial decision-making using observational data is that prior experience is an endogenous outcome. I overcome this challenge by utilizing the randomized allocation of NFTs among investors who purchase within the same collection during the initial sale. I compare the behaviors of investors who randomly received much more valuable NFTs to those who did not. Leveraging the transparent transaction activities on the blockchain, I document that personal experiences of exogenous gains in the NFT market substantially impact the investor's future investment behaviors in the NFT as well as the cryptocurrency markets.

I develop the main hypotheses from a model-free reinforcement learning framework in Barberis and Jin (2023). A notable characteristic of this model is its independence from the underlying asset return structure. The model setup fits the NFT market well because the asset class is new to investors, and its non-fungible nature and lack of cash flow information can make it difficult for investors to determine the return structure. Therefore, investors may rely more heavily on a model-free approach for decision-making in the NFT market. The model predicts that after experiencing a good outcome of an asset, the investor will likely choose the asset again and other assets similar to it in the future. In addition, such effects will diminish as the investor gains long enough good experiences. The reinforcement of past actions generates extrapolative demand for the asset, characterized by investors basing their demand on past returns. The heightened demand, in turn, will exert upward pressure on prices, which can create asset bubbles (Barberis et al., 2018). I derive three sets of hypotheses according to the model. First, investors who obtain rare NFTs in the primary market will purchase more NFTs in the future, both in the primary and secondary markets. They will also purchase more assets with similar characteristics, such as lottery-like cryptocurrencies. Second, the investors will react less to the random experiences of getting rare NFTs as they accumulate more good experiences. Lastly, investors who obtain rare NFTs in the primary market are more likely to contribute to the formation of NFT bubbles as their demand for the assets increases. I find compelling empirical evidence consistent with these hypotheses.

To ensure the quasi-experimental setting of random NFT allocation, I obtain all the NFT collections created on the Ethereum blockchain by 2022 and systematically review the detailed metadata underlying each NFT item. I construct a sample of 4,846 NFT collections, which randomly distributed individual items to buyers during the initial primary market sale (also called NFT *minting*). Next, I construct a comprehensive dataset of over 1 million investors who participate in minting and track all their investment activities on the blockchain. To my knowledge, this is the first comprehensive study of NFT investor behavior in combination with their investment in cryptocurrencies.

In addition to exploiting plausibly exogenous personal experience in the NFT market, the empirical results are meaningful and interesting as in recent years, it has become more important to understand investor behaviors in digital assets powered by the blockchain technology. The popularity of NFT and crypto investing has rapidly grown among investors. As of July 2023, the NFT market reached a total trading volume of over $78 billion, and cryptocurrencies had a global market capitalization of over $1 trillion.[1] I observe sizable investments for individual investors in the sample, with an average monthly trading volume of $7,000 and $17,000 in the NFT and cryptocurrency markets, respectively. These investments collectively account for approximately 10% of the median household portfolio size of $228,000 for wealthy retail investors in the U.S. as documented in Giglio et al. (2021).

NFTs are illiquid assets, and no theoretical framework exists that models the fundamental value of NFTs. To deal with the lack of price information, I use the measure of rarity to proxy for ex-ante NFT value *within* the same collection and focus on the relative value of individual items in the same collection. The literature on art and collectibles documents that the scarcity factor plays a fundamental role in price appreciation (Burton and Jacobsen, 1999; Mandel, 2009; Pénasse et al., 2021). Existing studies of NFTs also show empirically that rarer NFTs are generally sold at higher prices (Mekacher et al., 2022; Lee, 2022). I follow Mekacher et al. (2022) to calculate the rarity score, which is also commonly used in the NFT industry for investors. I employ the rarity measure to determine the relative value of NFTs within collections and infer the positiveness of investor experience from the

[1]Sources: IntoTheBlock and CoinMarketCap.

random allocation of NFTs with different levels of rarity. I define that an investor has a positive experience in the NFT primary market if he randomly obtains a rare NFT, a much more valuable asset than common NFTs in the same collection. I exploit the exogenous variation of experiences to empirically study the causal impact of personal experiences on subsequent investment decisions and show consistent evidence with the model-free learning predictions.

I start by examining the experience effect on future NFT primary market participation. I find that investors who mint rare NFTs are more likely to participate in future minting and spend more money compared with investors who mint common NFTs in the same collection during the same month. These results align with personal experience effects in the IPO market where investors with positive IPO experiences are more likely to apply for future IPOs (Kaustia and Knüpfer, 2008; Chiang et al., 2011; Anagol et al., 2021).

Next, I show that minting rare NFTs also causes investors to purchase more NFTs in the secondary market. I find a significant but smaller effect on subsequent decisions on NFT sales after minting rare NFTs. To account for the possible disposition effect that investors might tend to sell rare NFTs at a profit, I exclude the NFT item that the investor minted. I also compare the trading profits between investors who mint rare and common NFTs and find no significant differences. It suggests that investors who obtain more valuable NFTs from random minting do not possess superior skills in trading NFTs.

I then seek to understand whether such experience effects of minting rare NFTs could spill over to investing in the crypto market. Existing research documents that experience effects are domain-specific: experiences in one market do not necessarily influence behaviors in another market even when the two asset classes are correlated (Malmendier, 2021). By utilizing the blockchain as a transparent ledger of all on-chain transactions, I am able to observe all the transactions made by the same investor wallet and examine their crypto trading behaviors after prior randomized experiences in the NFT market. I first examine the overall crypto trading and find that NFT investors who mint rare NFTs do not trade more cryptos subsequently, which is consistent with the domain-specificity of experience effects in the prior literature. I then examine whether there exists spillover to cryptos that are more or less similar to NFTs. I find that investors who mint rare NFTs trade more cryptos with lottery-like characteristics. The evidence supports the generalized version of model-free learning that investors rely on their past experiences to invest in assets that are similar to their previous investments. Establishing the causal link between personal experience effects and investor behaviors in different markets is nontrivial, as various confounding factors can jointly determine investors' decision-making outcomes. The NFT collection minting process contributes to the causal interpretation of experience effects as the random allocation of experience outcome is orthogonal to any unobservable investor or time heterogeneity.

Overall, I document strong personal experience effects on subsequent investment decisions on NFTs and cryptocurrencies that are similar to NFTs. The spillover effect to the crypto market suggests that further theoretical guidance is needed on the "domain" of experience. Malmendier and Nagel (2011) document that macro-level exposure to the stock and bond market only impacts investor beliefs and behaviors within the same market but not across each other. I show that investors might view decision-making in the NFT and crypto markets as more related when the assets are more similar in some aspects. It would be helpful to understand better how investors rely on past experiences in a different but related market when making investment choices. Further theoretical foundation of “similar” investments will further facilitate our understanding of the domain-specific experience effects.

I also investigate how the effects of experiences vary based on the level of prior minting experiences. I divide the sample of investors into different groups based on how many times they have minted a rare NFT in a collection before. As investors gain a few good minting experiences from none, their responses to the random event of minting rare NFTs diminish, and most effects become statistically insignificant from zero. The magnitude of the effects diminishes even further as investors accumulate more good experiences.

After documenting the causal impact of personal experiences on investor trading behaviors, I further examine possible implications on market dynamics. I relate investors’ trading behaviors to the NFT boom and bust during the sample period. I construct a price index for each NFT collection using the repeat sales regression method and identify bubble-like NFTs following Greenwood et al. (2019). I then look at who seeds the NFT bubble by purchasing more NFTs at higher prices. Consistent with extrapolative theories of speculative bubbles, I find that investors who mint rare NFTs are net buyers during the initiation of bubble-like NFTs and purchase them at higher prices. Using auction data, I show that investors who mint rare NFTs bid 25% higher for NFTs from the same collection, implying that investors’ positive experiences in the NFT primary market lead them to overvalue NFTs in the secondary market and contribute to the emergence of bubbles. I also find that new wallets respond more to the prior experiences of minting rare NFTs, which is consistent with the attenuation of effects with more prior experiences. The time series of new investor entry also aligns with the trend in NFT prices, suggesting that the absence of new investors at the later stage of the bubble is a potential reason for the eventual bubble collapse.

Lastly, I discuss several alternative mechanisms that can potentially explain the empirical results. First, the experience effects cannot be entirely driven by the wealth effects or house money effects of getting rare NFTs, as I show that the effects are stronger for the subsample of investors holding their newly minted NFTs. It suggests that the results are not due to liquidity constraints of investors that mint rare NFTs. Moreover, I show the effects are stronger for investors with larger wealth in their crypto wallet. Since the relative change of wealth is larger for smaller wallets, we should expect stronger reactions from them if the experienced gains change their risk-taking preference. The opposite results show that the experience effects are not driven by the pure wealth story. The house money effect suggests that the experience effects would be larger if investors realized the gains from NFT minting, which is not supported in the data. Although I cannot entirely rule out the presence of the house money effect, as it can still exist with unrealized gains, the contradictive evidence still suggests that it is unlikely to be the sole driver of all the empirical findings. Second, Anagol et al. (2021) presents a learning-from-noise model that explains how people mistakenly attribute the random allocation of positive return IPOs to their ability. It is possible that investors who mint rare NFTs mistakenly learn about their ability to invest not only NFTs but also cryptos, but further assumptions are needed to explain why investors only purchase more lottery-like cryptos while their overall crypto trading remains at the same level.

This paper contributes to several strands of literature. First, it connects with the literature on experience effects, which shows that past experiences exhibit significant influences in different economic domains (Malmendier and Nagel, 2011, 2016; Malmendier et al., 2021; Malmendier and Wellsjo, 2023). More specifically, it adds to the studies of personal experience effects on individual financial decision-making. For the decision on saving, Choi et al. (2009) document that investors who experience positive outcomes from their 401(k) accounts increase their savings rate. For stock market investment, Kaustia and Knüpfer (2008) show that IPO returns personally experienced by investors positively impact future IPO subscriptions. Using the random IPO allocation setting in India and China, Anagol et al. (2021) and Gao et al. (2021) show that investors who win the IPOs increase their trading volume subsequently. Andersen et al. (2019) show that negative personal experiences in bank stocks make people shy away from risks. Huang (2019) provides evidence that individuals are more likely to invest in stocks of a specific industry after experiencing positive returns in that industry. I extend the evidence of personal experience effects to the emerging markets of NFT and cryptocurrency as well as further establish the spillover effects between different markets for the first time.

I also contribute to the literature that examines household investment behaviors using account-level data. Barber and Odean (2001, 2000) document that investors trade excessively and underperform the market using the broker data. Grinblatt and Keloharju (2009) show that overconfident and sensation-seeking investors trade more. I leverage the rich and transparent blockchain data to understand investor behaviors in the fast-growing Decentralized Finance (DeFi) space. Although I do not observe the demographic information and investments outside the blockchain, the quasi-experiment setting of the NFT minting experience alleviates this concern to some extent, as the random distribution of rare NFTs in the same collection is orthogonal to unobservable investor characteristics.

In addition, the paper is related to the literature on investor behaviors during asset bubbles. Pearson et al. (2021) show that investors engaged in positive feedback trading during the Chinese warrant bubble. Under the same setting, Li et al.

(2021) show that only a small fraction of skilled investors earn profit during the bubble. Greenwood and Nagel (2009) find that inexperienced mutual fund managers invest more heavily in technology stocks during the dot-com bubble. Barbon and Ranaldo (2023) examine asset bubbles in the NFT market and show that sophisticated investors outperform others. Using a different dataset, Huang and Goetzmann (2023) highlight the selection-neglect during the NFT bubble. I contribute to the literature by studying the effect of personal experience on bubble formation in a quasi-experimental setting and establishing causal evidence that extrapolative investors seed the NFT bubble by purchasing more NFTs at higher prices.

Finally, this paper adds to the growing literature on NFT and crypto investing. Using a comprehensive dataset of NFT collections, Oh et al. (2022) show that experienced investors tend to outperform inexperienced investors in the NFT market systematically. Borri et al. (2022) build NFT price indices and analyze the pricing dynamics. Other work seeks to understand cryptocurrency investor behaviors. Kogan et al. (2022) use investor trade-level data from a brokerage platform and compare the strategies when investing cryptos versus stocks or gold. Aiello et al. (2023) use data from a financial aggregation firm to show that investors treat crypto as part of their investment portfolio and use crypto wealth to increase spending. I utilize the on-chain data to study investor behaviors over two markets within the blockchain ecosystem.

The rest of the paper proceeds as follows. Section 2 provides the institutional background of the NFT and cryptocurrency market. In section 3, I describe the blockchain transaction data, empirical methodology, and model predictions from the model-free learning framework. In Section 4, I document the experience effects of minting rare NFTs on future NFT and cryptocurrency investing. In Section

5, I examine how extrapolative investors contribute to the NFT bubble formation. In Section 6, I explore alternative mechanisms that potentially explain the empirical facts. Section 7 concludes.

2 Institutional Background

Non-fungible tokens (NFTs) have emerged as a novel approach for establishing ownership and verifying the authenticity of digital assets, such as art, music, and videos. NFTs operate on blockchains, which offer a decentralized and secure mechanism for recording transactions and verifying ownership. The ease of certifying and transferring NFT ownership makes it possible to create markets for a wide variety of goods (Kaczynski and Kominers, 2021). One distinctive aspect of NFTs is their non-interchangeable and unique nature, which means they cannot be traded on a one-to-one basis like fungible cryptocurrencies such as Bitcoin. This property is a crucial attribute of NFTs, driving their popularity in the realm of digital art and collectibles. The Ethereum blockchain is currently the most widely used blockchain for minting NFTs, generating more than $78 billion in trading volume as of 2022.

NFTs are created and traded using smart contracts on the blockchain. Smart contracts are computer programs that execute contractual agreements between parties and facilitate exchanging value in an automated and conflict-free way (Cong and He, 2019). When creating an NFT, the first step involves *minting* it on a blockchain and creating the initial record. Subsequent transactions will be recorded on the blockchain to monitor any changes in ownership of the NFT, producing an immutable and traceable record. Generally speaking, minting refers to the first-time sale of an NFT from the creator to the investor in the primary market, and afterward secondary sales or trading of that same NFT happens in the secondary market.

NFTs are often released in the form of collections. A collection consists of a limited number, typically 5,000 to 10,000, of individual items under the same theme. All NFTs in the same NFT collection are administrated by a single smart contract, and each has a unique token ID as the identifier. I provide an example of an NFT collection and its individual items in Figure A1. Moreover, each item in the collection possesses a unique combination of traits that sets it apart. The rarity of an NFT, a metric measuring the uniqueness of an NFT in comparison with the other tokens within the collection, has become a crucial factor in how market participants assess its value. The rarity score was first introduced by Rarity Tools and became popular among the NFT community. It is a statistical measure of rarity using the frequency of NFT traits, and I discuss its methodology and intuition in detail in Section 3.2. Generally, rarer NFTs are perceived to command higher prices in the secondary market (Sothebys, 2021).

To ensure fair distribution of NFTs in a collection, the artwork underlying the NFT and associated traits are not revealed before minting. That is, investors cannot specify which individual item to mint and will get a random item from the collection. The NFT creator typically sets up a reveal date of the entire collection after the minting, and by that time, investors will have information about the appearance and traits of their NFTs.[2] This quasi-experiment setting provides an opportunity to causally identify the effect of a random event on subsequent financial behaviors.

Once an investor mints an NFT from the primary market, she can choose to sell it to another investor in the secondary market. Such transactions are facilitated by

[2]See more at https://opensea.io/learn/what-are-nft-drops.

NFT marketplaces such as OpenSea. Like the online retail marketplace, NFT sellers can list their NFT for sale, and potential buyers can browse and purchase it via the platform. To perform various activities on the blockchain, such as minting and trading NFTs, investors need a crypto wallet. The wallet address is a unique identifier and is used to interact with the NFT smart contract for transaction purposes.

The crypto wallet is not only used for NFTs but also for fungible cryptocurrencies. To buy NFTs, investors usually need to pay with cryptocurrencies. Ether (ETH), the native token of the Ethereum blockchain, is the most common medium of exchange to trade NFTs. The smart contract on the Ethereum blockchain also enables Decentralized exchanges (DEXs), through which investors trade cryptocurrencies on a peer-to-peer basis. DEXs have become an important innovation in the rapidly growing decentralized finance (DeFi) ecosystem built on the blockchain technology (Makarov and Schoar, 2022).

3 Data and Methodology

3.1 NFT Collection

I obtain all the NFT collection addresses complying with the ERC-721 standards created on the Ethereum blockchain until December 31, 2022.[3] Each individual NFT in a collection has the same address and a unique token ID as the identifier. To distinguish the value of NFTs in a collection based on their unique rarity, I focus on collections with different traits for each individual NFT item documented in the metadata. Such collections are often called "generative" NFT collections, in which

[3] ERC-721 was launched in January 2018 and has since become the most widely used standard for NFTs. It enables the creation and transfer of unique digital assets on the Ethereum blockchain. Another common NFT standard is ERC-1155, which allows multiple tokens under one smart contract. The total trading volume of NFTs complying with ERC-721 is about 95% of all Ethereum-based NFTs in my sample period.

the individual items share a common theme and distinguish from each other with unique variations (Oh et al., 2022). I only choose NFT collections with at least 100 items to apply the criterion of defining rare NFTs at the 90 percentile of the rarity score. I also download all the asset URLs embedded in the smart contracts of NFTs and remove collections that contain duplicate URLs to ensure that each NFT item in the collection is unique and has distinctive attributes of rarity.

After selecting the sample of NFT collections, I extract all the minting and sale events of these NFTs on the blockchain, with information about the buyer, seller, transaction price, gas fees, and timestamp for each transaction. For the price paid in ETH, I use the daily price from CoinMarketCap to convert the unit to USD. For less than 1% of transactions that use other cryptocurrencies for price, I use the end-of-day token price computed using the Ethereum DEX data. The resulting prices are winsorized at the 1st and 99th percentile level. The NFT transaction data allow me to track individual-level investment behavior and performance in the NFT market.

Table 1 presents summary statistics at the NFT collection level. The average collection contains 2,802 items, with a total minting revenue of $300 thousand and a total trading volume of $6 million. The average price to mint an NFT is $81, and the average price is more than $887 for the most expensive collections. Similarly, the average trading price for an item in the average collection is $691, and the price varies substantially across different collections. Noticeably, about 700 NFT collections in the sample are never traded since minting, implying that the sample selection process is not biased toward popular collections only. The key element of the empirical design is that the minting process of each NFT collection should be random. That is, no investors have information regarding the appearance and traits of the underlying artwork before they mint. To alleviate the concerns that the NFT creators use their private information and mint the rare items themselves, I only include the NFT collections whose creators never minted any NFT item in that collection. The final sample contains 4,846 NFT collections and 7.9 million individual tokens. To further test whether there might exist investors who select to mint rare NFTs in front of others during the minting process, I plot the time of mint to the rarity score percentile in Figure 1. The y-axis is the number of hours between the NFT minting time and when minting starts, assuming the time of the first NFT minted marks the minting start. As shown in the scatterplot, the minting time distribution is almost uniform across all NFT rarity levels in the collection. It indicates that no investors with private information about the NFT rarity appear to front-run the other participants and get the rarest items first.

3.2 Rarity Score

One key measure in the quasi-experiment of the NFT minting process is the rarity of each NFT item in a collection. When investors mint a particular NFT collection, they do not observe the underlying artwork and its traits, which determine the ranking of rarity within a collection and the positiveness of an investor's experience in each experiment. To measure the rarity, I download the metadata of every individual NFT item using its smart contract address and unique token ID, where the traits of each NFT are encoded. In Figure A2, I show an example of NFT trait data and how the information is usually displayed to NFT investors on the NFT trading platform. While the returns of individual NFTs are exposed to the NFT market-level trend and other asset markets (Borri et al., 2022), I focus on the relative performance of NFTs *within* a collection and employ the rarity metrics commonly used by the NFT industry and investors. The economic literature has documented theoretically and empirically that rarer goods have higher market value in the collectibles market, such as coins, vinyl music records, and baseball cards (Dickie et al., 1994; Cameron and Sonnabend, 2020; Ghazi and Schneider, 2022). Similar to previous studies that use the inverse of the quantity of an item as the proxy of rarity, I rely on the quantity distribution of traits in the NFT collection to measure the rarity.

Following Mekacher et al. (2022), I calculate the rarity of a NFT i in a collection $Rarity_i$ as the sum of individual trait rarity score r_j:

$$r_j = \left(\frac{m}{n}\right)^{-1} \tag{1}$$

$$Rarity_i = \sum r_j \tag{2}$$

The variable n is the total number of items in an NFT collection, and m is the number of NFTs having trait j in the collection.[4] Intuitively, m captures the quantity of traits supplied in the entire collection, and r_j represents the relative rarity of a trait normalized the total supply of the collection. The rarity score of an NFT item is a composite of its trait rarity. The higher the rarity score, the rarer an NFT is in its collection. Mekacher et al. (2022) document that the median sale price of the 10% rarest NFTs increases by 195% over the rest, and I define an NFT as *"rare"* if its rarity score is above the 90 percentile in its collection. The results are robust if using a higher threshold such as 95%.

Figure 2 shows the binned scatterplot of the secondary market NFT sale price on rarity score percentiles. Panel A uses all historical transactions, and Panel B uses the first sale price after the initial mint. The original transaction price is in the ETH unit, which is the native token of the Ethereum blockchain. I convert

[4]This measure is first implemented by Rarity Tools, a website ranking generative NFT collections by rarity. Their methodology and rationale are described in https://raritytools.medium.com/ranking-rarity-understanding-rarity-calculation-methods-86ceaeb9b98c.

the price to USD using the ETH price on that day. All the plots present the same pattern that the average price of NFTs is mostly flat up to 90% of the rarity score and increases exponentially afterward. This suggests that common NFTs tend to exhibit a more homogeneous price trend in the market, and investors who are able to obtain rare NFTs from mint can profit much more. The outcome of whether an investor gets a rare or common NFT from a collection minting event determines the treatment and control groups in the analysis.

3.3 Cryptocurrency Portfolio

To examine the causal effects of personal experience of NFT minting on investor behaviors in different domains, I obtain data on individual cryptocurrency trades to analyze how investors respond to an NFT investment experience in a different market. I collect all the cryptocurrency trading data on the decentralized exchanges of the Ethereum blockchain. The wallet address is the unique identifier of each trader. Thus, I am able to map all the on-chain activities of NFT and cryptocurrency investing for each individual. This means that I observe the entire portfolio of the investors on the Ethereum blockchain, which makes it possible to analyze the individual trading behavior and portfolio choice across two asset markets. To quantify the price and return of the cryptocurrencies and investor performance, I compute the daily price of cryptocurrencies using the trading data. I first identify the major numeraire tokens ranked by the total number of trades. Then, I use the last transaction at the end of each day (GMT) to calculate the transaction price. If a token is not traded on a particular date, I use the most recent price to proxy the price on that day.

3.4 Empirical Strategy

My approach to estimating the personal experience effect is similar to Anagol et al. (2021), who exploit the random allocation of India's initial public offerings (IPOs) to identify the causal effect of investment experiences on future investment behavior. While their experiment groups are IPO share categories in each IPO, I use each NFT collection minting as a separate experiment. The treatment group in each experiment consists of investors who mint rare NFTs in a collection, and the control group comprises investors who mint only common NFTs. The specification is as follows:

$$y_{i,t+1} = \beta \mathbb{1}_{Rare_{i,c,t}} + \rho_t X_{i,t} + \gamma_j + \epsilon_{i,c,t}, \tag{3}$$

where $y_{i,t+1}$ is the investment outcome in month t+1 for investor i who minted NFT collection c in month t. $\mathbb{1}_{Rare_{i,c,t}}$ is a dummy variable that equals to 1 if investor i minted at least one rare item in collection c (the rarity score is above the 90% in collection c). γ_j is experiment-level fixed effects at the collection, month, and number of items the investor chooses to mint. Given that the supply of NFTs in a collection is fixed, investors who mint the same number of items have an identical probability of getting a rare NFT. Conditional on the fixed effects, the effects are identified only using the variation across investors in the same minting event in the same month with random treatment.

Another concern is that certain investor characteristics would be reflected in the estimate of experience effect, and I include a set of the investor-level controls $X_{i,t}$. First, I control for measures of investor experience in the NFT market, including the wallet age in months, the total number of NFTs minted, and the total expense spent on minting up to date. Second, Oh et al. (2022) show that NFT investors with more trading frequencies are more likely to outperform, and therefore, I include the total number of NFT trades as another control. Lastly, I include the investor's cryptocurrency wallet balance. To handle heteroscedasticity caused by skewed variables, the experience control variables related to NFT count and dollar expenses are transformed using $log(1 + x)$.

3.5 Conceptual Framework

How should investors react to random experiences in the newly developed NFT market? For fully rational investors who understand the random nature of NFT distribution within a collection in the primary market, there should be no difference in their future behaviors when comparing one who mints a rare NFT with the other who does not. The random nature of NFT minting is public information, and investors should understand the rule because they do not know the NFT they will get or the distribution of the collection until minting ends and the underlying artwork is revealed. Suppose that the investor has knowledge that the good experience of minting a rare NFT is created by a random draw, and it does not imply that next time he will get a rare one again. Then a fully rational benchmark predicts that a good random experience will not impact future investment behaviors. As I will document empirically in Section 6, this prediction is not supported by the data. For example, I find that investors who mint rare NFTs are more likely to participate in minting again next month.

To guide my empirical analysis with an alternative framework, I use the model-free reinforcement learning setting developed by Barberis and Jin (2023). The theory of reinforcement learning is well-established in the psychology and neuroscience literature. It predicts that investors tend to repeat past rewarding actions naively. Reinforcement learning has also been applied in economics to study behaviors in strategic games in the experimental setting (Roth and Erev, 1995; Camerer and Ho, 1999; Charness and Levin, 2005). Existing literature also provides evidence of reinforcement learning in household investment decision-making such as IPO subscription, retirement saving, and stock investment (Kaustia and Knüpfer, 2008; Choi et al., 2009; Barber et al., 2011; Huang, 2019). I provide novel causal evidence that reinforcement learning is not restricted to the same market but can extend to other markets with similar characteristics. One feature of model-free learning is that the model uses no information about the structure of asset returns. The NFT market setting fits the model-free learning framework well because it is an emerging market, and investors might be unfamiliar with this new asset class. Moreover, NFT valuation can be difficult due to its non-fungible nature and lack of cash flow information. Therefore, model-free learning is a natural choice for studying investor behaviors in the NFT market. In addition, the unique nature of blockchain economics enables testing additional predictions of model-free learning, such as spillover effects across markets and heterogeneity effects by different levels of experiences. It is worth noting that multiple theoretical mechanisms may be at play, and I discuss alternative mechanisms in Section 6.

Next, I briefly describe the model-free learning framework in Barberis and Jin (2023) and provide testable predictions from the model. An investor in the model decides on action a with its associated Q value. After taking action a at time t, the model updates the Q value next period $Q_a(t+1)$ using equation 4, where α_t is the learning rate and RPE is the reward prediction error. The reward prediction is positive if the realized outcome is better than anticipated and negative vice versa. Intuitively, the value of an action will increase after a good experience, and the investor will be more likely to repeat the action in the future. In a generalized version of the model, it also updates the Q value of similar actions with the same reward prediction error.

$$Q_{t+1}(a) = Q_t(a) + \alpha_t(RPE) \tag{4}$$

Now let's consider the NFT setting, where investors participate in the primary market and get a randomly allocated NFT. For an investor who mints a rare NFT, the action of minting will have a higher Q value. The model-free learning predicts that this investor will be more likely to participate in future minting. In addition, the investor will also purchase more NFTs in the secondary market if they consider NFTs a good investment opportunity and regard NFT trading in the secondary market as similar actions to minting. I test the predictions of investor behaviors in the NFT market in Section 4.1.

For investing in the cryptocurrency market, the model suggests that the higher Q value of NFT after a good experience will also allow the investor to raise the value associated with similar cryptos. To determine the "similarity" between NFTs and cryptocurrencies, I consider two broad categories of cryptos. First, NFTs should be least similar to stablecoins because stablecoins are a type of cryptos whose values are pegged to fiat currency, for example, the U.S. dollar. Second, the return of NFT minting is highly skewed, and the average price increase from primary market minting to secondary market sale is tenfold. Investors who mint rare NFTs might regard cryptos with such lottery-like payoffs as similar to NFTs. The model predicts that the experience effect of minting a rare NFT will likely spill over to cryptos similar to NFTs but not to those very different. I examine the differential effects of spillover based on similarity in Section 4.2.

The model also suggests that there should be a diminishing sensitivity to past experiences when the investor gains long enough good experiences. The intuition is that the Q value keeps increasing as more good experiences are observed, and when it becomes very high, a bad experience will not affect subsequent decision-making much. I show evidence consistent with this prediction in Section 4.3.

In addition to the predictions above, the model-free learning framework also provides a micro foundation for extrapolative demand, which can be used to explain the pattern of asset bubbles (Barberis et al., 2018; Liao et al., 2022; DeFusco et al., 2022). The extrapolative bubble explanation posits that investors' demand for a financial asset positively depends on the past returns of the asset. The increased demand thus pushes up the asset prices even further, potentially leading to the formation of bubbles. The NFT market surged in the summer of 2021 and dramatically declined by the end of 2022. Existing research also documents classic features of an asset bubble in the NFT market (Barbon and Ranaldo, 2023; Huang and Goetzmann, 2023). Leveraging the quasi-experimental setting, I explore the role of personal experiences in seeding the NFT bubble in Section 5.

4 Experience Effects

4.1 Experience Effects on NFT Market Activities

I begin by looking at the experience effects on investor behaviors in the NFT market. As illustrated in Section 3.5, the model-free learning framework predicts that investors who randomly minted rare NFTs will participate more in the NFT market, including both minting in the primary market and purchasing in the secondary market. Table 2 Panel A shows the results of NFT primary market participation. In column 1, I validate the random distribution of NFTs within a collection by showing that conditional on future participation in minting, the probability of obtaining a rare NFT next month is uncorrelated with the outcome of minting rare this month. I then show a positive and significant relationship between past experiences and future minting activities. In column 2, the independent variable of interest is an indicator equal to 1 if the investor participates in NFT minting next month. I find that investors are more likely to participate in minting next month if they mint rare NFTs this month compared with those who do not mint any rare NFTs in the same collection. The increase in the likelihood of participation is 0.21 percentage points, corresponding to a 1% increase relative to the mean of the dependent variable. Next, I look at investor minting expenses next month, which include the amount paid to the NFT creator and the fees to proceed with transactions on the Ethereum blockchain. Column 3 suggests that the money investors spend on minting is 1.6% more for investors minting rare NFTs.

Similarly, I find strong and significant experience effects on NFT trading in the secondary market in Table 2 Panel B. Columns 1 and 2 are the log volume of NFT purchases and sales plus one excluding the NFT minted by the investor. The results show that following a positive experience of minting a rare NFT in the collection, the investor will purchase 2.3% more NFTs in the secondary market. I also find a statistically significant but smaller effect on NFT sales, with an increase of 1.3%. Although the model does not directly speak to investor selling behaviors, the result suggests certain flipping behaviors in the secondary market. In column 3, the outcome variable is an indicator variable that equals to 1 if the investor earns positive trading profit. It suggests that investors who mint rare NFTs do not make positive profits solely from peer-to-peer trading without the sale profit from minting. It suggests that NFT investors who randomly get rare NFTs do not seem to possess superior trading skills in the secondary market.

4.2 Experience Effects on Cryptocurrency Investment

I then examine whether the experience effects in the NFT market spill over to the fungible cryptocurrency market. With the transparency of blockchain data that record all transactions made by each wallet, I can directly test the personal experience effects across two asset markets. Identifying the effect of personal experiences in one market on another can be challenging because potential investor- and time-varying omitted variables can jointly determine the investment decisions. Using the quasi-experimental setting of NFT minting, I argue that the variation of NFT minting outcome is exogenous to other confounding factors after controlling the probability of winning. Thus, I can causally interpret the effect of NFT minting experiences on investing in cryptos.

I present the results in Table 3 using the outcomes of investor cryptocurrency trading. Column 1 examines whether there exists spillover to the overall cryptocurrency trading. I show that NFT investors who mint a rare NFT do not trade more cryptos than those who mint common NFTs. According to the model-free learning framework, the investor is more likely to choose an asset that is similar to the prior investment that resulted in a good experience. I broadly define two categories of cryptocurrencies to consider the similarity between NFTs and cryptos. First, I use the maximum daily return in the previous month as a proxy for a cryptocurrency's ex-ante lottery-like characteristic and classify a cryptocurrency as lottery-like if its maximum daily return is above 90 percentile (Bali et al., 2011). Since the average return from NFT minting is tenfold, investors might regard cryptos with such lottery-like payoffs as similar to NFTs. I examine this hypothesis in columns 2 and 3 of Table 3. I find that the NFT minting experience effect increases the purchase of lottery-like cryptos by 0.5%, and there is no significant effect on sales.

In addition to cryptos that are similar to NFTs, I also use stablecoins as the type of cryptos that are the most different. Stablecoins are designed to peg their prices with fiat currencies, thereby serving as a secure asset that remains insulated from the overall crypto market (Makarov and Schoar, 2022). I examine the trading of stablecoins in columns 4 and 5 and show that investors tend to sell more stablecoins after experiencing a rare NFT minting. These results are consistent with the model-free learning prediction that the investor is more likely to purchase cryptos that are similar to NFTs. Moreover, they seem to substitute assets that are different from NFTs by selling more. This result sheds light on how prior experience in one asset market changes the portfolio choice in another market. An investor might overweight their idiosyncratic personal experience of minting a rare NFT and assess the probability of tail events differently when they invest in cryptos. Experimental studies in psychology provide support for this hypothesis. For example, Cohen et al. (2020) show that decision-makers may not only consider the payoff distribution of the current event but also select the strategy that led to the most favorable outcome in a small set of similar past experiences. This is also related to extant evidence in finance that people overweight tail events when they make decisions based on experience (Barberis, 2013).

Taken together, these results suggest spillover from the NFT market to the cryptocurrency market for cryptos that are similar to NFTs. The existing literature documents the domain specificity of experience effects, that is, experiences in one asset market do not necessarily affect decision-making in other risky assets, even if they are correlated (Malmendier, 2021). For example, Malmendier and Nagel (2011) demonstrate that there is no significant cross-over effect of experiences in the stock market experiences and bond market experiences on investment decisions, and the evidence is based on exposure to macro-finance realizations. In contrast, I rely on personal experiences in the NFT market rather than macro-level heterogeneity and document the spillover effect to the cryptocurrency market. It invites more theoretical frameworks built on neuroscience foundations to guide the “domain” and “context” that impact individual decision-making (Bordalo et al., 2020; Wachter and Kahana, 2022).

4.3 Heterogeneous Effects

In this section, I estimate the experience effects across the number of NFTs minted by investors previously. The model predicts an attenuation effect as investors accumulate long enough good experiences. I compute how many times an investor ever minted rare NFTs prior to the current minting event and group the sample into investors who have zero experience, one to five experiences, and greater than five experiences. I plot the coefficient estimates and confidence intervals for the main outcome variables in Figure 3 and show the detailed estimates in Table A2.

Panel A of Figure 3 shows the heterogeneous effects of NFT primary market participation. I find that once investors start to have a few minting experiences, they appear to respond less to a successful experience of minting NFTs, and the likelihood of future minting participation diminishes as investors gain more good experiences. The same attenuation applies to total minting expenses. I then examine the NFT trading activities in the secondary market in Panel B. The model prediction directly relates to NFT purchases, and I show a clear negative relationship between prior minting experiences and investors’ responses to the next experience of minting a rare NFT. The prediction of NFT sales is more loosely connected to the model. I find that investors with more than five good minting experiences no longer respond to another good experience by selling more NFTs. Turning to cryptocurrency investing in Panel C, I show monotonically decreasing coefficients for future purchases of lottery-like cryptocurrencies as investors gain more good NFT minting experiences, consistent with the model prediction of reinforcing the investment decision on assets similar to NFTs. I also find that investors respond less to future experiences and sell fewer stablecoins, suggesting that the substitution effect of lottery-like cryptos and stablecoins also diminishes after investors accumulate a series of positive minting experiences.

4.4 Robustness Check

4.4.1 First-time Experience

One concern about the causality interpretation is that the treatment group of investors select to participate more in the NFT and cryptocurrency market, and the effects are biased by their prior experiences. To alleviate this self-selection concern, I replicate the main results using NFT investors' first-time minting experience and show the results in Appendix B.1. The results are robust and consistent with the baseline results.

4.4.2 Multiple Wallets

To handle the possible measurement errors resulting from cases in which an investor has more than one wallet, I use the wallet clustering algorithm in the computer science literature to test the robustness of the results. Specifically, I follow the deposit address reuse heuristic in Victor (2020) to identify wallets that possibly belong to the same entity. I find that only 1,073 out of the 1 million wallets do not belong to a unique investor. I describe the algorithm in detail and show robust results in Appendix B.2.

5 NFT Boom and Bust

The previous sections show the effect of personal experience on future investment behaviors in the NFT and cryptocurrency market. A natural question is whether such investor behaviors have further implications on market dynamics. The boom-bust cycle of the NFT market during the sample period provides a natural laboratory to further examine possible speculative behaviors during the NFT "bubble".

5.1 NFT Price Index and Bubble-like NFTs

To examine the NFT boom and bust, I first construct a price index at the daily level using the repeat sale regression methodology in Bailey et al. (1963).[5] Figure 4 shows the estimated price index constructed using all the NFTs in the sample. The NFT price increases extensively in September 2021 and falls substantially after July 2022. Therefore, the current sample period covers a full boom-bust cycle of the NFT market. Next, I apply the repeat sale regression to each NFT collection and construct individual NFT collection price indices to identify collections that exhibit bubble episodes.

I use the approach in Greenwood et al. (2019) and Barbon and Ranaldo (2023) to identify bubble-like NFTs. Specifically, I check if the price index of an NFT collection has increased by more than 100% in the past month and decreased by more than 40% during the subsequent month. If so, I define the NFT as a bubble-like NFT. The results are robust if I use different time windows to detect the bubble episodes. I identify 2,036 NFT collections that experienced such boom-bust cycles during the sample period. Figure 5 plots the total trading volume of bubble-like and non-bubble NFTs collections each month. The high trading volume of bubble-

[5] Borri et al. (2022) discuss the advantage of using repeat sale regression to construct price indices over other methods, such as hedonic regression.

like NFTs shares the same characteristics as other financial market bubbles.

5.2 Who Contributes to NFT Bubble Formation?

The exogenous experiences during NFT minting provide a unique opportunity to understand who seeds the NFT bubble at the origination. Using the sample of bubble-like NFTs, I test whether investors who mint more valuable NFTs play a more important role in NFT bubble formation. I employ equation 3 and compare the subsequent NFT purchase behaviors in the same NFT collection. The results are reported in Table 4. In the first three columns, I use the NFT collections that are ex-post bubble-like. Column 1 uses the log number of NFT purchases as the dependent variable and shows that investors who mint rare NFTs subsequently purchase more NFTs in the same bubble-like NFT collection. Next, I check whether these investors with good minting experiences are also more likely to become the net buyers of the NFT collection. The outcome variable in column 2 is an indicator variable that equals to one if the total purchase value minus the total sale value of NFTs in the collection is greater than zero. The result indeed supports the hypothesis. Lastly, I examine whether these investors inflate the bubble by purchasing NFTs at a higher price. I use the log median purchase price in column 3 and show consistent evidence.

Besides using NFT trading records to understand the investors' purchasing behaviors, I also test whether these investors exhibit extrapolative beliefs by using the bid data to infer their beliefs. The bids are not recorded on the Ethereum blockchain. I obtained the bid data from Reservoir API starting from February 2022, the earliest data is available. Ideally, bids on the same NFT item will allow a direct comparison of investors' valuations. Due to insufficient data on bids on the same NFT, I compare the bid prices for investors who bid on the same collection next month. Since rare NFTs are bid higher than non-rare NFTs, I add the fixed effect of rarity dummy to only compare the bid price among the same rarity dimension. The results in Table 5 show that the median bid price for investors with good experiences of minting is 25% higher for the bubble-like NFT collections. It provides additional evidence that investors extrapolate from past experiences and overvalue the asset during the bubble formation.

Taken together, the results suggest that the effects of personal experiences on investor behaviors might have an aggregate impact on the market dynamics. During the NFT bubble episode, investors with positive minting experiences tend to seed the bubble by purchasing more NFTs at higher prices. Existing theoretical literature suggests that extrapolators can be key drivers of historical bubbles (Shiller, 2014; Barberis et al., 2018). Using the Chinese warrant bubble episode, Pearson et al. (2021) empirically show that investors engaged in positive feedback trading in which their trading depends on past realized returns. Huang and Goetzmann (2023) present evidence that the lead-lag relationship of volume and price during the NFT bubble is consistent with extrapolative explanations. The NFT experimental setting provides further causal evidence of extrapolative bubbles in which the investors extrapolate from past good experiences and purchase on the price way up.

5.3 The Role of New Investors

In Section 4.3, I provide evidence that the experience effects attenuate as investors gain more NFT minting experiences. I further explore whether the inflow of new investors can explain the NFT boom and bust. Kindleberger and Aliber (2008) characterize the bubble formation with the entrance of new investors. Greenwood and Nagel (2009) study the role of inexperienced investors in forming the technology bubble. Using investor-level data, I first test whether new investors play a more important role in bubble formation. I use the same specification as in Table 4 and interact the mint rare dummy variable with an indicator of new wallets. The results show that new wallets are more sensitive to the experience effects and purchase more NFTs at higher prices. Next, I explore whether the NFT bubble collapsed due to a lack of new investors. I show suggestive evidence in Figure 6 by plotting the number of new wallets participating in minting during the sample period. The trend of new investor inflow aligns with the NFT price index pattern. It is noticeable that the number of new wallets dropped by more than 50% after July 2022, which is the same period as the NFT bubbles collapsed.

6 Alternative Explanations

I observe an increase in NFT minting and trading activities for NFT investors who mint rare NFTs, and such effects spill over to lottery-like crypto purchases. These results align well with the predictions of the model-free learning framework. This section explores several alternative mechanisms that can potentially explain my empirical findings.

6.1 Wealth Effect

I argue that the experience effect is not purely driven by the wealth gains from minting rare NFTs. There are two dimensions that wealth effects might be at play. First, if some investors are budget-constrained and profit from selling a rare NFT at a much higher price than what they pay for minting, the increase of liquidity could increase their trading in both NFT and cryptocurrency markets. Second, wealth gains from minting rare NFTs might increase investors' risk tolerance, and therefore, they will invest more actively in NFTs and lottery-like cryptos.

I test the two hypotheses by dividing the investors into different groups. First, I test whether the experience effects are stronger when investors obtain liquidity from selling their NFTs. I show in the first two columns of Table 7 that the effects are stronger when investors hold their newly minted NFTs, which is opposite to the liquidity constraint story. Furthermore, I test whether the experience effects exist for larger cryptocurrency wallets in columns 3 and 4 in Table 7. Since the relative wealth change after minting a rare NFT is larger for smaller wallets, we should expect that the effects are stronger for them if the experienced gains change their risk-taking preferences. However, the results appear much stronger for larger wallets and verify that wealth effects are not the primary cause of the observed experience effects.

6.2 House Money Effect

Another plausible explanation is the house money effect (Thaler and Johnson, 1990). Investors might put the gains from NFT minting in a mental account and use the gains to perform future trading activities. The mental accounting story implies that the effects would be larger for wallets that realize the gain from NFT minting due to the additional cash in the mental account (Anagol et al., 2021). As I already show in Table 7, the experience effects are actually stronger for the investors who hold their newly minted NFTs rather than sell them. It implies that the effects on subsequent investment activities are not from the new cash generated from prior NFT mints. Therefore, the house money effect is unlikely to be the key driver of the findings.

6.3 Learning about Ability from Noise

Next, I explore the learning-about-own-ability model illustrated in Anagol et al. (2021). The idea is that investors mistakenly attribute random successful events to their own ability measured by signal precision. This model can explain the increased trading of NFTs, assuming that agents believe NFT return signals they receive in the future are more precise after a successful NFT minting experience. However, if investors do learn about their own ability, they should also increase their overall trading of cryptocurrencies. The data do not support this hypothesis because no significant differences exist in the total crypto trading volume between investors who mint rare NFTs and those who do not.

The learning about ability explanation is also related to a leading explanation of household excessive trading, overconfidence (e.g., Gervais and Odean, 2001; Barber and Odean, 2001; Grinblatt and Keloharju, 2009). The literature documents that overconfident investors have a higher portfolio turnover ratio and worse investment performance. To test the overconfidence channel, I calculate log monthly investor returns in the crypto market by aggregating their daily log returns. I compute the daily simple return as the weighted average of crypto daily returns using the portfolio weight as of the day before. Following Barber and Odean (2001), I also calculate the monthly investor portfolio turnover as the average of monthly sales turnover and monthly purchase turnover:

$$Turnover_{i,t} = \frac{1}{2}\left(\sum_{j=1}^{N_{i,t-1}} p_{i,j,t-1} \min\left(1, \frac{S_{i,j,t}}{H_{i,j,t-1}}\right) + \sum_{j=1}^{N_{i,t}} p_{i,j,t} \min\left(1, \frac{B_{i,j,t}}{H_{i,j,t}}\right)\right) \quad (5)$$

$S_{i,j,t}$ and $B_{i,j,t}$ are the number of token j sold and purchased by investor i during month respectively, $p_{i,j,t-1}$ is the portfolio weight of token j at the end of month $t-1$.

I use the monthly crypto portfolio turnover and return as the outcome variable and run the baseline specification. The results are presented in Table A3. I do not find statistically significant effects on an increasing turnover and a decreasing investment return. This contradicts the overconfidence interpretation and suggests that the experience effects are not likely to be driven by overconfidence.

7 Conclusion

This paper exploits the quasi-experimental setting of NFT minting and provides new evidence of personal experience effects on investment decisions. I find that exogenous exposure to the success of minting a rare NFT item significantly increases investors' future involvement in the NFT market. This leads them to mint more NFTs, incur higher expenses in the primary market, and trade more NFTs in the secondary market. More importantly, such experience effects spill over to the cryptocurrency market and make investors purchase more lottery-like cryptos. The experience effects tend to attenuate as investors gain more NFT minting experiences. The NFT market also provides an opportunity to explore experience effects during a boom-bust cycle. I identify bubble-like NFTs and show that new wallets with exogenously determined good experiences in the NFT primary market contribute more to the NFT price booms.

The results indicate that when investors make investment decisions in one asset market, they may also rely on past experiences in another related asset market. This paper contributes to the literature on experience effects by providing a causal identification of the spillover effects from one market to another. While prior research suggests that experience effects are domain-specific, I leverage the unique blockchain setting that captures not only NFT-related transactions but also all the on-chain investment activities, including cryptocurrency trading at the individual level. I show that the experience effect is not necessarily confined to the same market but can extend to other markets with similar characteristics. These novel findings in the emerging digital asset markets invite further theoretical guidance on under what circumstances investors tend to draw inferences from past experiences in different markets to inform their decision-making.

I also show how investors' past random experiences can play a pivotal role in explaining the boom-bust episodes observed in the NFT market over the past two years. Positive experiences of randomly getting a rare NFT in the primary market can cause investors to overvalue NFTs in the secondary market, thereby contributing to the formation of speculative bubbles. It highlights the potential consequences of the gamified distribution of random assets in the emerging blockchain-based economy. Such gamification design may inadvertently cater to investors' behavioral biases, resulting in undesirable market dynamics. It highlights the importance of future regulation and oversight to mitigate these potential risks for the long-term stability of the NFT market and the broader blockchain-based economy.

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FIGURE 1. Minting Time and Rarity

This figure provides a binscatter plot of NFT minting time on rarity score percentile. y-axis is calculated as the number of hours between the individual NFT minting time and when the collection minting starts. NFT collection fixed effects are included.

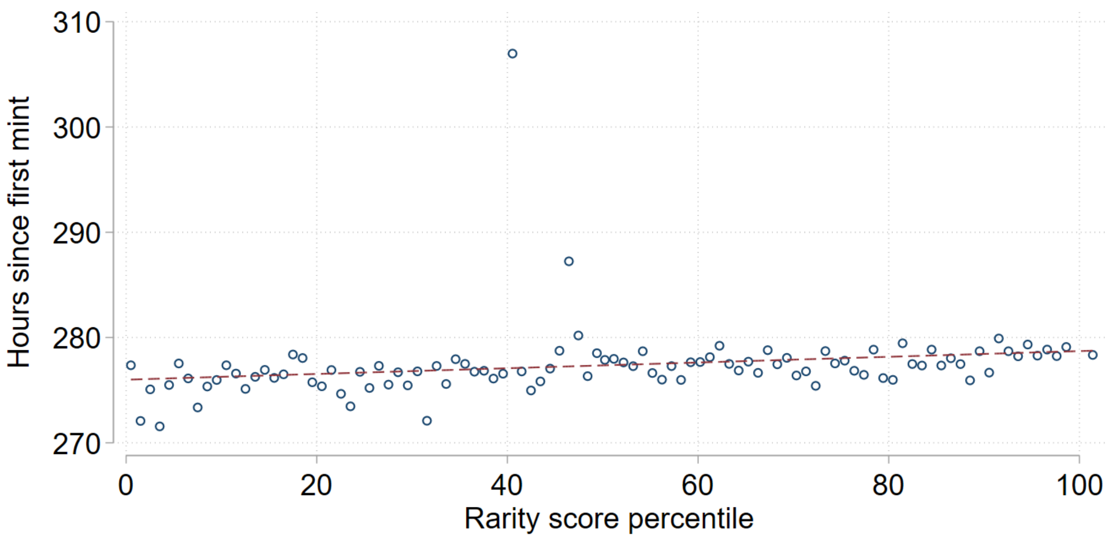
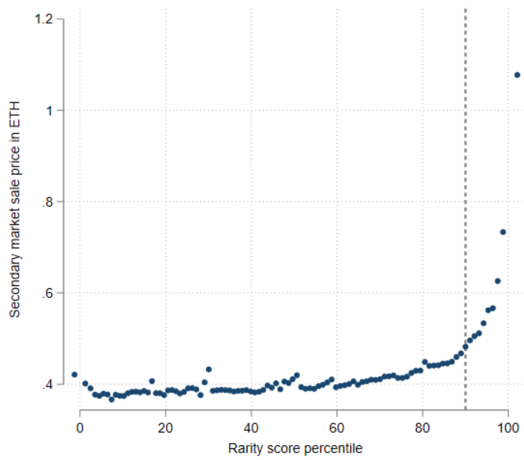


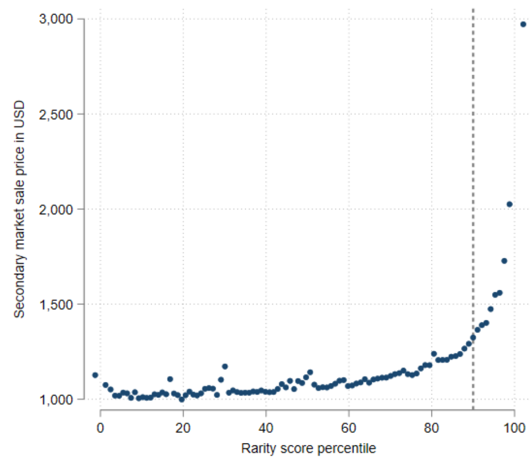
FIGURE 2. Secondary Market Sale Price and Rarity

This figure shows binscatter plots of NFT secondary market sale price on rarity score percentile. Panel A uses all historical transactions, and Panel B uses the first sale price after the initial mint. The prices are measured in both ETH and USD. I control for collection and date fixed effects.

Panel A: All sales

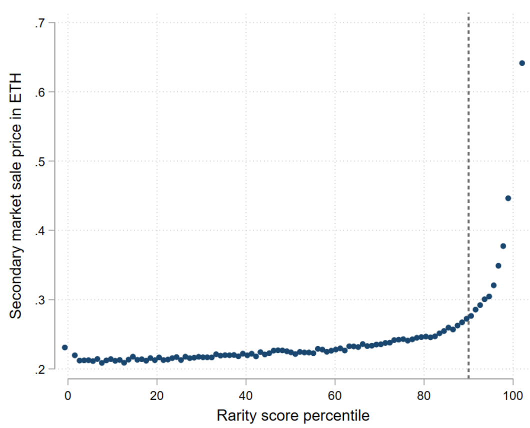


(a) Price in ETH

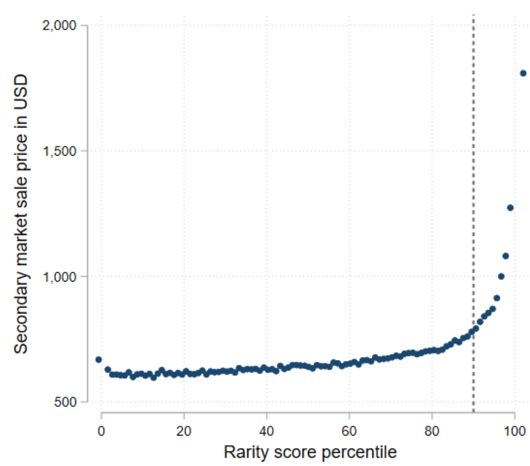


(b) Price in USD

Panel B: First Sale after Initial Mint



(c) Price in ETH

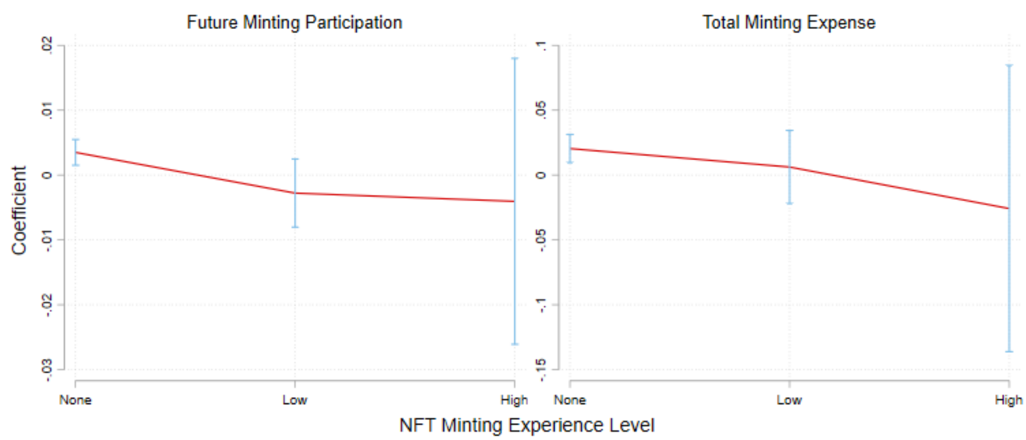


(d) Price in USD

FIGURE 3. Experience Effect by Level of Prior Experiences

This figure shows the coefficient estimates of experience effects by different levels of prior minting experiences.

Panel A: Primary Market Effects



Panel B: Secondary Market Effects

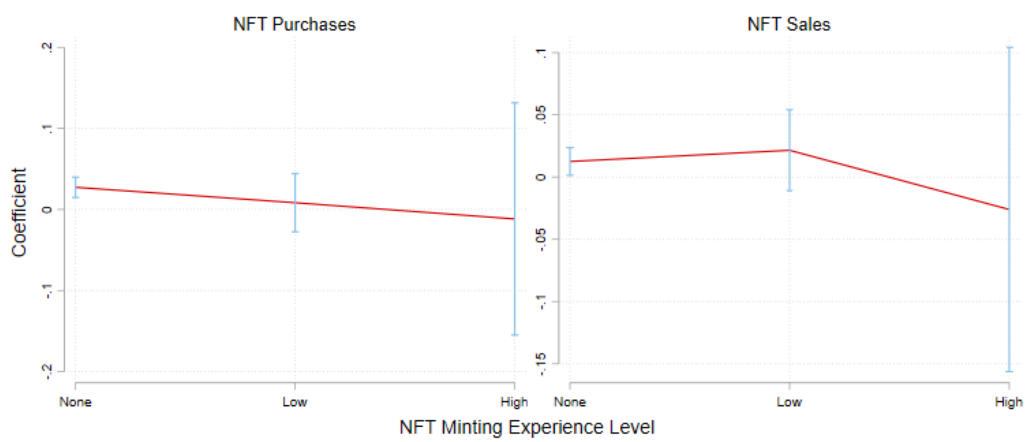


FIGURE 3 continued

Panel C: Cryptocurrency Market Effects

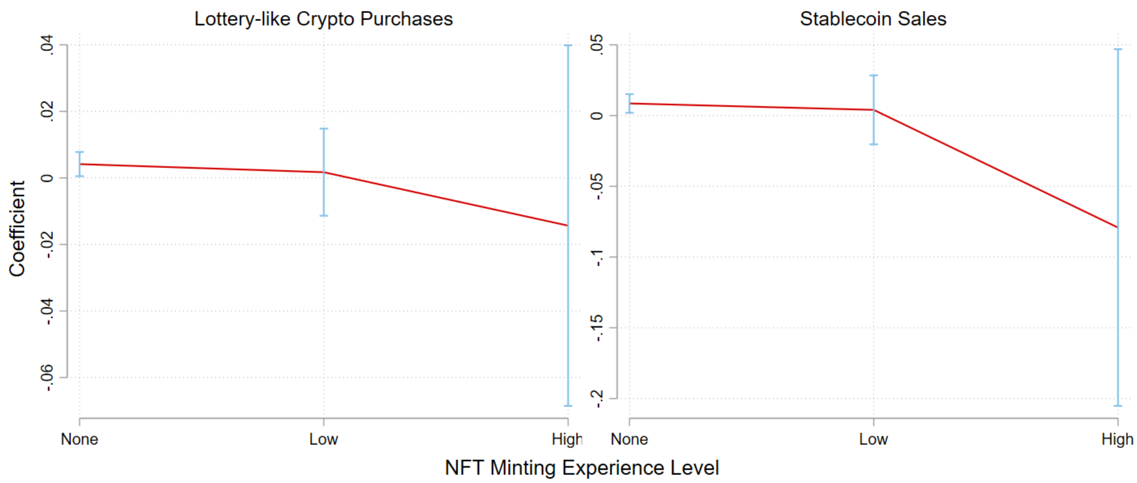


FIGURE 4. NFT Price Index

This figure provides the time series of the NFT price index using the repeat sale regression method during the sample period.

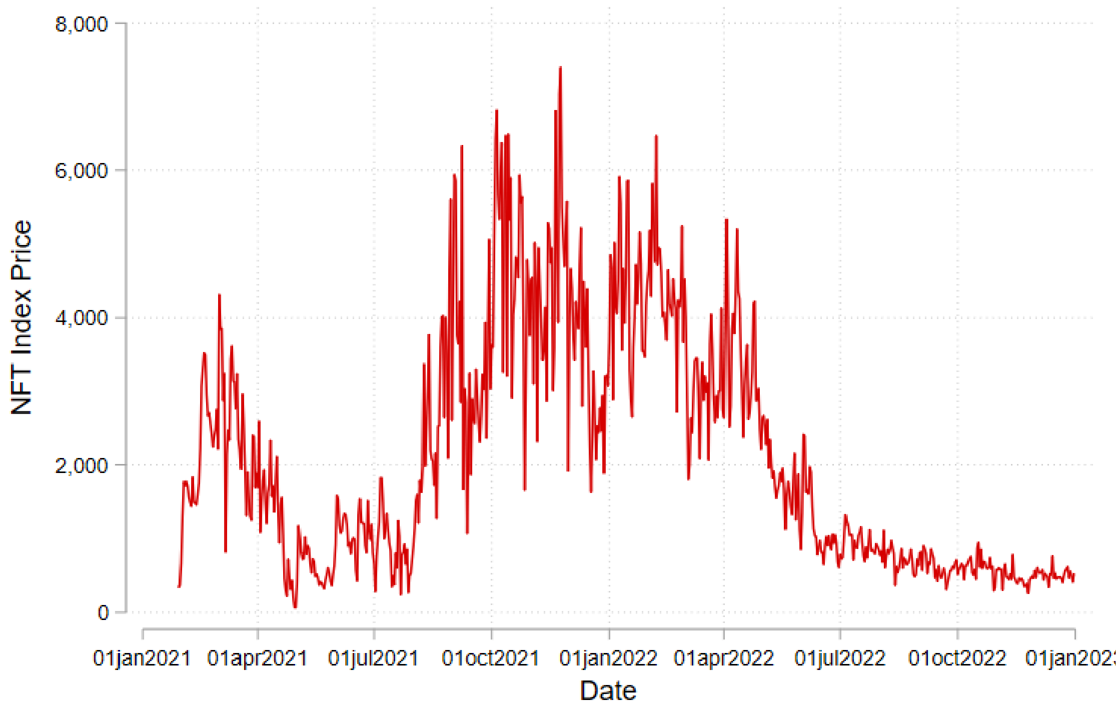


FIGURE 5. NFT Trading Volume

This figure compares the total trading volume of bubble-like and non-bubble NFT collections during the sample period. The y-axis is in million USD.

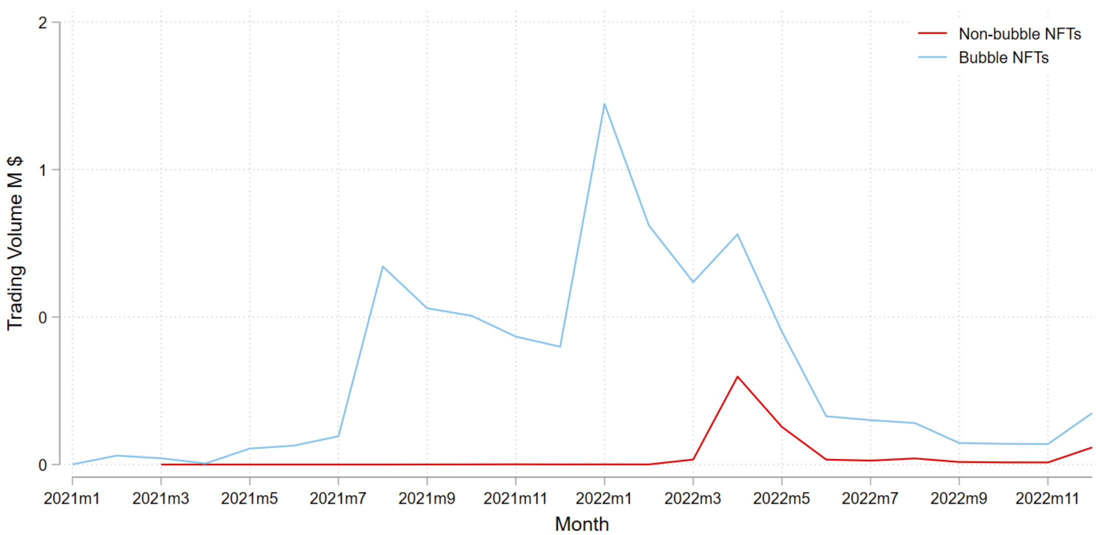


FIGURE 6. Inflow of New Investors

This figure plots the number of new wallets participating in NFT minting monthly over the sample period.

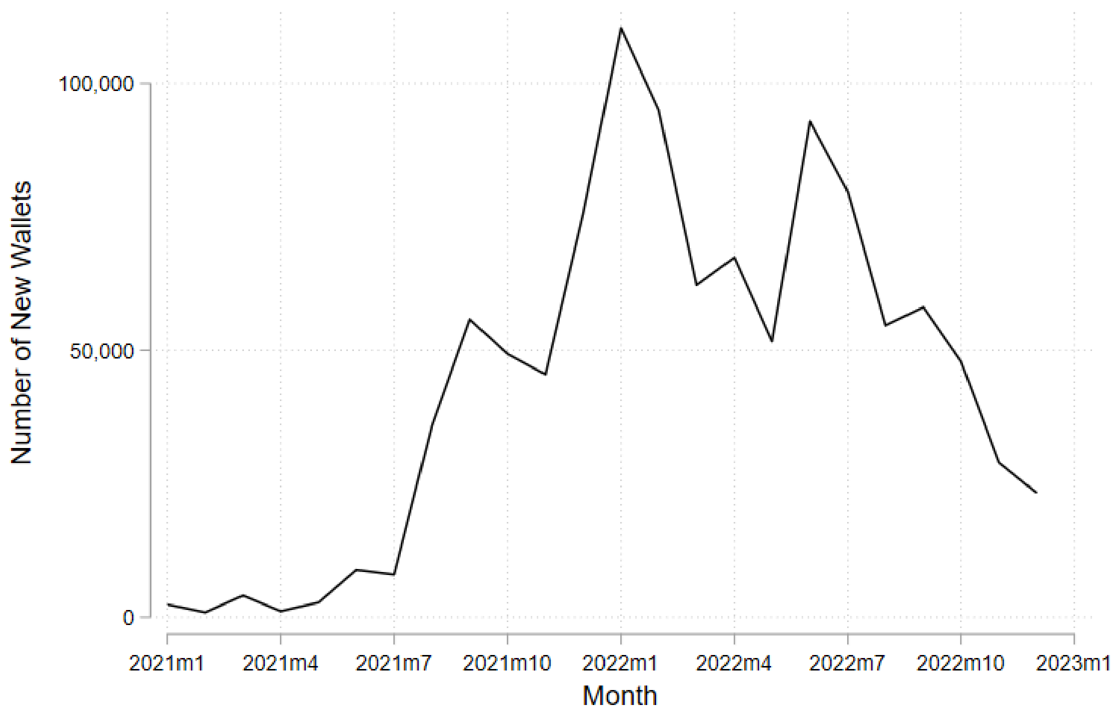


TABLE 1. Summary Statistics

This table presents summary statistics, including mean, standard deviation, and percentiles of NFT collections in the sample. Panel A shows NFT minting in the primary market, and Panel B shows trading in the secondary market.

	Mean	Median	Std. Dev.	1%	99%	Count
Primary Market Mint						
Number of Items Minted	2,802.095	1,271.500	3,170.646	100.000	10,001.000	4,846
Value Minted ETH	104.638	1.427	707.023	0.000	1,602.600	4,846
Value Minted USD (k)	300.502	2.571	2,124.860	0.000	4,663.527	4,846
Average Mint Price ETH	0.029	0.001	0.102	0.000	0.315	4,846
Average Mint Price USD	81.231	2.163	302.396	0.000	887.027	4,846
Average Gas Fee ETH	0.006	0.002	0.016	0.000	0.043	4,846
Average Gas Fee USD	17.298	2.852	57.125	0.067	151.133	4,846
Secondary Market Trade						
Number of Items Traded	1,711.578	125.500	4,188.247	1.000	20,666.000	4,138
Trading Volumn ETH	2,186.660	2.380	60,981.126	0.002	13,835.477	4,138
Trading Volumn USD (k)	5,894.497	4.823	166,049.027	0.003	42,613.945	4,138
Average Trade Price ETH	0.271	0.022	3.773	0.001	2.052	4,138
Average Trade Price USD	691.493	43.724	9,670.568	1.086	5,339.539	4,138
Average Gas Fee ETH	0.008	0.005	0.007	0.001	0.028	4,138
Average Gas Fee USD	21.774	8.485	25.478	1.363	99.906	4,138

Table 2. Experience Effect on Future NFT Investment

This table reports the impact of personal experience of minting a rare NFT on future NFT investment decisions. Panel A and B study the primary and secondary market behaviors, respectively. The sample period is from January 2021 to December 2022. The variable *Mint Rare* is an indicator variable that equals to one if an investor mints a rare NFT in a collection in a given month, and zero otherwise. *Future Participation* is an indicator variable that equals to one if an investor participates in NFT minting next month. *Total Minting Expense* is the logarithmic value of the total expenses the investor pays to the NFT creator and blockchain transaction fees for minting next month plus one. *NFT Purchases* and *NFT Sales* are the log of one plus the total value of NFTs that the investor purchase and sell in the secondary market next month, respectively. *Positive Trading Profit* is an indicator variable equal to one if the investor's net trading profit is positive next month. The secondary market trading outcome variables in Panel B do not include the NFT the investor minted this month. Standard errors are clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Panel A: NFT Primary Market Participation

	Future Minting Rare	Future Participation	Total Minting Expense
	(1)	(2)	(3)
Mint Rare	0.0009	0.0021**	0.0158***
	(0.0027)	(0.0009)	(0.0052)
Individual Level Controls	Yes	Yes	Yes
Experiment FE	Yes	Yes	Yes
Observations	291,097	1,375,426	1,375,426
Adjusted R-squared	0.0478	0.1488	0.1563

Panel B: NFT Secondary Market Trading

	NFT Purchases	NFT Sales	Positive Trading Profit
	(1)	(2)	(3)
Mint Rare	0.0229***	0.0130**	0.0006
	(0.0064)	(0.0056)	(0.0006)
Individual Level Controls	Yes	Yes	Yes
Experiment FE	Yes	Yes	Yes
Observations	1,375,426	1,375,426	1,375,426
Adjusted R-squared	0.1883	0.1841	0.0894

TABLE 3. Spillover to Cryptocurrency Trading

This table reports the impact of personal experience of minting a rare NFT on future trading activities in the cryptocurrency market. The sample period is from January 2021 to December 2022. The variable *Mint Rare* is an indicator variable that equals to one if an investor mints a rare NFT in a collection in a given month, and zero otherwise. *Trading Volume* is the logarithmic value of total crypto trading volume by the investor next month plus one. *Lottery-like Purchases* and *Lottery-like Sales* are the logarithmic values of the total purchase and sell volume of lottery-like cryptos next month plus one. *Stablecoin Purchases* and *Stablecoin Sales* are the logarithmic values of the total purchase and sell volume of stablecoins next month plus one. Standard errors are clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Trading Volume	Lottery-like Purchases	Lottery-like Sales	Stablecoin Purchases	Stablecoin Sales
	(1)	(2)	(3)	(4)	(5)
Mint Rare	0.0066	0.0047**	0.0032	0.0019	0.0066*
	(0.0065)	(0.0019)	(0.0020)	(0.0041)	(0.0036)
Individual Level Controls	Yes	Yes	Yes	Yes	Yes
Experiment FE	Yes	Yes	Yes	Yes	Yes
Observations	1,375,426	1,375,426	1,375,426	1,375,426	1,375,426
Adjusted R-squared	0.3019	0.0481	0.0528	0.1275	0.1136

TABLE 4. Experience Effect and Bubble Formation

This table reports the impact of personal experience on bubble formation. The number on the top of each cell shows the coefficients of *Mint Rare*, and the number in the bracket below shows the robust standard error. Standard errors are double-clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Bubble-like NFTs			Non-bubble NFTs		
	(1) NFT Purchases	(2) Net Capital Flows	(3) Median Price	(4) NFT Purchases	(5) Net Capital Flows	(6) Median Price
Mint Rare	0.0012***	0.0005***	0.0064***	0.0000	0.0000	-0.0000
	(0.0003)	(0.0002)	(0.0011)	(0.0001)	(0.0001)	(0.0002)
Individual Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Experiment FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,615,215	2,615,215	2,615,215	1,005,303	1,005,303	1,005,303
Adjusted R-squared	0.0858	0.0551	0.0634	0.0417	0.0568	0.0384

TABLE 5. NFT Bidding

This table reports the impact of personal experience on investor bids. The number on the top of each cell shows the coefficients of *Mint Rare*, and the number in the bracket below shows the robust standard error. Standard errors are double-clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Median Bid Price	
	(1) Bubble-like NFTs	(2) Non-bubble NFTs
Mint Rare	0.2502***	-0.0955
	(0.0579)	(0.1176)
Individual Level Controls	Yes	Yes
Experiment FE	Yes	Yes
Rarity FE	Yes	Yes
Observations	2,262	676
Adjusted R-squared	0.8168	0.7441

TABLE 6. New Wallets and Bubble Formation

This table reports the impact of new wallets on bubble formation. The number on the top of each cell shows the coefficients of *Mint Rare,* and the number in the bracket below shows the robust standard error. Standard errors are double-clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	NFT Purchases	Net Capital Flows	Median Price
	(1)	(2)	(3)
Mint Rare X New Wallet	0.0012**	0.0006**	0.0049**
	(0.0006)	(0.0003)	(0.0024)
Mint Rare	0.0007**	0.0002	0.0044***
	(0.0003)	(0.0002)	(0.0013)
New Wallet	-0.0085***	-0.0046***	-0.0391***
	(0.0006)	(0.0003)	(0.0030)
Individual Level Controls	Yes	Yes	Yes
Experiment FE	Yes	Yes	Yes
Observations	2,615,215	2,615,215	2,615,215
Adjusted R-squared	0.0859	0.0552	0.0635

TABLE 7. Experience Effect by Selling Decision and Wealth

This table reports the impact of personal experience based on different selling decisions after minting and cryptocurrency wallet wealth. Each row corresponds to a main outcome presented in previous tables. The number on the top of each cell shows the coefficients of *Mint Rare*, and the number in the bracket below shows the robust standard error. Standard errors are double-clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Action after Minting NFTs		Crypto Wallet Balance	
	(1) Sell	(2) Hold	(3) Below Median	(4) Above Median
Future Minting Participation	-0.0006	0.0020**	0.0014	0.0024*
	(0.0021)	(0.0010)	(0.0014)	(0.0012)
Minting Expense Including Fees	-0.0027	0.0165***	0.0107*	0.0179**
	(0.0119)	(0.0054)	(0.0063)	(0.0075)
NFT Purchases	0.0270*	0.0168***	0.0169***	0.0259***
	(0.0151)	(0.0065)	(0.0057)	(0.0096)
NFT Sales	0.0050	0.0066	0.0121**	0.0129
	(0.0141)	(0.0055)	(0.0052)	(0.0083)
Positive Trading Profit	0.0008	-0.0002	0.0001	0.0008
	(0.0017)	(0.0006)	(0.0007)	(0.0009)
Crypto Trading Volume	-0.0002	0.0077	0.0061	0.0014
	(0.0133)	(0.0074)	(0.0044)	(0.0098)
Lottery-like Crypto Purchases	-0.0022	0.0061***	-0.0006	0.0079**
	(0.0045)	(0.0021)	(0.0009)	(0.0031)
Lottery-like Crypto Sales	-0.0002	0.0034*	-0.0011	0.0057*
	(0.0048)	(0.0021)	(0.0009)	(0.0031)
Stablecoin Purchases	-0.0031	0.0036	0.0023	-0.0008
	(0.0088)	(0.0046)	(0.0022)	(0.0064)
Stablecoin Sales	0.0016	0.0082**	0.0016	0.0087
	(0.0085)	(0.0039)	(0.0020)	(0.0055)
Individual Level Controls	Yes	Yes	Yes	Yes
Experiment FE	Yes	Yes	Yes	Yes
Observations	297,350	1,071,830	557,498	808,454

Appendix

A Appendix Figures and Tables

FIGURE A1. NFT Collection Example: Shiboshis

This figure shows an example of an NFT collection, Shiboshis, and six items from the entire 10,000 in the collection. Each image represents the digital art associated with the individual NFT, which is uniquely identified by the Token ID. The screenshot is accessed from Etherscan.

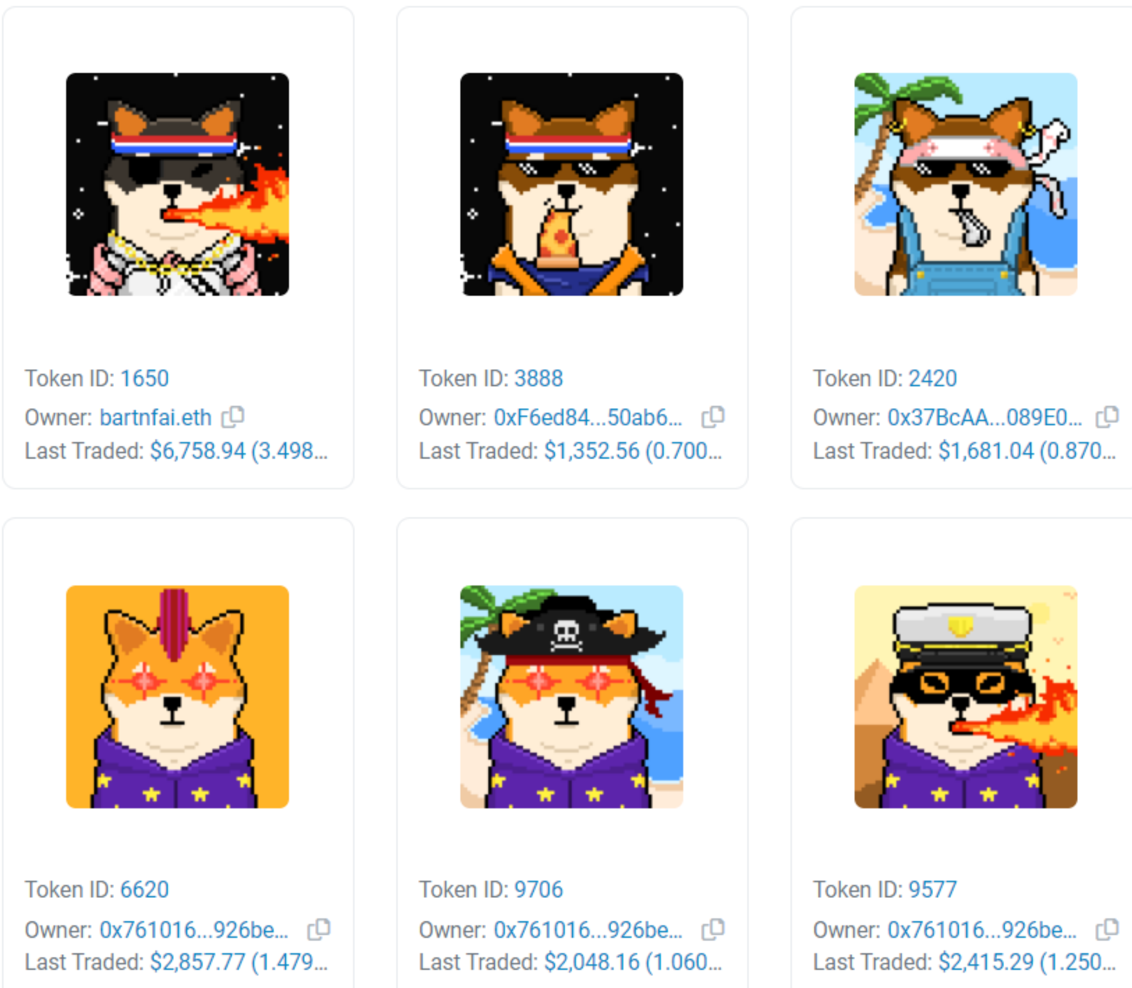
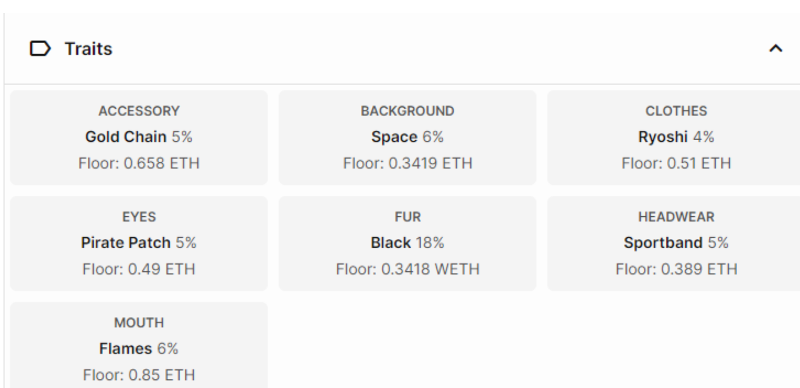


FIGURE A2. NFT Trait Example

This figure takes Token ID 1650 of the Shiboshis NFT collection from Figure A1 as an example and presents its traits. Figure (a) shows the raw trait data downloaded from the NFT metadata, and (b) shows how the trait data are displayed to NFT investors at the NFT trading platform OpenSea.

(a) Metadata for Token ID 1650



(b) Trait data displayed at Opensea

TABLE A1. Summary Statistics

This table presents summary statistics, including mean, standard deviation, and percentiles of investors in the sample.

	Mean	Median	Std. Dev.	1%	99%
Wallet Age	2.336	1.000	3.053	0.000	13.000
Crypto Wallet Balance (k $)	132.852	0.815	2,850.358	0.000	1,398.977
Number of NFTs Mints	26.821	5.000	74.348	1.000	302.000
Minting Expense ($)	1,163.010	164.444	5,752.769	1.171	17,067.107
Number of NFTs Purchases	2.429	0.000	13.626	0.000	37.000
Number of NFTs Sales	7.428	1.000	23.652	0.000	88.000
NFT Trading Profit (k $)	1.375	0.014	13.370	-12.457	34.646
Crypto Portfolio Turnover	0.058	0.000	0.186	0.000	1.000
Crypto Portfolio Return	0.001	0.000	0.737	-0.616	0.577

Table A2. Experience Effect by Level of Prior Experiences

This table reports the impact of personal experience based on subgroups of investors' prior minting experiences. Each row corresponds to a main outcome presented in previous tables. The number on the top of each cell shows the coefficients of *Mint Rare*, and the number in the bracket below shows the robust standard error. Standard errors are double-clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Past NFT Minting Experience Level		
	(1) None	(2) Low	(3) Medium
Future Minting Participation	0.0035***	-0.0028	-0.0041
	(0.0010)	(0.0027)	(0.0112)
Minting Expense Including Fees	0.0204***	0.0062	-0.0258
	(0.0055)	(0.0144)	(0.0562)
NFT Purchases	0.0274***	0.0084	-0.0117
	(0.0064)	(0.0183)	(0.0730)
NFT Sales	0.0125**	0.0215	-0.0261
	(0.0057)	(0.0166)	(0.0664)
Positive Trading Profit	0.0004	0.0014	0.0020
	(0.0006)	(0.0019)	(0.0088)
Crypto Trading Volume	0.0066	0.0078	-0.1042
	(0.0070)	(0.0193)	(0.0757)
Lottery-like Crypto Purchases	0.0041**	0.0017	-0.0143
	(0.0019)	(0.0067)	(0.0276)
Lottery-like Crypto Sales	0.0030*	0.0025	-0.0210
	(0.0018)	(0.0069)	(0.0297)
Stablecoin Purchases	-0.0008	0.0240*	-0.0462
	(0.0039)	(0.0137)	(0.0695)
Stablecoin Sales	0.0086**	0.0040	-0.0791
	(0.0034)	(0.0124)	(0.0642)
Individual Level Controls	Yes	Yes	Yes
groupfe	Yes	Yes	Yes
Observations	1,131,362	216,429	14,800

TABLE A3. Overconfidence

This table reports the impact of personal experience of minting a rare NFT on crypto portfolio turnover and monthly log return. Standard errors are clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Crypto Turnover Ratio	Crypto Protfolio Return
	(1)	(2)
Mint Rare	0.0003	-0.0006
	(0.0004)	(0.0004)
Individual Level Controls	Yes	Yes
Experiment FE	Yes	Yes
Observations	1,375,426	1,375,426
Adjusted R-squared	0.1924	0.1014

B Robustness Tests

B.1 First-time NFT Minting Experience

TABLE B1. Experience Effect on Future NFT Investment

This table reports the impact of personal experience of minting a rare NFT on future NFT investment decisions. Panel A and B study the primary and secondary market behaviors, respectively. The sample period is from January 2021 to December 2022. The variable *Mint Rare* is an indicator variable that equals to one if an investor mints a rare NFT in a collection in a given month, and zero otherwise. *Future Participation* is an indicator variable that equals to one if an investor participates in NFT minting next month. *Total Minting Expense* is the logarithmic value of the total expenses the investor pays to the NFT creator and blockchain transaction fees for minting next month plus one. *NFT Purchases* and *NFT Sales* are the log of one plus the total value of NFTs that the investor purchase and sell in the secondary market next month, respectively. *Positive Trading Profit* is an indicator variable equal to one if the investor's net trading profit is positive next month. The secondary market trading outcome variables in Panel B do not include the NFT the investor minted this month. Standard errors are clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Panel A: NFT Primary Market Participation

	Future Minting Rare	Future Participation	Total Minting Expense
	(1)	(2)	(3)
Mint Rare	0.0009	0.0033***	0.0193***
	(0.0027)	(0.0011)	(0.0062)
Individual Level Controls	Yes	Yes	Yes
Experiment FE	Yes	Yes	Yes
Observations	291,097	840,335	840,335
Adjusted R-squared	0.0478	0.1500	0.1399

Panel B: NFT Secondary Market Trading

	NFT Purchases	NFT Sales	Positive Trading Profit
	(1)	(2)	(3)
Mint Rare	0.0304***	0.0170***	0.0008
	(0.0075)	(0.0061)	(0.0006)
Individual Level Controls	Yes	Yes	Yes
Experiment FE	Yes	Yes	Yes
Observations	840,335	840,335	840,335
Adjusted R-squared	0.1542	0.1258	0.0626

Table B2. Spillover to Cryptocurrency Trading

This table reports the impact of personal experience of minting a rare NFT on future trading activities in the cryptocurrency market. The sample period is from January 2021 to December 2022. The variable *Mint Rare* is an indicator variable that equals to one if an investor mints a rare NFT in a collection in a given month, and zero otherwise. *Trading Volume* is the logarithmic value of total crypto trading volume by the investor next month plus one. *Lottery-like Purchases* and *Lottery-like Sales* are the logarithmic values of the total purchase and sell volume of lottery-like cryptos next month plus one. *Stablecoin Purchases* and *Stablecoin Sales* are the logarithmic values of the total purchase and sell volume of stablecoins next month plus one. Standard errors are clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Trading Volume	Lottery-like Purchases	Lottery-like Sales	Stablecoin Purchases	Stablecoin Sales
	(1)	(2)	(3)	(4)	(5)
Mint Rare	0.0125	0.0046**	0.0029	0.0033	0.0096***
	(0.0077)	(0.0021)	(0.0019)	(0.0043)	(0.0037)
Individual Level Controls	Yes	Yes	Yes	Yes	Yes
Experiment FE	Yes	Yes	Yes	Yes	Yes
Observations	840,335	840,335	840,335	840,335	840,335
Adjusted R-squared	0.2742	0.0531	0.0531	0.1332	0.1159

B.2 Multiple Wallets

The idea of the wallet clustering algorithm is that wallets belonging to the same investor on the Ethereum blockchain will be linked by the same deposit address from the centralized exchange. To transfer the cryptocurrencies from the blockchain and exchange them for money, the investor needs to have a centralized exchange account.[6] In order to allocate funds to the appropriate centralized exchange accounts, the centralized exchanges commonly generate deposit addresses for each customer. These deposit addresses are responsible for redirecting incoming funds from investors' on-chain wallets to the main addresses of centralized exchanges. Each deposit address is unique to individual investors, which quickly forward to the centralized exchange wallet. These on-chain wallets are probably under the control of the same investor.

I follow Victor (2020) to identify the deposit addresses first. To do this, I filter all the historical transfers of Ethereum from one wallet to another as of December 31, 2022. I identify forwarding transactions of deposit wallets by restricting two parameters. First, the maximum difference between the amount of receiving and sending. A deposit address should forward the exact amount of funds received from the on-chain wallet minus a small amount of transaction fee. In addition, I require that the time between receiving and sending the funds falls within a threshold. I use the same parameter value as in Victor (2020), where the amount difference is set to 0.01 Ether and the maximum time is set to 3,200 blocks. I also exclude addresses involved in mining activities to avoid misidentifying transfer events in mining pools.

[6] In contrast, decentralized exchanges only facilitate transactions on the blockchain.

TABLE B3. Experience Effect on Future NFT Investment

This table reports the impact of personal experience of minting a rare NFT on future NFT investment decisions. Panel A and B study the primary and secondary market behaviors, respectively. The sample period is from January 2021 to December 2022. The variable *Mint Rare* is an indicator variable that equals to one if an investor mints a rare NFT in a collection in a given month, and zero otherwise. *Future Participation* is an indicator variable that equals to one if an investor participates in NFT minting next month. *Total Minting Expense* is the logarithmic value of the total expenses the investor pays to the NFT creator and blockchain transaction fees for minting next month plus one. *NFT Purchases* and *NFT Sales* are the log of one plus the total value of NFTs that the investor purchase and sell in the secondary market next month, respectively. *Positive Trading Profit* is an indicator variable equal to one if the investor's net trading profit is positive next month. The secondary market trading outcome variables in Panel B do not include the NFT the investor minted this month. Standard errors are clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Panel A: NFT Primary Market Participation

	Future Minting Rare	Future Participation	Total Minting Expense
	(1)	(2)	(3)
Mint Rare	0.0009	0.0021**	0.0158***
	(0.0027)	(0.0009)	(0.0052)
Individual Level Controls	Yes	Yes	Yes
Experiment FE	Yes	Yes	Yes
Observations	290,843	1,374,457	1,374,457
Adjusted R-squared	0.0479	0.1488	0.1563

Panel B: NFT Secondary Market Trading

	NFT Purchases	NFT Sales	Positive Trading Profit
	(1)	(2)	(3)
Mint Rare	0.0231***	0.0132**	0.0005
	(0.0064)	(0.0056)	(0.0006)
Individual Level Controls	Yes	Yes	Yes
Experiment FE	Yes	Yes	Yes
Observations	1,374,457	1,374,457	1,374,457
Adjusted R-squared	0.1883	0.1841	0.0894

TABLE B4. Spillover to Cryptocurrency Trading

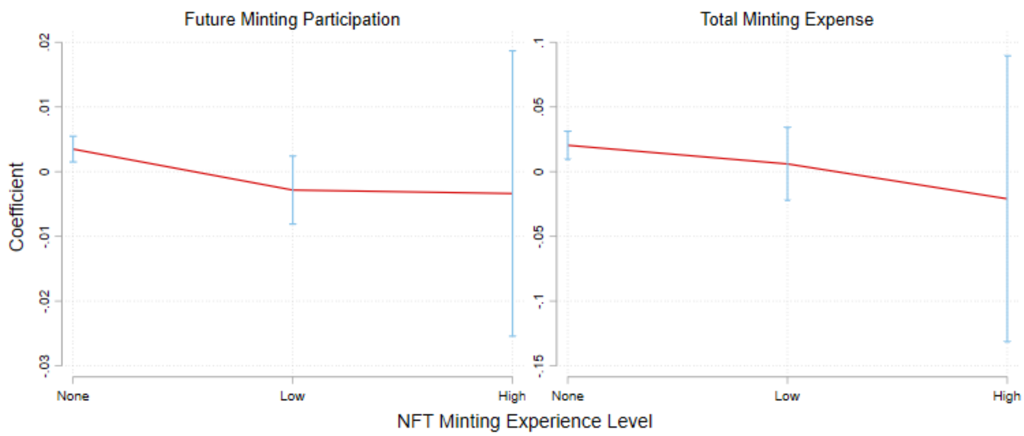
This table reports the impact of personal experience of minting a rare NFT on future trading activities in the cryptocurrency market. The sample period is from January 2021 to December 2022. The variable *Mint Rare* is an indicator variable that equals to one if an investor mints a rare NFT in a collection in a given month, and zero otherwise. *Trading Volume* is the logarithmic value of total crypto trading volume by the investor next month plus one. *Lottery-like Purchases* and *Lottery-like Sales* are the logarithmic values of the total purchase and sell volume of lottery-like cryptos next month plus one. *Stablecoin Purchases* and *Stablecoin Sales* are the logarithmic values of the total purchase and sell volume of stablecoins next month plus one. Standard errors are clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Trading Volume	Lottery-like Purchases	Lottery-like Sales	Stablecoin Purchases	Stablecoin Sales
	(1)	(2)	(3)	(4)	(5)
Mint Rare	0.0066	0.0048**	0.0032	0.0020	0.0066*
	(0.0065)	(0.0019)	(0.0020)	(0.0041)	(0.0036)
Individual Level Controls	Yes	Yes	Yes	Yes	Yes
Experiment FE	Yes	Yes	Yes	Yes	Yes
Observations	1,374,457	1,374,457	1,374,457	1,374,457	1,374,457
Adjusted R-squared	0.3016	0.0483	0.0529	0.1274	0.1136

FIGURE B1. Experience Effect by Level of Prior Experiences

This figure shows the coefficient estimates of experience effects by different levels of prior minting experiences.

Panel A: Primary Market Effects



Panel B: Secondary Market Effects

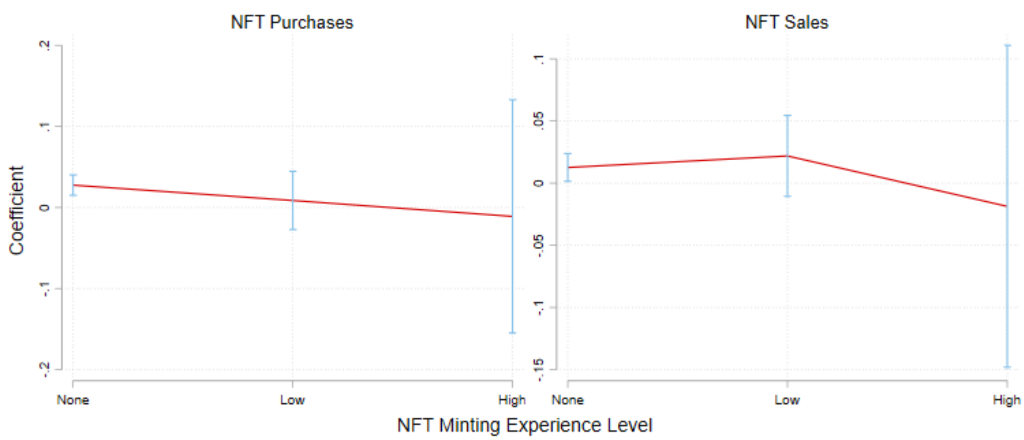


FIGURE B1 continued

Panel C: Cryptocurrency Market Effects

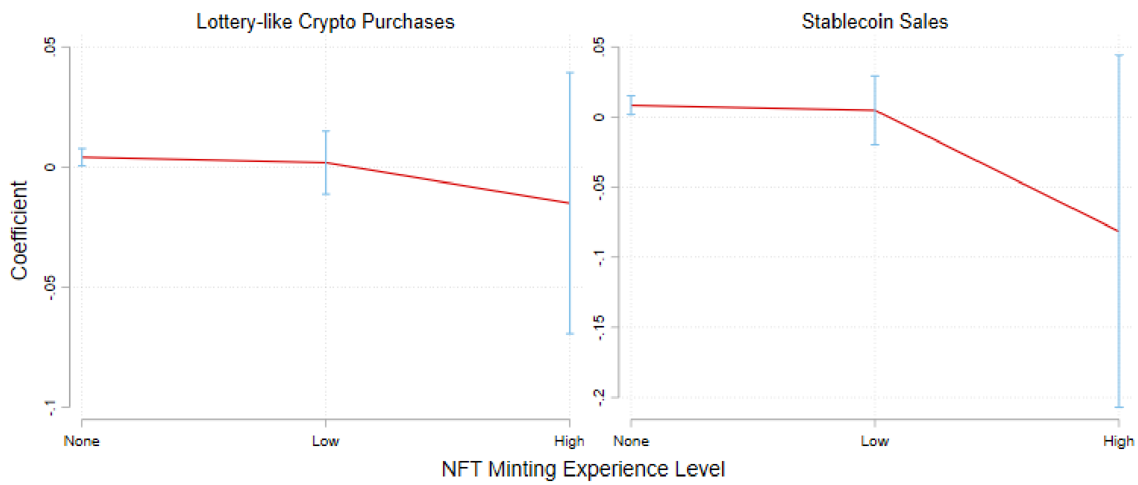


TABLE B5. Experience Effect by Level of Prior Experiences

This table reports the impact of personal experience based on subgroups of investors' prior minting experiences. Each row corresponds to a main outcome presented in previous tables. The number on the top of each cell shows the coefficients of *Mint Rare,* and the number in the bracket below shows the robust standard error. Standard errors are double-clustered by collection and year-month and are reported in parentheses. Asterisks denote significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Past NFT Minting Experience Level		
	(1) None	(2) Low	(3) High
Future Minting Participation	0.0035***	-0.0028	-0.0034
	(0.0010)	(0.0027)	(0.0112)
Minting Expense Including Fees	0.0204***	0.0060	-0.0210
	(0.0055)	(0.0144)	(0.0563)
NFT Purchases	0.0276***	0.0086	-0.0110
	(0.0064)	(0.0183)	(0.0733)
NFT Sales	0.0126**	0.0219	-0.0187
	(0.0057)	(0.0166)	(0.0660)
Positive Trading Profit	0.0004	0.0013	0.0018
	(0.0006)	(0.0019)	(0.0088)
Crypto Trading Volume	0.0066	0.0084	-0.1030
	(0.0070)	(0.0193)	(0.0754)
Lottery-like Crypto Purchases	0.0041**	0.0019	-0.0150
	(0.0019)	(0.0067)	(0.0277)
Lottery-like Crypto Sales	0.0029	0.0027	-0.0186
	(0.0018)	(0.0069)	(0.0295)
Stablecoin Purchases	-0.0008	0.0246*	-0.0448
	(0.0039)	(0.0138)	(0.0694)
Stablecoin Sales	0.0085**	0.0049	-0.0816
	(0.0034)	(0.0125)	(0.0640)
Individual Level Controls	Yes	Yes	Yes
groupfe	Yes	Yes	Yes
Observations	1,130,663	216,191	14,770