Investor Experience Matters: Evidence from Generative Art Collections on the Blockchain*

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Abstract

In the market for non-fungible tokens (NFTs) on the blockchain, experienced investors systematically outperform inexperienced investors. Controlling for holding period, experienced investors make 8.6 percentage points more per trade on average. This outperformance is mostly explained by experienced investors' greater participation in primary market sales of NFT collections, which produced significantly higher average returns during our sample period. Our results shed light on the frictions present in NFT markets, and have implications for the design of NFT investment strategies.

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1 Introduction

Non-fungible tokens (NFTs) are "digital collectibles": unique, indivisible, durable digital assets on blockchains, often used to represent works of visual art. The NFT market has experienced explosive growth, increasing from \$94.9 million in trading volume in 2020 to \$24.9 billion in 2021,[1] and a number of traditional non-crypto firms have started initiatives to sell NFTs.[2] Many well-known NFT collections have generated outsized returns for investors. For example, Bored Ape Yacht Club NFTs sold for 0.08 ETH in primary markets in April 2021 (roughly \$160 USD at the time) and the cheapest Bored Ape NFT is currently listed in February 2022 for sale at 93 ETH (roughly \$255,000 USD). As a result, many investors have flooded into NFT markets in the hopes of achieving similar returns.

NFTs are indivisible, and most are one-of-a-kind, meaning that it is difficult to execute indexing strategies in the NFT market. NFT investors must pick specific assets to purchase, and these choices affect how investors perform relative to the market as a whole. A natural question in these kinds of markets is whether certain classes of investors achieve systematically higher returns than others. This paper asks whether more experienced investors are able to attain higher returns in NFT markets. How large is experienced investor outperformance in NFT markets, and what are the mechanisms that drive their outperformance? We address these questions using a comprehensive dataset of NFT transactions on the Ethereum blockchain. Ethereum is and has been the dominant blockchain for NFTs given its advantages in decentralized applications and non-native tokens (John, O'Hara and Saleh, 2022; Irresberger et al., 2021).

We find that experienced investors attain roughly 8.6 percentage points higher returns on each trade compared to inexperienced investors. Experienced investors' outperformance is fully explained by their higher propensity to purchase NFTs in primary markets (the "mint" stage), where expected returns are systematically higher. Our results have implications for understanding the frictions present in NFT markets, and may also be useful for institutions and individuals designing NFT investment strategies.

We begin by compiling a comprehensive list of NFT collections featured on OpenSea, the most popular NFT marketplace. From this list, we restrict attention to 692 "generative" collections (henceforth "GCs") that comprise 2.9 million individual NFTs. We define GCs as NFT collections which consist of unique images based around a common theme, for which NFTs are created through a public primary market sale. NFTs from GCs appear to provide value to their owners as verifiable and tradable status goods: they are commonly used as

[1] See Reuters.

[2] Some examples are the NBA, the Australian Open, the British Museum, and Adidas.

profile pictures on social media, and many provide access to exclusive events and communities, both online and in the real world. Our sample of GCs represents a significant share of the broader NFT market, and they include many of the most successful and well-known NFT collections, such as the Bored Ape Yacht Club.

A key benefit of studying digital blockchain-based assets is the availability of comprehensive transaction-level data. We manually compile a dataset of all on-chain transactions for our sample of GCs between April 10, 2019, and March 31, 2022. The dataset has over 6 million transactions, of which 48% are primary market sales (commonly referred to as "mints"), and the remainder are secondary market transactions. The data include the wallet addresses for both the seller and buyer in each transaction that allows us to perform our investor-based analysis. We also collect data on various fees incurred in trading NFTs: gas fees paid to Ethereum miners for processing transactions, transaction fees collected by Opensea, and royalty fees paid to NFT issuers for each secondary market trade.

Using transaction-level data, we define experienced investors at any given point in time as wallets with high activity in both primary and secondary markets up to that point in time. Note that our definition of experience is fully backward-looking: the set of experienced investors at time t is defined only based on trading activity prior to time t. Trading in the NFT market is quite concentrated: as of the end of our sample, we identify 3% of investors as experienced, but these investors are responsible for 26% of total trade volume in primary and secondary markets combined.

Our headline result is that experienced investors achieve higher returns than inexperienced investors. We measure returns in units of ETH, the native asset of the Ethereum blockchain, since this is the main unit of account in the NFT ecosystem over our time horizon. In aggregate for all realized trades, experienced investors earned 71.3% returns for each unit of ETH invested, compared to 63.1% for inexperienced investors. Controlling for the dates at which investors buy and sell NFTs produces a similar estimate of experienced investors' outperformance, at 8.6 percentage points per trade. We show that the main driver of outperformance is that experienced investors do a larger share of their trades as "mints," buying from the primary market for NFTs. In our dataset, controlling for buy and sell dates, mints have over 100 percentage points higher returns on average than secondary market NFT purchases. Experienced investors' higher propensity to mint explains the entirety of their outperformance: after controlling for whether a trade is a mint, experienced investors actually underperform by -2.2 percentage points.

We proceed to analyze experienced investors' performance separately for primary and secondary market transactions. Experienced investors actually underperform inexperienced investors by 6.2 percentage points per trade in primary markets. Experienced investors also appear to pick successful collections to mint: NFT collections purchased by experienced investors are more likely to sell out in primary markets, sell out faster, and experience subsequent higher price growth in secondary markets. However, experienced investors pay significantly higher transaction fees on average. These higher fees are driven by a strategy of entering primary market sales relatively later, when the majority of NFTs in the given collection have already been sold. These collections are more likely to sell out, but buying late into a mint leads to higher transaction ("gas") fees on the Ethereum blockchain, lowering experienced investors' returns. Experienced investors do not appear to pay lower prices when minting, and sell NFTs from any given collection at slightly lower prices. Thus, experienced investors' strategy of targeting NFTs close to minting out appears to allow them to pick successful collections, but they suffer from poor trade execution, both in terms of gas fees and sale prices.

In secondary markets, experienced investors do 4.4 percentage points better than inexperienced investors per trade. This outperformance is largely driven by superior trade execution, rather than superior collection-picking ability. Experienced investors outperform even when comparing items within the same GC, purchased and sold on the same dates. The driver of this outperformance is simply that experienced investors sell at higher prices compared to inexperienced investors even after controlling for holding period and within the same NFT collection. This effect explains the entirety of experienced investors' outperformance: we find no evidence that experienced investors have collection-picking or market-timing ability in secondary markets. Experienced investors also pay slightly higher gas fees, but this does not substantially offset their higher sale prices.

The fact that there is a large experienced investor premium in NFT markets has implications for individuals and institutions considering investing in NFTs as an asset class. Investors in some canonical asset classes, such as equities and bonds, can relatively easily purchase market-cap-weighted portfolios which closely track market indices. Yet in many large asset classes, such as real estate, private equity and venture capital, indexing strategies are essentially impossible due to the uniqueness and illiquidity of the underlying assets. Investors cannot purchase proportional shares of every house or private company in existence; they must instead take stances on particular assets to purchase. In such markets, the quality of an investor's exposure to an asset class can substantially affect her total returns. Our results suggest that would-be investors in NFTs should not expect to be able to perfectly track the performance of the asset class as a whole: as inexperienced investors, they are likely to underperform relative to experienced investors by a sizable amount.

Our results also shed light on the extent to which the NFT market is a level playing field, informationally and in terms of market access. Our results push against a prevailing narrative that experienced investors' returns are driven by preferential access in primary markets. Experienced investors actually mint from collections later than inexperienced investors on average, pay higher gas fees, and do not pay lower mint prices; these facts would be unexpected if experienced investors had preferred access allowing them to mint valuable collections early and at low prices. We also do not find substantial evidence that experienced investors have strong informational advantages: experienced investors underperform slightly on mints, and display no collection-picking or market-timing abilities in their secondary market trades.

We also highlight a large difference between average returns in primary and secondary market NFT trades, which to our knowledge is novel to the literature. One interpretation of this result is that the mechanisms for price-setting in NFT primary markets are inefficient. Mint prices are usually fixed, rather than set based on an auction, and collections may be systematically setting too low mint prices.[3] Another interpretation is that investors require a premium for investing in risky NFT collections. The return gap for mints persists even when accounting for transaction costs, suggesting that congestion at the level of the Ethereum blockchain does not fully dissipate the rents. An interesting direction for future work would be to characterize the drivers of the mint premium in NFT markets.

First and foremost, our paper contributes to the emerging literature on NFTs. Kräussl and Tugnetti (2022) provide a review of the development of NFT market and evaluate the financial and econometric models that have been used in the literature for the pricing of NFTs.[4] Using a comprehensive dataset of NFT transactions, Borri, Liu and Tsyvinski (2022) create indices for the NFT market and its components, and analyze their properties. Kong and Lin (2022) study returns within the earliest and largest NFT collection, CryptoPunks. Nadini et al. (2021) analyze statistical properties of the network of NFT transactions using data between June 2017 through April 2021. White, Wilkoff and Yildiz (2022) examine properties of NFT news and subsequent returns. Relative to these papers, our key contribution is to document evidence for excess returns to experienced investors. Our results also shed light on various frictions that affect returns in NFT investing.

More broadly, this paper is also related to a body of work studying the properties of art as a financial asset. Renneboog and Spaenjers (2013) measure returns on a large dataset of art transactions. Korteweg, Kräussl and Verwijmeren (2016) shows that accounting for selection

[3]See Kominers, Roughgarden and Chokshi (2022) for a discussion of auction design in NFT markets.

[4]Kaczynski and Kominers (2021) and Wang et al. (2021) also provide helpful overviews of NFTs and the development of their markets.

into sale is important for quantifying the returns on art investments. Lovo and Spaenjers (2018) construct a model of trading in art markets. Penasse and Renneboog (2021) show evidence of speculative bubbles in the art market, and Pénasse, Renneboog and Scheinkman (2021) shows evidence that an artist's death is associated with permanent increases in price and volumes of the art.

We also contribute to a literature which analyzes return differences between experienced and inexperienced investors in asset classes characterized by high degrees of asset heterogeneity and asymmetric information. A number of papers have analyzed persistent differences in returns across VC and PE funds. Sørensen (2007) shows that companies funded by more experienced VCs are more likely to go public. Relatedly, Nahata (2008) shows that firms backed by more reputable VCs are more likely to successfully exit. Kaplan and Schoar (2005) show that there are large and persistent differences in the performance of different partnerships in private equity. In the online fundraising space, Dmitri and Risteski (2021) study the investment behavior of serial and large investors in initial coin offerings, while Kim and Visawanathan (2019) study the role of experienced early investors on a crowdfunding platform.

There is also a literature on differences in performance of different investors in housing markets. Kurlat and Stroebel (2015) show that, when the composition of home sellers in a neighborhood shifts towards more informed agents, neighborhood prices tend to decline, suggesting that a subset of market participants have superior information about common values of the asset. Chinco and Mayer (2016) show that out-of-town home buyers behave like misinformed speculators, driving up prices, but achieving lower than average returns. Bayer et al. (2020) show that experienced house flippers substantially outperformed speculators who entered the housing market during the housing boom. DeFusco, Nathanson and Zwick (2021) show that, over the 2006 housing boom and bust, cities which experienced a larger increase in the share of short-term buyers had larger price booms and busts. Cvijanović and Spaenjers (2021) show that out-of-country buyers in the housing market of Paris buy at higher prices and sell at lower prices than local investors.

The remainder of our paper proceeds as follows. We describe the institutional background for NFTs and our data sources in Section 2. We describe our data in Section 3 including several stylized facts and how we measure our key variables of interest. Section 4 contains our empirical results. We conclude in Section 5.

2 Institutional Background and Data

2.1 Institutional Background

Non-fungible tokens (NFTs) are digital assets that exist on a blockchain. Like other blockchain-based digital assets, an NFT is necessarily associated with a blockchain-based digital wallet (henceforth "wallet") at any given point in time. Each wallet has a public address, as well as a private key that only the wallet owner is supposed to know. For any given wallet, any person who knows its public address can view its contents. However, the wallet's private key is needed in order to spend cryptocurrencies, and buy, sell, or transfer NFTs.

As their name implies, NFTs differ from cryptocurrencies, such as Bitcoin and Ethereum, in that each NFT is indivisible and distinct from other NFTs. The distinct nature of any given NFT can most clearly be seen in its unique identifier on the blockchain, but this is not the only aspect that makes it unique. NFTs generally represent pieces of digital artwork by embedding metadata about the associated file.[5] NFTs are most often meant to uniquely represent their associated digital artwork.[6] In this sense, owning an NFT is like having the unique digital certificate of authenticity for the associated artwork.[7]

On their surface, NFTs have a lot in common with both collectibles and art. They are identifiable and scarce goods whose only tangible benefits can be tied to the ownership claim itself. As such, one key way that NFTs appear to provide value to their owners is as verifiable and tradable status goods. For example, NFTs are often used as profile pictures on social media. In fact, Twitter introduced an NFT profile picture integration feature in January 2022 that allows users to demonstrate the blockchain ownership of their profile picture NFTs. This feature works by presenting verified NFT profile pictures with a hexagonal border in contrast to the circular shape of non-NFT profile pictures. Further, one can click on an NFT profile picture to obtain a description of the NFT collection and related links. The Twitter profile picture integration thus allows NFT owners to verifiably signal ownership of high-value NFTs.

[5]In theory, NFTs can represent any digital good but digital artwork is by far the most common in practice.

[6]In some cases, an artist will create multiple NFTs for the same piece of digital artwork. Each of these NFTs will have a unique address on the blockchain although they clearly do not uniquely represent the associated artwork in this case. This situation would be like if an artist painted multiple copies of the same object that visually appeared identical. In our analysis, we focus on NFTs that are intended to be unique in representing their associated artwork.

[7]There is an ongoing debate in the legal world about whether and how NFTs can be seen as a legitimate ownership claim on the associated artwork. Our empirical analysis and conclusions do not require taking a stand in this debate as all of our main findings remain after controlling for unobservable aggregate factors (time fixed effects) and unobservable collection-level features (collection fixed effects). By controlling for these factors, we are also accounting for potential time-varying beliefs about whether ownership of a given NFT or collection would entail intellectual property rights as well.

NFTs from a given collection often grant access to exclusive virtual social groups,[8] and there have also a number of in-person events restricted to verified owners of NFTs from certain collections.[9] Finally, NFTs can be displayed in virtual art galleries in the "metaverse."[10]

NFT Collections. Individual NFTs are usually associated with a broader collection, an aspect that also makes NFTs similar to collectibles and art. NFT collections are often formalized through a smart contract on the blockchain (i.e., a piece of software code) that is connected to each NFT within the collection. The fact that many NFTs are formally assigned to collections provides two benefits for our empirical analysis. The first is that we can easily identify and group together NFTs in our data. The second is that we will be able to control for common collection-level features across sets of NFTs.

Our analysis in this paper focuses on "generative" NFT collections (henceforth "GCs"). These are collections of roughly 5,000-10,000 NFTs around a common theme. We provide a formal definition for these types of collections in Section 2.2. A specific example of a GC is SupDucks, which consists of 10,000 pictures of cartoon ducks. We provide a few examples of NFTs from the SupDucks GC in Figure 1. Other GCs are often similar in nature except that they are based on a different central object (e.g., apes). We rely on SupDucks as a concrete example throughout the remainder of the paper as needed.

Primary Market ("Minting"). When we refer to the primary market, we are referring to the process in which NFTs are initially created on the blockchain and sold to investors. An NFT is generated on a blockchain in either one of two broad methods. The first method is that a creator can simply generate an NFT, associated with any image, into their own wallet. From this point, the creator can sell or transfer this NFT to another wallet as they would in any secondary market transaction. The second method is that the creator can set up a smart contract to deploy the NFTs directly to the public. In this setup, buyers "mint" NFTs from the smart contract by sending a pre-specified cryptocurrency amount (i.e., the "mint price") to the smart contract. The smart contract then creates the NFT and sends it to the purchaser's wallet.

The GCs that we analyze in this paper use the latter "minting" method to sell NFTs.

[8] For example, the Bored Ape Yacht Club collection has a private chat group which require verified ownership of a Bored Ape NFT to enter. It is also very common for NFT collections to have private chat groups on Discord gated to verified token holders: examples of collections which have such groups are Doodles, Cool Cats, and Pudgy Penguins. The mechanism through which these chat groups work is that the NFT owner must "sign" a message, proving private-key ownership of a wallet which can be publicly proven to possess a certain NFT, in order to join the private chat groups.

[9] One prominent example is that there have been a number of in-person meetups for members of the Bored Ape Yacht Club. Another example is that VeeFriends token holders get access to a multi-day exclusive event hosted by the creator called VeeCon.

[10] For example, Sotheby's has a virtual gallery in Decentraland.

(a) #3733, 8.88 ETH (b) #6670, 4.10 ETH (c) #1699, 4.09 ETH

Figure 1: SupDucks Example: Select Items Traded on September 25, 2021

Notes. The items displayed in this figure are 3 examples from among the 25 items from the SupDucks GC that traded on September 25, 2021. The 25th percentile price value on this date was 4.10. The captions include the specific item numbers within the collection and corresponding prices in ethereum (ETH) observed in the trades.

Collections have websites with key details of the collection, such as the price per NFT and the start date of the public sale. Buyers can initiate the smart contract transaction to mint the NFT simply by clicking a "mint" button on the NFT website, and will then pay the mint price and receive a random NFT from the collection. Thus, at the mint stage, buyers purchase from collections but cannot target specific NFTs within the collection.

GC primary market sales can differ along a few dimensions. Perhaps most importantly, the number of NFTs within a collection and the collection's pre-specified mint price both can vary substantially. GC creators can also choose to restrict the set of potential purchasers to a "whitelist" of pre-determined wallet addresses, limiting the "public" nature of the sale. The decision to do so is often motivated by the desire to reward early investors and active community members.

Secondary Market. After being minted, NFTs can be traded in a secondary market. As of the time of writing, the largest NFT secondary market platform is OpenSea.[11] OpenSea serves both as a catalog of the NFT universe and a platform through which buyers and sellers can initiate trades. OpenSea organizes the NFTs by collection and reports key collection-level statistics on the associated collection page. For example, OpenSea reports the "floor"

[11] In our baseline sample of transaction-level data, roughly 99% of the secondary market transactions occurred on OpenSea. In the early period of our sample, OpenSea is essentially a monopolist in the NFT market. In the later period, LooksRare is the largest competitor to Opensea. We drop LooksRare data because LooksRare is known to have produced significantly wash trading volume, hence we do not view prices and returns on LooksRare as reliable. See Section 2.2 for additional discussion of this issue.

price (i.e., the lowest currently listed price for an NFT from a given collection) as a way to communicate the cheapest price at which an investor can buy into a collection. To initiate a trade, potential NFT purchasers and sellers first connect their wallets to OpenSea by showing their public address, which allows OpenSea to detect all NFTs and funds within their wallets. NFT sellers can then list each NFT they wish to sell at a specified price. Listed offers are binding: buyers can immediately purchase any listed NFT at the posted price. Buyers can also make an unsolicited bid on a given NFT that the owner can accept if they are willing to accept the bid price. In exchange for its services, OpenSea charges a flat 2.5% transaction fee for each realized trade.

In addition to the OpenSea transaction fee, there are two important fees that investors pay in the secondary market. The first is the royalty fee, which determines the share of the transaction price paid back to the creator. The most common royalty rate among GCs is 5%, with other common values being 2.5%, 7.5%, or 10%. If present, the royalty rate is specified directly in the collection-level smart contract so that it is automatically paid in every secondary market transaction captured on the blockchain. The underlying technology for NFTs (i.e., programmable smart contracts) makes such royalties both feasible and convenient. By giving an NFT creator an ongoing stake in the success of their collection, royalties provide both an additional source of revenue and an incentive to work to increase its market value.

The second important additional fee that investors pay in secondary market transactions is "gas." Gas refers to the transaction fee which must be paid on any interaction with the Ethereum blockchain: both mints and secondary market trades. These fees are paid to Ethereum "miners", computer nodes which solve computationally hard problems in order to embed transactions into the blockchain through a "proof-of-work" process. Gas fees tend to be high when there is high demand for transactions on the Ethereum blockchain. These fees are a potentially important factor in NFT investor decisions especially during primary market sales in which volume (and therefore gas fees) can suddenly spike. The purchaser usually pays the gas fee in any transaction except that the seller pays the gas when a trade was initiated from the buyer as a bid.

NFT investors care about fees because they reduce potential and realized returns. In our empirical analysis, we find that royalties are the largest type of fee paid, followed by OpenSea transaction fees, and then gas.

2.2 Data

In our analysis, we focus on a set of collections we call "generative" NFT collections (henceforth "GCs"). We define an NFT collection as a GC if the associated digital artwork features a common theme and each individual NFT represents a unique variation on that theme. As an example, the associated artwork for SupDucks are 10,000 unique pictures of cartoon ducks (see, e.g., Figure 1) that feature various sets of characteristics combined essentially randomly and combinatorially. Additionally, we require GCs to mint their NFTs through a public sale in which buyers pay a fixed amount to receive a random NFT within the collection. See Appendix A for our complete formal GC definition as well as justifications for each individual restriction. The main reason we restrict attention to GCs is so that the NFT collections in our sample are comparable to each other.

The first step in assembling the data for our analysis is to identify the universe of GCs. We first compile the full list of NFT collections featured on OpenSea, the most popular NFT marketplace as noted in Section 2.1. This step, which we performed on a few dates in October 2021, generated an initial list of 7,987 NFT collections. After applying the filters from our GC definition, we find 692 GCs in total (see Appendix A for a more detailed description of this process). Despite being a relatively small set of NFT collections, GCs represent a relatively large share of the broader NFT market. For example, many of the largest and most well-known NFT collections are GCs in our sample such as the Bored Ape Yacht Club, Cool Cats, World of Women, and Pudgy Penguins (Appendix Table A.2). GCs are also a relatively popular form of NFT collection, accounting for approximately half of the amount of funds raised in the broader NFT primary market from April through September 2021.[12]

Our primary data source is a transaction-level dataset scraped from Etherscan.io, which is a website that captures and displays data from the Ethereum blockchain. Our data include nearly all on-chain transactions for the GCs in our sample between April 10, 2019, and March 31, 2022.[13] Aggregate volume only truly picks up in April 2021, with only a handful

[12]A notable exception is that the CryptoPunks collection, arguably the first and one of the most successful generative NFT collections, is not in our sample because its NFTs are not ERC-721 tokens (see, e.g., the FAQ section on the creator's website). We require that the GCs in our sample use the ERC-721 smart contract standard (see Appendix A.2). Most NFT marketplaces including OpenSea are built to trade ERC-721 tokens. Although it is technically possibly to trade "wrapped" CryptoPunks on Opensea, the majority of trading occurs on a platform built by LarvaLabs, the creator of CryptoPunks.

[13]We filter our transaction-level data in two ways. First, we drop all trades that occurred on the LooksRare NFT trading platform, which produced significant fake trading volume during our sample. LookRare launched near the end of our sample (January 2022). It attempted to gain market share quickly by incentivizing traders on its platform through rewards based on the total value of their trades. However, these incentives led to significant fake trading (also known as "wash trading") volume, an issue that is well-known and acknowledged among NFT market participants (see, e.g., here or here). Prices from LooksRare are therefore unreliable. Second, we drop "swap" transactions because they do not represent straightforward purchases of an NFT

of collections trading beforehand. The dataset has over 6 million transactions of which approximately 48% are mints and the remainder are secondary market transactions (Table 1). Importantly, the data include the wallet addresses for both the seller and buyer in each transaction that allows us to perform our investor-based analysis in Section 4. See Appendix A for additional data details regarding the contents of the data and how we prepare it for analysis.

Our transaction-level data also allows us to precisely quantify the three kinds of fees paid in the process of trading NFTs as described in Section 2.1. First, the gas fees paid in ETH for each transaction are reported directly on Etherscan. The purchaser usually pays the gas fee except that the seller pays it when a transaction was initiated from the buyer as a bid. Therefore we are careful to attribute the gas paid to the correct party when computing post-fee returns in Section 4. Second, we compute the platform fee charged by OpenSea as 2.5% of a transaction's value.[14] Finally, we compute the royalty fees charged as the product of the collection-specific royalty rate and the transaction's value. In our data and at the aggregate level, royalties represent the largest type of transaction fee paid followed by OpenSea transaction fees and then gas (Appendix Figure A.2).

Table 1: Overview of Transaction-Level Data

Notes. In this table, we describe the sample size of the transaction-level data available for the GCs in our sample. "Mint" is the common term in practice to refer to the primary market sale and on-chain creation of a new item. "Transfer" refers to any observed post-mint transaction.

	N	Mean
Is Mint	6,095,115	0.48
Is Transfer	6,095,115	0.52
Positive Price if Mint	2,916,832	0.91
Positive Price if Transfer	3,178,283	0.73

We supplement our transaction-level dataset with data on collection-level features. Specifically, we manually gather these data from GC-specific websites and Twitter accounts. They include variables such as whether the collection has a dedicated Twitter profile and whether the specific artist(s) of the associated digital artwork are explicitly named. We describe these features in more detail in Appendix Section A.3. The main purpose of gathering these data is to use them as control variables in our collection-level analyses in Section 4. We provide

using ETH.

[14]OpenSea charged a fixed 2.5% rate throughout our entire sample period and comprises roughly 99% of the total secondary trading volume in our data.

summary statistics for these characteristics in Appendix Table A.1.

3 Stylized Facts and Measurement

In this section, we document several stylized facts about the GC market using our data. We also explain how we construct the key variables used in our empirical analysis.

3.1 Secondary Market Activity

First, we discuss trading patterns of GC NFTs. In Figure 2, we show the distribution of all GC NFTs according to their cumulative secondary market trading activity in our sample. Here, we observe that 54% of the total 2.9 million GC NFTs minted never trade in the secondary market within our sample period. In other words, only 46% of GC NFTs have ever traded in the secondary market.

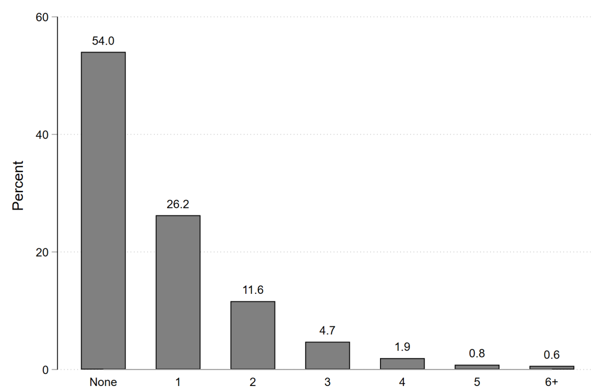

Figure 2: GC Sample: Shares of All NFTs by Number of Times Traded

Notes. This figure reports the shares of all GC NFTs according to the amount of times the item is traded during our sample period. We only consider an observed transaction to be a trade if the price is nonzero. “None” refers to the case in which an item never trades after its mint.

In Table 2, we summarize measures of secondary market activity at the collection level. Our first takeaway from this table is that the volume of trading varies substantially across GCs. For example, the median GC experiences at least 5 trades on 8% of the days following its minting period. This figure, however, ranges from 0% to 100% when we look across GCs. In fact, roughly 70 GCs never experienced a day with at least 5 trades.

Table 2: GC Sample: Trading Period Variables

Notes. In this table, we summarize variables pertaining the trading period of a GC. With the exception of royalty rate, which was manually gathered, all of these variables are computed from transaction-level data. We only consider an observed transaction to be a trade if it the price is nonzero. Royalties earned are estimated as the royalty rate times the volume traded. Total funds raised is the sum of funds raised through minting and royalties earned.

	N	Mean	SD	Min	10%	50%	90%	Max
N Trades and Transfers	692	4,592.89	7,584.52	2.00	56.00	928.00	14,104.00	51,752.00
N Trades	692	3,367.08	5,546.65	0.00	18.00	589.00	11,027.00	35,433.00
N Trades / N Items	692	0.50	0.58	0.00	0.04	0.23	1.32	3.62
N Trades / N Days	692	14.77	24.38	0.00	0.08	2.51	47.99	163.29
Frac. Items Ever Traded	692	0.31	0.26	0.00	0.04	0.21	0.72	0.97
N Days with At Least 5 Trades	692	56.14	71.99	0.00	0.00	18.50	179.00	332.00
Frac. Days with At Least 5 Trades	692	0.25	0.31	0.00	0.00	0.08	0.80	1.00
Frac. Days with At Least 5 Trades (> 0)	620	0.28	0.32	0.00	0.01	0.12	0.86	1.00
Volume Traded (ETH)	692	2,524.47	20,993.85	0.00	0.90	40.34	2,805.48	501,696.07
Royalty Rate	692	0.05	0.03	0.00	0.02	0.05	0.09	0.10
Royalties Earned (ETH)	692	88.66	589.76	0.00	0.02	1.61	99.33	12,542.40
Royalties Earned to Total Funds Raised	692	0.09	0.16	0.00	0.00	0.01	0.29	0.94

3.2 Collection-Level Price Indexes

Next, we analyze NFT prices from secondary market transactions and propose a method to compute collection level price indexes. GCs essentially consist of two types of items: rare and common. The select "rare" items trade at prices much higher than others in the collection while the remaining "common" items tend to trade around the same much lower price. To demonstrate this fact, we regress log NFT prices on collection-date fixed effects:

$$\log p_{j,c,t} = \nu_{tc} + \epsilon_{j,c,t} \tag{1}$$

where $p_{j,c,t}$ is the price in ETH for NFT j from GC c sold on date t. Figure 3 plots the distribution of the exponentiated price residuals, $\exp(\epsilon_{j,c,t})$, from specification (1). The distribution is noticeably right-skewed (skewness value of 4.5). This means that a small number of NFTs trade at prices much higher than others in the same collection, but few NFTs trade substantially below the median price. Quantitatively, our estimates from (1) imply that the 90th percentile NFT price for a given collection-day (1.79) is roughly 90% higher than the median (0.94), whereas the 10th percentile price (0.63) is only roughly 33% lower.

In order to calculate total returns to investors accounting for unsold NFTs, we need to value unsold NFT inventory. Doing so can be tricky, however, given that most NFTs never

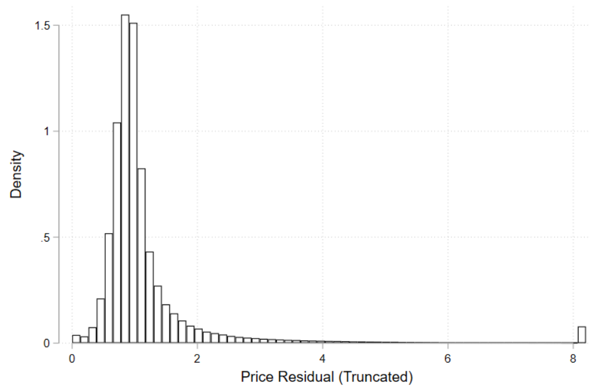

Figure 3: Price Regression Results

Notes. This figure reports the distribution of residuals from the regression specification in (1) of log NFT prices on date-collection fixed effects. The residuals used for plotting are truncated at their 99th percentile value and the distribution statistics discussed in the text are also computed from these data.

trade (Figure 2). This problem exists at the collection level too where we observe similar fraction-ever-traded numbers (Table 2). To account for this issue, we rely on the above takeaway from Figure 3 that most NFTs in a collection tend to trade around the same price. This fact can be quantified using the regression result that GC-level fixed effects captures nearly half of the variation in log prices, according to the R^2 statistic from the estimates of Specification (1). Further, we observe that date-GC-level fixed effects capture over 80% of the variation. These results imply that a collection-level price index would be a reasonable approximation for the value of any NFT in that collection.

Based on the above facts, we propose to measure daily collection-level price indexes as the median price provided that there are at least 5 trades. The choice of 50th percentile is to ensure that we grab a price from the middle of the distribution, which is where the majority of NFTs in a given collection appear to be valued (Figure 3). The choice of 5 trades as a minimum is to ensure that the 50th percentile value is reasonably well estimated. This approach to pricing a collection is similar to the concept of a "floor" price, which is reported on OpenSea and often discussed in NFT market commentary. The key difference is that the "floor" price is based on the lowest available offers to purchase an item at any given moment, while our measure is based on realized trades that are observable on the Ethereum blockchain.

Table 3: GC Sample: Minting Period Variables

Notes. In this table, we summarize variables pertaining to the minting period of a GC. With the exception of genesis supply, which was manually gathered from GC-specific webpages, all of these variables are computed from transaction-level data. Weighted average mint price is the total amount of ETH raised in mint transactions divided by the total number of items minted. Average items minted per wallet is the total number of items minted divided by the number of minting wallets. Days to mint the full collection is only computed for GCs that raised over 99% of their collection. It is measured in fraction of days and the ending time is the time of the mint that pushes the GC over the 99% minted threshold.

	N	Mean	SD	Min	10%	50%	90%	Max
N Items Minted	692	4,214.34	4,084.61	12.00	293.00	2,443.50	10,000.00	25,000.00
Genesis Supply	692	7,388.49	3,933.11	99.00	1,111.00	8,888.00	10,000.00	29,886.00
N Items Minted / Genesis Supply	692	0.63	0.42	0.00	0.05	0.99	1.00	1.39
N Items Minted / Genesis Supply (< 99%)	344	0.25	0.26	0.00	0.02	0.15	0.67	0.99
Frac. Minted at Price > 0	692	0.88	0.20	0.05	0.60	0.97	1.00	1.00
Dummy Minted All Genesis	692	0.50	0.50	0.00	0.00	1.00	1.00	1.00
Weighted Average Mint Price (ETH)	692	0.07	0.21	0.00	0.02	0.05	0.09	3.92
Funds Raised through Minting (ETH)	692	269.64	904.75	0.10	9.70	99.54	667.40	22,070.66
Implied Funds Raised Goal (ETH)	692	490.94	1,540.73	2.46	49.95	292.06	786.19	22,082.80
Number of Minting Wallets	692	894.57	948.37	1.00	98.00	596.00	2,010.00	8,207.00
Average Items Minted per Wallet	692	10.09	126.97	1.00	2.21	3.96	8.26	3,333.00
Max Frac. Items Minted by Wallet	692	0.09	0.12	0.00	0.02	0.05	0.20	1.00
Days to Mint Full Collection	348	17.67	56.97	0.00	0.14	3.78	37.93	869.67

3.3 Primary Market Activity and Outcomes

Next, we analyze the primary market for GCs. Recall that the simultaneous purchase and creation of an NFT is commonly referred to as "minting," and therefore we will use this term synonymously with primary market activity. We report summary statistics for variables that characterize the minting periods of our GCs in Table 3 and Figure 4.

Our first takeaway from Table 3 is that GCs experience different degrees of success in selling their collection of NFTs in the primary market. Here we focus on the fraction of NFTs sold by the GC relative to the initial set that it planned to sell, which we refer to as the "genesis supply." Only 50% of GCs are successful in selling their entire genesis supply. Many GCs are very unsuccessful: conditional on not selling their entire genesis supply, a GC only sells 25% of their supply on average. This dichotomy in outcomes can be further validated by the bimodal cross-sectional distribution for the fraction of genesis supply sold variable presented in Figure 4. Of course this variation in success can be similarly seen in other outcome variables of interest. For example, conditional on selling their entire genesis supply, GCs differ in how quickly they sell out. The 90th percentile successful collection takes over one month to sell out whereas the 10th percentile GC takes less than one day.

The second takeaway from Table 3 is that GCs aim to earn different amounts of funds in

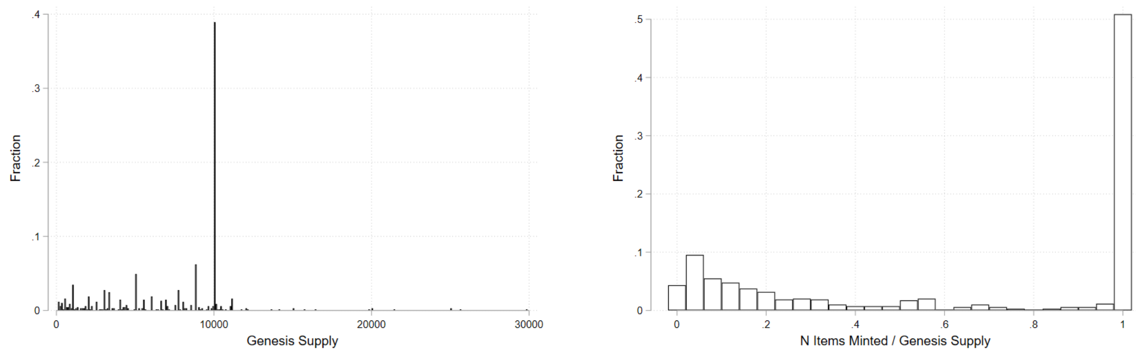

Figure 4: Distributions of Genesis Supply Amount and Fraction Actually Minted
Notes. This figure shows the distribution of the genesis supply and the fraction of the genesis supply actually minted during the primary market sale (N Items Minted / Genesis Supply). Each data point is one GC.

their primary market sales. The average and median collection have an implied fundraising goal of roughly 500 ETH and 300 ETH, respectively. Using an exchange rate of $3,000 per ETH, these numbers imply that the typical GC aims to raise between $0.9 and $1.5 million through the sale of their NFTs. Given low rates of success, however, the median GC in our sample actually raised 100 ETH (approximately $300,000) through minting.[15] The implied fundraising goal of a GC is calculated as the product of two GC-specific choices: the average mint price and the genesis supply. In our sample, we find that the typical GC has a mint price of around 0.05 ETH, or $150 based on an exchange rate of $3000 per ETH.[16] We also find that approximately 40% of GCs plan to sell 10,000 NFTs, although this number ranges from around 100 to almost 30,000 (Figure 4).

The success of a primary market sale is important because GCs which mint out successfully and quickly tend to experience higher price growth. This occurs for two reasons. First, minting out quickly is a signal to the market that the NFT collection is in high demand. Second, if a GC does not mint out, the primary market serves as competition for the secondary market.

[15] At the largest end, we observed that a GC raised the equivalent of roughly $66 million. This GC is Meebits, which was launched in May 2021 by the same company that launched the first wildly successful NFT collection in 2017 named CryptoPunks. In general, the largest GCs are among the largest NFT collections.

[16] In practice, mint prices denominated in ETH are established in advance of the minting period. However, there are two complications in determining a representative mint price for any given GC. The first is that GC creators have the ability to mint items for free. These are typically done as part of giveaways and related promotions to generate interest in the GC. We find that the typical GC mints 90%–95% of its collection at a positive price. The second complication is that there can be a schedule of mint prices that are based on factors such as number of items minted. Given these two complications, we compute the weighted average mint price as the total amount of ETH raised in mint transactions divided by the total number of items minted. This average price has the helpful property that multiplying it by the number of NFTs actually minted yields the total amount of funds raised.

If the secondary market floor price rises above the mint price, an investor can simply mint a new NFT from the GC rather than buying one from the secondary market. Figure 5 shows how minting period success is associated with price growth using the ratio of the post-minting GC price index to average mint price. In the left panel, we compare the distributions for this ratio between the set of collections that successfully and the set of collections that did not. In line with our expectation, we find that secondary market prices tend to be higher than mint prices for collections that mint out, and lower for collections that do not. Focusing only on collections that successfully minted out, the right panel shows a binned scatter plot of the price index ratio against the time it takes for a collection to mint out. Collections that mint out more quickly also experience higher price growth relative to mint prices.

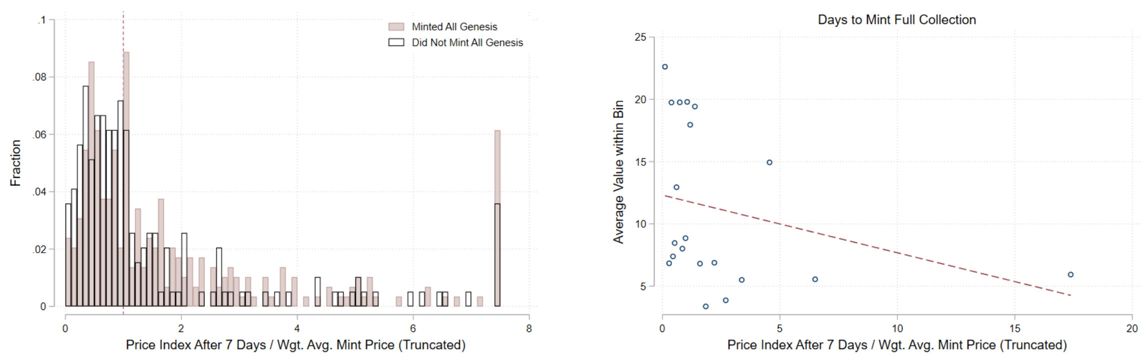

Figure 5: GC Sample: Post-Mint Price Index Growth by Minting Period Success

Notes. The left panel reports the cross-sectional distributions of the ratio of the GC's price index 7 days after minting began compared to the weighted average mint price. The underlying values are truncated at the 95th percentile value for the ratio in the entire sample for visual purposes. These distributions are reported separately for the set of GCs that sold over 99% of their genesis supply and the set of GCs that did not. The right panel reports a binned scatter plot for the same two variables but only uses data for GCs that sold over 99% of their genesis supply.

In sum, when we analyze collection-level success measures, the above observations motivate using various measures of minting success in our analysis: a dummy for whether a collection mints out, the fraction of genesis supply minted, and the time it takes for a collection to mint out.

On the investor side, we note that the minting period for the typical collection includes between 600-900 wallet addresses. For the purposes of our analysis, we consider each wallet to effectively be a unique investor. This assumption is mainly so we can use the term "investors" rather than "wallets" throughout our exposition, which makes the intuition for our findings more clear. Combined with the number of items minted, these wallet address counts imply that the typical investor in any GC mints between 4 to 10 items. To provide a sense of concentration, we also measure the maximum share of items minted across minting wallets within each GC. Here, we find that the typical GC minting period features a largest investor that purchases between 5% and 10% of the entire collection.

3.4 Defining Experienced Investors

The main object of our analysis is to study how experienced investors differ from inexperienced investors in the NFT market. In short, we will define experienced investor wallets as those that conducted a relatively large number of transactions. For the purposes of our analysis, we consider each wallet to effectively be a unique investor. This assumption is mainly so we can use the term "investors" rather than "wallets" throughout our exposition, which makes the intuition for our findings more clear. There are over 500,000 unique wallet addresses that appear in our transaction-level data.

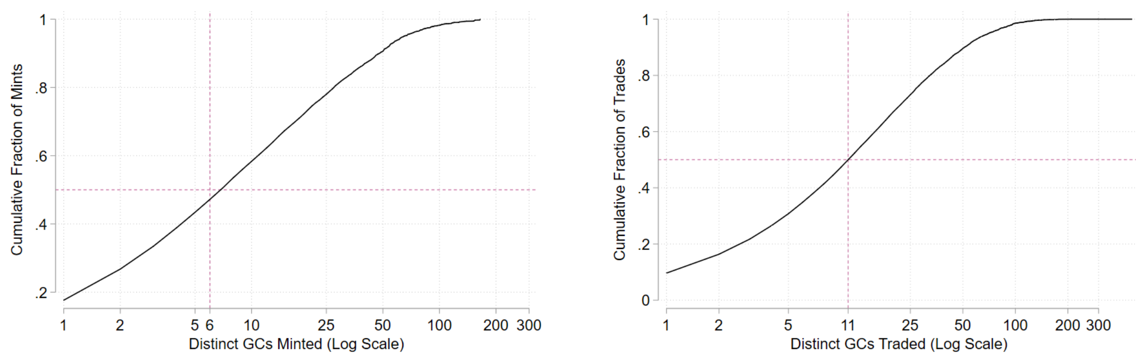

Figure 6: Investor Concentration in GC Activity

Notes. This figure reports the cumulative shares of mints (trades) when wallets are grouped and ordered by the number of distinct GCs with which they minted (traded) in the left (right) panel. We only consider an observed transaction to be a trade if the price is nonzero. The vertical dashed line in the left (right) panel denotes the maximum number $\overline{N}$ such that at least 50% of GC items minted (traded) were done so by wallets that had minted from (traded within) $\overline{N}$ or more GCs.

Figure 6 demonstrates the high degree of concentration for both NFT minting and trading activity among investors. We observe that a relatively large share of NFT market activity is attributable to a relatively small fraction of wallets. In the top left panel, the x-axis displays the number of distinct GCs minted from by a given wallet, and the y-axis shows the fraction of all GC mints executed by wallets that minted from at most the given number of GCs. For example, the value of the line at x =6 is around 50%, implying that half of all NFT mints are performed by wallets that minted from at least 6 GCs in our data. Analogously, the right plot shows the number of distinct GCs that a wallet traded within on the x-axis, and the cumulative fraction of trades on the y-axis. Half of all NFT trades are performed by wallets that traded within at least 11 trades in our data.

We identify "experienced" investors, at any given point in time in our sample, as investors that had above-median mints and trades. Formally, at every date, we identify thresholds M_t and T_t for mint count and trade count, such that 50% of mints (trades) prior to time t were performed by wallets with below M_t mints (T_t trades). We then define a wallet as experienced as of time t, if the wallet performed at least M_t mints, and at least T_t trades, prior to time t. When we set t to the end of our sample period, March 31, 2022, these thresholds are exactly the numbers described in the previous paragraph: M_t is equal to 6, and T_t is equal to 11. Our procedure classifies around 16,000 (or 3%) of investors are "experienced" at the end of the sample. In Appendix Figure A.4, we report the thresholds M_t and T_t, and the number of experienced investors we identify, over time in our sample.

We characterize experienced GC investors further by comparing their entry dates into the sample and relative trading activity in Figure 7. Both panels use the experienced classifications as of the end of our sample. There are two main takeaways from this figure. First, experienced GC investors entered the sample much earlier than inexperienced in general (see the left panel). This finding, however, is simply a consequence of the way we define experienced investors. Those entering the sample earlier have had more time to interact with different GCs, and therefore are more likely to meet our "experienced" definition. The second takeaway is that, controlling for the total number of active days, experienced investors simply trade more (see the right panel). While this feature is also related to how we define them, it is interesting to note that the bulk of experienced investors only trade less than 10 times per day on average.

4 Results

4.1 Realized Returns

Using our transaction-level data, we can compute the realized return attributable to any given transaction. We define returns, inclusive of fees, as:

$$r^{realized}_{i,j,c,t,\tau} \equiv \frac{Price^{Sold}_{i,j,c,t} - Fees_{i,j,c,t} - Price^{Purch}_{i,j,c,\tau} - Gas_{i,j,c,\tau}}{Price^{Purch}_{i,j,c,\tau}} \tag{2}$$

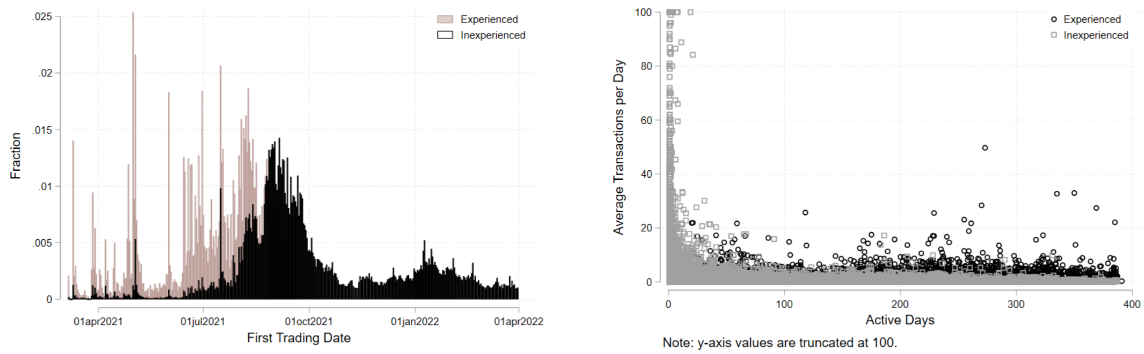

Figure 7: Characterizing Investor Groups: Experienced versus Inexperienced

Notes. The left panel of this figure reports the cross-sectional distribution of an investor's first trade date within our sample by investor type entry date. Even though our sample begins on April 10, 2019, the x-axis begins on March 1, 2021, for visual purposes. The right panel reports a scatter plot comparing the number of active days withnin our sample to the average tranactions per day for each investor in our sample. Experienced investors are defined as those with sufficient minting and trading activity (see Figure 6). We only consider an observed transaction to be a trade if it the price is nonzero.

where $Price^{Sold}_{i,j,c,t}$ is the price received by investor i when they sell NFT j from collection c on date t, $Fees_{i,j,c,t}$ are the royalty and platform fees paid by i during that sale, $Price^{Purch}_{i,j,c,\tau}$ was the price paid by i to purchase the NFT on date τ, and $Gas_{i,j,c,\tau}$ was the gas fee paid by i during that purchase.[17] Recall from the discussion in Section 2 that the seller pays the gas fee when a transaction was initiated from the buyer as a bid. So if investor i had purchased NFT j on date τ through a bid then $Gas_{i,j,c,\tau} = 0$. Another variable we will use in our analysis is the returns made by i ignoring fees:

$$r^{realized,nofees}_{i,j,c,t,\tau} \equiv \frac{Price^{Sold}_{i,j,c,t} - Price^{Purch}_{i,j,c,\tau}}{Price^{Purch}_{i,j,c,\tau}} \tag{3}$$

Throughout most of our analysis, we focus on returns from trades in which the both legs of the trade only involved the single NFT, with the exception that the prior trade can involve multiple NFTs if it was a mint. The alternative approach would be to assume that the price of any NFT in a multi-NFT transaction is equal to the transaction value divided

[17]The purchase price is observed in a different transaction that we need to connect to the ultimate sale. We identify the investor i and the previous purchase price as the wallet address and price observed in the most recent transaction with a positive price for the given NFT j. In other words, before computing realized returns we drop all transactions with a zero price, which we interpret as transfers between wallets of the same investor. In most of our trade-level return analysis, we restrict our attention to returns for which the purchase transaction only included a single NFT. Otherwise, for multi-NFT transactions we divide the transaction value evenly across the NFTs to estimate each individual purchase price.

by the number of NFTs involved. While this may be a reasonable assumption, our concern is that the corresponding measured returns in those cases are not precisely measured. We allow minting transactions to include multiple NFTs given that the assumption of equal value across NFTs seems valid in this circumstance. In the end, these filters reduce our sample of realized returns by 3.8%. Importantly, all of our results remain qualitatively the same and quantitatively very similar if we follow our alternative approach to include them.

Before proceeding to a formal regression analysis, we first visualize the returns for experienced and inexperienced investors in Figure 8. In the top panel, we report the cross-sectional distributions at the trade level. Here we see that experienced distribution appears slightly shifted to the right compared to the inexperienced one. In the bottom panels, we report the aggregate returns before and after fees within each group, which we calculate as sum of realized profits divided by the sum of amounts paid.

There are two clear takeaways from Figure 8. First, aggregate returns to investors were very high during our sample. Experienced and inexperienced investors earned aggregate returns of 71.3% and 63.1% after fees. Second, experienced investors appear to outperform inexperienced investors in general at the trade level.

To formally assess the apparent outperformance of experienced investors shown in Figure 8, we estimate regression specifications of the following form:

$$r_{i,j,c,t,\tau} = \beta \times \mathit{Experienced\ Seller\ Dummy}_i + \gamma X_{i,j,c,t,\tau} + \epsilon_{i,j,c,t,\tau} \tag{4}$$

where the dependent variable is the realized return to investor i for NFT j in collection c, with or without fees, as defined in (2) or (3). The key right-hand side variable is a dummy for whether the associated investor was in our experienced group as of date τ. Depending on specification, the vector of control variables, $X_{i,j,c,t,\tau}$, includes the log of the fractional number of days the position was held and sets of fixed effects for dates, whether the initial trade was a mint, collections, or the interactions of these features.

The results from our trade-level realized return regressions are shown in Table 4. Columns (1)–(3) use $r^{realized}_{i,j,c,t,\tau}$, realized returns inclusive of fees, as the dependent variable. Column (1) shows that, in a simple OLS specification, experienced investors in fact achieve 4.6% lower returns per trade compared to inexperienced investors. However, this is largely due to the fact that experienced sellers have much shorter average holding periods than inexperienced sellers, and NFT prices are rising quickly on average over this time horizon. Column (2) controls for holding period, thus comparing experienced and inexperienced investors who held NFTs for the same amount of time; this increases our estimate of β to 9.3%. Column (3) further adds buydate-selldate FEs, comparing experienced and inexperienced investors who purchased and

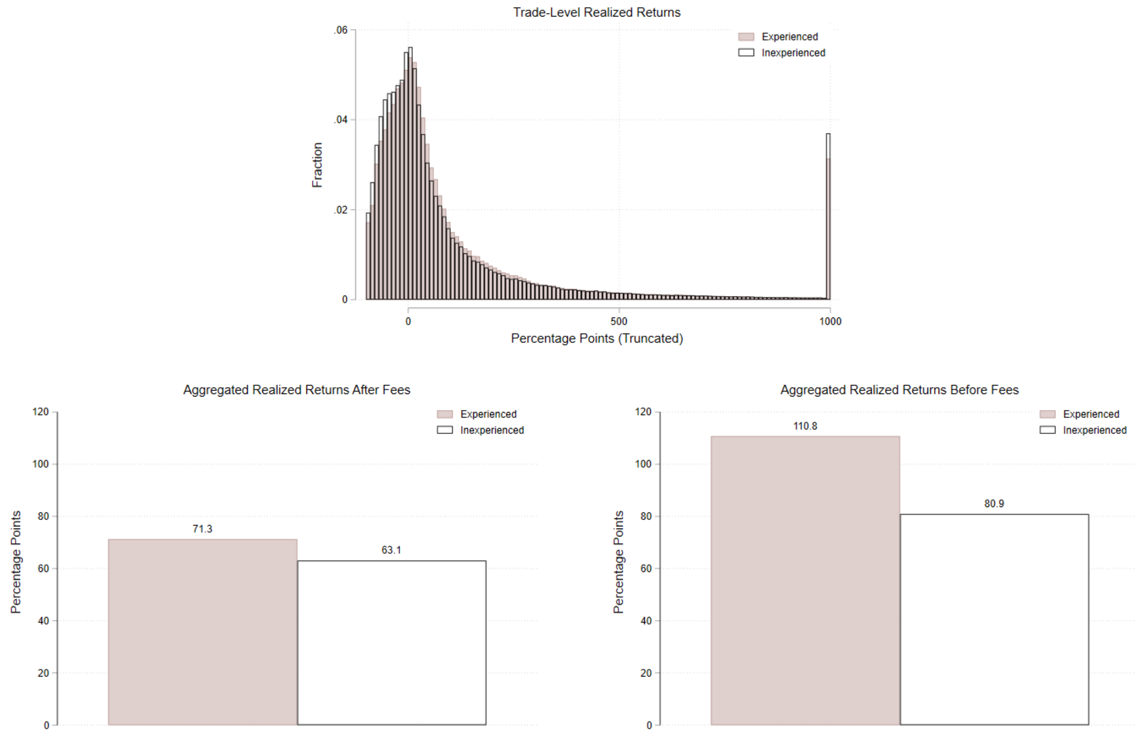

Figure 8: Realized Returns by Investor Type

Notes. The top panel reports the distribution of realized returns after fees at the trade level by investor type. Realized returns after fees are computed as in (2). Investor type is assigned to each trade based on the investor's experienced status as of the purchase date (see Section 3.4 for details). The bottom panels report aggregate returns after and before fees, respectively. Aggregate returns are computed as weighted averages of the trade-level returns. For all panels, we only use returns from trades in which the both legs of the trade only involved the single NFT with the exception that the prior trade can involve multiple NFTs if it was a mint. For the top panel, we further restrict our sample to those in which the purchase price is at least 0.01 ETH.

sold NFTs on the same day. This can be thought of as accounting for experienced investors' ability to time the overall NFT market. This produces a similar estimate of β equal to 8.6%.

In Columns (4)-(6) of Table 4, we use $r_{i,j,c,t,\tau}^{realized,nofees}$, returns exclusive of fees, as the dependent variable. We find that experienced investors' return premium is much larger – approximately 36.9% higher, with buydate-selldate fixed effects – when we ignore fees paid. This suggests that experienced investors tend to make trades with higher fees, and this has a substantial effect on experienced investors' aggregate performance.

Next, we show that a first-order driver of experienced investors' outperformance is that experienced investors tend to mint more often – that is, they participate in primary markets

Table 4: Regressions at Trade Level: Realized Returns

Notes. In this table, we report the results from estimates of specification (4) in which we regress realized returns for each NFT on an experienced seller dummy for investor i as of date τ, the log of the holding period, and buydate-selldate fixed effects. The dependent variable is $r^{realized}_{i,j,c,t,\tau}$ in the first three columns, and $r^{realized,nofees}_{i,j,c,t,\tau}$ in the last three columns. We only include realized return values where the purchase price was 0.01 ETH or more and these values are further truncated at the 99th percentile level. We also only include returns from trades in which the both legs of the trade only involved the single NFT with the exception that the prior trade can involve multiple NFTs if it was a mint. Holding period is the fractional number of days the position was held. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Return Including Fees			Return Before Fees		
	(1)	(2)	(3)	(4)	(5)	(6)
Experienced Seller Dummy	-0.046***	0.093***	0.086***	0.348***	0.414***	0.369***
	(-8.69)	(17.20)	(17.95)	(44.92)	(52.05)	(51.60)
ln(Days to Realize)		0.134***			0.062***	
		(131.33)			(41.45)	
BuyDate-SellDate FE	No	No	Yes	No	No	Yes
R^2	0.000	0.007	0.324	0.001	0.002	0.292
N	2,135,986	2,135,984	2,128,389	2,135,986	2,135,984	2,128,389

where NFTs are first purchased from issuers – and mints are systematically more profitable than secondary-market purchases. In Column (1) of Table 5, we regress returns on a dummy for whether the purchase leg of the transaction was a mint. Column (2) controls for holding period, and Column (3) adds buydate-selldate fixed effects. In all cases, the coefficient on the mint dummy is positive, significant, and large in economic magnitude. Quantitatively, mint transactions are over 100 percentage points more profitable than secondary market transactions, on average across our sample.

Experienced investors have a higher propensity to mint (see, e.g., Appendix Figure A.6), which may contribute to their excess returns. To quantify the extent to which experienced investors' excess returns are driven by their higher mint propensity, in Column (4), we estimate β controlling for a mint dummy. Doing so decreases their estimated outperformance to -14.8pp. In Column (5), we add buydate-selldate-mint FEs. In this specification, the coefficient β is identified by comparing the returns of experienced and inexperienced sellers, who purchased and sold items on the same dates, and for which both purchase transactions were either mints or secondary market transactions. This specification would thus also eliminate any component of experienced sellers' excess returns which arise from mints being more profitable than secondary market transactions on average. The resultant estimate of β is -2.2pp. This suggests that we can explain more than the entirety of experienced sellers'

Table 5: Regressions at Trade Level: Role of Mints

Notes. In this table, we report the results from estimates of specification (4) in which we regress realized returns for each NFT on an experienced seller dummy for investor i as of date τ, the log of the holding period, buydate-selldate fixed effects, and a mint dummy. The dependent variable is $r^{realized}_{i,j,c,t,\tau}$. We only include realized return values where the purchase price was 0.01 ETH or more and these values are further truncated at the 99th percentile level. We also only include returns from trades in which the both legs of the trade only involved the single NFT with the exception that the prior trade can involve multiple NFTs if it was a mint. In Columns (1)–(5), we use the full sample. Column (6) uses only trades in which the NFT was purchased through a mint, and Column (7) uses the complementary set of trades in which the NFT was purchased in the secondary market. Holding period is the fractional number of days the position was held. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	All	All	All	All	Mints	Secondary
Experienced Seller Dummy				-0.148***	-0.022***	-0.062***	0.044***
				(-26.71)	(-4.60)	(-9.14)	(7.79)
Last Trade Was Mint Dummy	1.138***	1.348***	1.016***	1.373***			
	(230.84)	(251.92)	(197.78)	(248.84)			
ln(Days to Realize)		0.188***		0.184***			
		(175.91)		(171.04)			
BuyDate-SellDate FE	No	No	Yes	No	No	Yes	Yes
BuyDate-SellDate-IsMint FE	No	No	No	No	Yes	No	No
R^2	0.022	0.036	0.337	0.037	0.402	0.406	0.323
N	2,135,986	2,135,984	2,128,389	2,135,984	2,122,249	1,193,796	928,453

excess returns, through their higher propensity to mint.

Next, in Columns (6) and (7), we examine experienced sellers' outperformance separately for mint and secondary market transactions, with buydate-selldate fixed effects in both cases. Column (6) shows that experienced investors underperform by 6.2pp in mint transactions, and Column (7) shows that experienced investors outperform by 4.4pp in secondary market transactions. We proceed to analyze experienced sellers' outperformance in minting and secondary market transactions separately.

4.2 Minting returns

In this section, we will show that experienced investors appear to mint collections which are more likely to be successful. Experienced investors mint collections relatively late, close to the end of their minting periods. As a result, collections with a larger fraction of experienced investors participating are more likely to "mint out," selling their entire initial supply, and conditional on minting out, experience higher post-mint returns. However, experienced investors also pay higher fees on their mint transactions. This is due to two reasons. Experienced investors pay higher gas fees, and also tend to buy collections with high royalty rates. After accounting for fees, experienced investors in fact do slightly worse than inexperienced investors on minting transactions.

4.2.1 Experienced sellers' collection-picking ability

First, we analyze experienced sellers' timing of entry into mints. For each collection which mints its entire genesis supply, we define the average entry timing of experienced and inexperienced investors, respectively, as:

$$AvgRelEntry_{type,c} \equiv \frac{AvgTime_{type,c} - StartTime_c}{EndTime_c - StartTime_c} \tag{5}$$

Where *type* is either inexperienced or experienced. In words, (5) says that $AvgRelEntry_{type,c}$ for experienced investors is the average mint time across all experienced investors, minus the time of the first mint, divided by the time between the first time and when the collection mints out. Figure 9 shows the distribution of $AvgRelEntry_{type,c}$. The top left panel shows that the distribution of $AvgRelEntry_{Experienced,c}$ is much more concentrated towards 1, indicating that experienced investors tend to mint towards the end of a collection's mint period, when it is fairly clear that a collection will mint out. The top right panel shows a scatterplot of $AvgRelEntry_{type,c}$ for experienced and inexperienced investors. Most points lie above the line $y = x$, indicating that, for the majority of collections, experienced investors mint on average later than inexperienced investors.

The bottom panel shows a binscatter of average gas fees, against the relative timing of mints. Analogous to (5), the relative timing of item i in collection c is defined as:

$$RelEntry_{i,c} \equiv \frac{Time_{i,c} - StartTime_c}{EndTime_c - StartTime_c}$$

The plot shows that minting late is associated with high fees: gas fees tend to be higher for mints close to the end of the minting period. This suggests that, as a result of their tendency to mint late, experienced investors should tend to pay higher gas fees; we will confirm this finding in our regression analyses below.

Likely as a result of entering mints later, experienced investors tend to purchase collections which are more likely to succeed, according to a number of different metrics. Collections purchased by more experienced investors are more likely to mint out, mint out faster, and experience higher post-mint price growth. For each collection, regardless of whether it

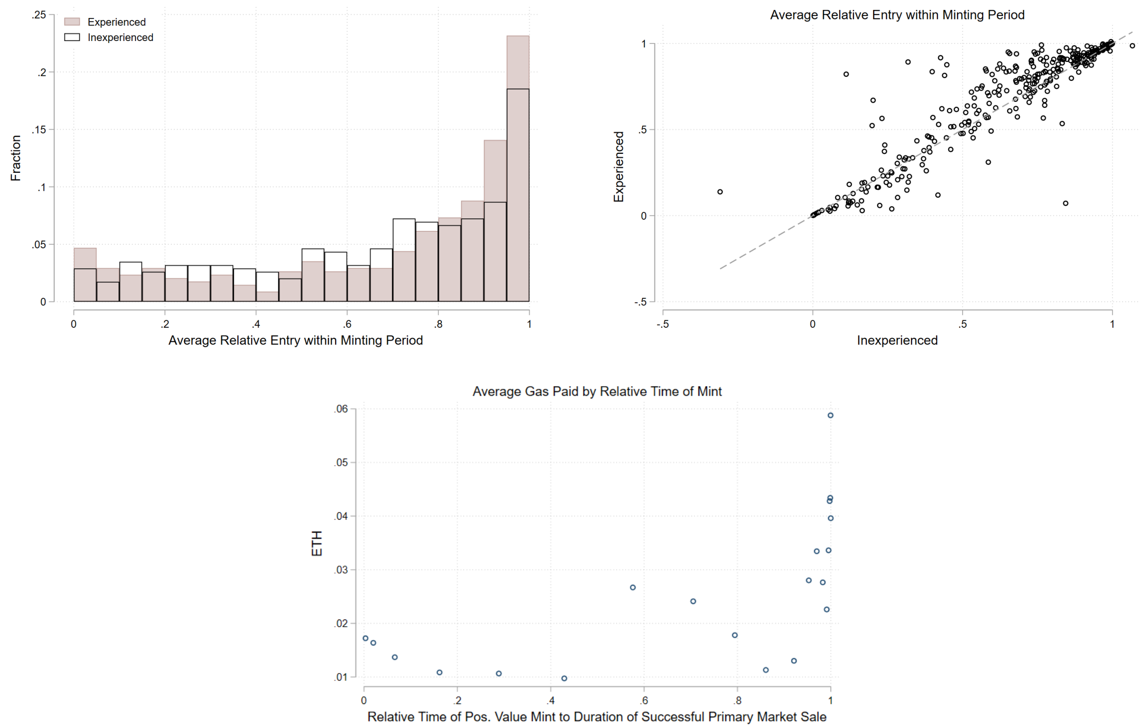

Figure 9: Mint Entry Timing, Gas Fees, and Investor Experience

Notes. This figure shows the distribution of entry times across collections, for experienced and inexperienced investors, and the relationship between entry time and gas fees. The top left plot shows stacked histograms of $AvgRelEntry_{Inexperienced,c}$ and $AvgRelEntry_{Experienced,c}$. The top right plot shows a scatterplot with $AvgRelEntry_{Inexperienced,c}$ on the x-axis, and $AvgRelEntry_{Experienced,c}$ on the y-axis. In both plots, each data point is one collection. The bottom plot shows a bin scatter of the relative entry time of a mint, against the gas fees paid in the mint. In all three plots, the sample consists of all GC collections in our baseline sample which minted their entire genesis supply.

successfully minted out or not, we measure the share of primary market sales to experienced investors as:

$$Frac.\, Minted\, by\, Experienced = \frac{NFTs\, Minted\, by\, Experienced}{All\, NFTs\, Minted}. \tag{6}$$

Figure 10 shows binned scatter plots of the relationship between Frac. Minted by Experienced and various outcome measures. The top left panel shows that collections in which a larger fraction of investors are experienced investors are much more likely to "mint out" (i.e., sell their entire genesis supply). The relationship is very strong: the highest quantile of experienced investor participation is around 80% likely to mint out, whereas the lowest quantile is associated with only a 10% probability of minting out. The top right panel shows that this result also holds if we use a continuous measure for the dependant variable, which is the fraction of genesis supply that is sold. The bottom panel shows that collections with more experienced participation mint out faster. Specifically, collections with around 60% experienced participation mint out in a few days on average, whereas collections with less than 10% usually take closer to a month.

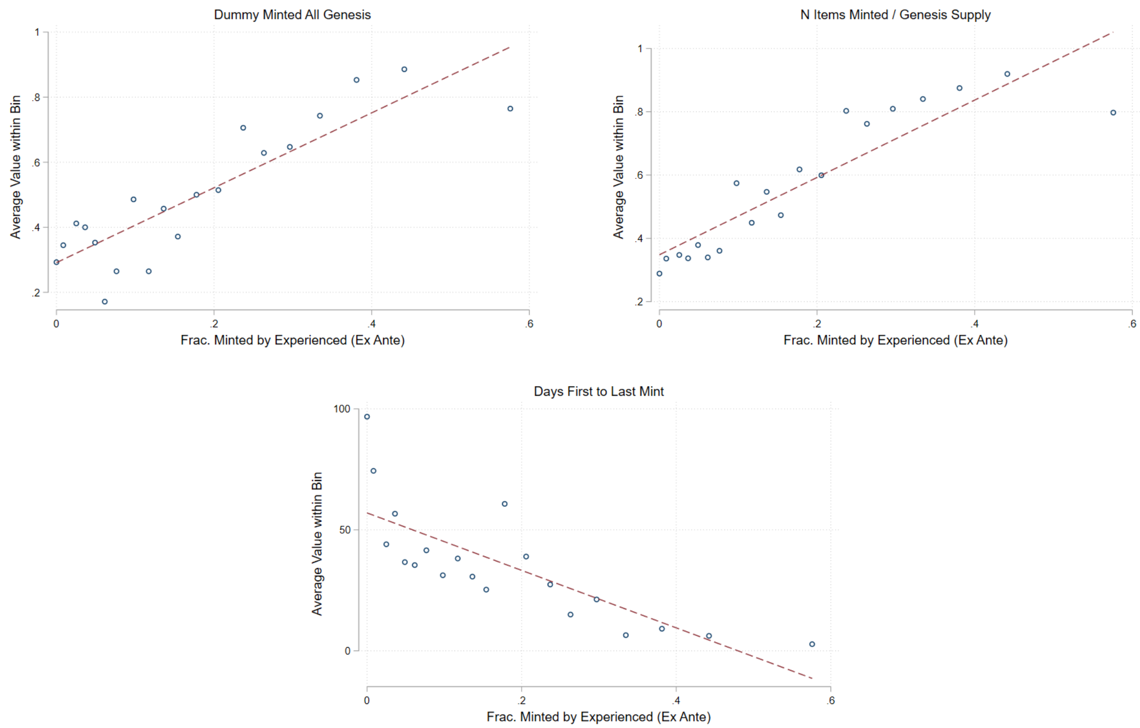

Figure 10: Fraction of Experienced Investors and Minting Period Success

Notes. The figure reports binned scatter plots to visualize the relationship between our measure of experienced investor involvement from (6) and collection-level measures of success.

We next estimate cross-sectional regression specifications of the following form:

$$y_{c,t} = \beta \times Frac.\, Minted\, by\, Experienced_c + \Gamma' X_c + \nu_t + \epsilon_{c,t} \tag{7}$$

where the dependent variable is a collection-level outcome from the minting period of GC c that started during week t. Specifically, we consider the measures of GC success described in Subsection 3.3 as well as post-minting price index returns. The key explanatory variable is our collection-level measure of experienced investor involvement as defined in (6). We also control for other observable features of the collection and its minting period in addition to including fixed effects for the week in which the GC's primary market sale began.

The regression results reported in Table 6 confirm the suggestive findings from Figure

10. Specifically, we find that higher experienced investor participation is robustly associated with greater minting period success across all of our key measures controlling for many collection-level features. For example, our estimate in Column (2) implies that a collection with a 1pp higher fraction of experienced investors is also 1.006pp more likely to sell its entire genesis supply in its primary market sale (i.e., "mint out"). Additionally, we note that the fraction of experienced investors explains the majority of the variance in the minting period outcome variables according to the R^2 values without and with the other control variables.

Table 6: Predicting Minting Period Success

Notes. In this table, we report the results from the cross-sectional regression specified in (7) where the dependent variable is a minting period outcome for a GC. The key explanatory variable is our collection-level measure of experienced investor involvement as defined in (6). GC-level controls displayed in the table include the fraction of NFTs minted at a positive price, the largest value for the fraction of NFTs minted by a single wallet, whether the project has a roadmap, the log of the weighted average mint price, whether the artist who created the art is explicitly named on the project's website or roadmap, and whether that artist has professional web presence independent of the NFT project (zero if no artist). GC-level controls omitted from the table include the average number of items minted per wallet, the royalty rate, and all of the dummy variables shown in Appendix Table A.1. See Appendix Table A.5 for the full table of results with all control variables shown. See Section 2 and Appendix Section A for more detailed variable descriptions. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Dummy Minted All Genesis		N Items Minted / Genesis Supply		ln(Days to Mint Full)	
	(1)	(2)	(3)	(4)	(5)	(6)
Frac. Minted by Experienced (Ex Ante)	1.199***	1.006***	0.966***	0.741***	-6.569***	-7.162***
	(10.03)	(7.46)	(9.31)	(6.40)	(-7.31)	(-10.09)
Frac. Minted at Price > 0		0.354***		0.158		-1.005
		(2.98)		(1.58)		(-1.32)
Max Frac. Items Minted by Wallet		-0.586***		-0.818***		1.178
		(-2.64)		(-3.95)		(0.69)
Has Roadmap		-0.075*		-0.090**		0.295
		(-1.77)		(-2.55)		(1.22)
ln(Weighted Average Mint Price)		-0.001		0.010		-0.171
		(-0.03)		(0.50)		(-1.40)
Has Named Artist		0.011		0.002		0.172
		(0.23)		(0.06)		(0.68)
Named Artist Has Twitter/Website		0.115**		0.088**		0.138
		(2.15)		(1.99)		(0.48)
Other GC-Level Controls	No	Yes	No	Yes	No	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.165	0.240	0.155	0.256	0.331	0.418
N	686	686	686	686	342	342

Next, we show that collections purchased by more experienced investors also experience greater post-mint price growth. In Table 7, we report our cross-sectional regression results using GC post-mint price index returns as the dependent variables.[18] These measures, which

[18]Compared to the specifications used in Table 6, the only difference in Table 7 aside from the dependent variables is that we do not control for the weighted average mint price given that it is used directly to compute the GC-level returns.

use mint price as the reference level, are meant to capture the initial success of a GC in the weeks following its minting period. Recall that our daily collection-level price indexes are computed as the median prices observed on days with at least 5 trades (see Section 3.2). Therefore we are measuring the hypothetical return to an investor who minted from a collection and then sold it at the "common" collection price after N days. Across horizons up to 28 days, we find that higher experienced investor participation is associated with collections that experience higher post-mint price growth.

Table 7: Predicting Post-Minting-Period Price Index Returns

Notes. In this table, we report the results from the cross-sectional regression specified in (7) where the dependent variable is the post-minting-period price index return for a GC relative to its weighted average mint price. The key explanatory variable is our collection-level measure of experienced investor involvement as defined in (6). GC-level controls displayed in the table include the fraction of NFTs minted at a positive price, the largest value for the fraction of NFTs minted by a single wallet, whether the project has a roadmap, whether the artist who created the art is explicitly named on the project's website or roadmap, and whether that artist has professional web presence independent of the NFT project (zero if no artist). GC-level controls omitted from the table include the average number of items minted per wallet, the royalty rate, and all of the dummy variables shown in Appendix Table A.1. See Appendix Table A.6 for the full table of results with all control variables shown. See Section 2 and Appendix Section A for more detailed variable descriptions. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	1 Day		7 Days		14 Days		21 Days		28 Days	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Frac. Minted by Experienced (Ex Ante)	0.989***	0.841**	0.793**	0.818**	1.505***	1.408***	1.741***	1.602***	1.965***	1.521***
	(2.91)	(2.54)	(2.31)	(2.16)	(3.85)	(3.47)	(4.26)	(3.46)	(4.24)	(2.93)
Frac. Minted at Price > 0		-1.855***		-0.987**		-1.402***		-1.409**		-1.130*
		(-5.49)		(-2.30)		(-3.22)		(-2.50)		(-1.79)
Max Frac. Items Minted by Wallet		-0.757		-0.163		0.641		-1.275*		-1.038
		(-1.50)		(-0.12)		(0.74)		(-1.68)		(-1.19)
Has Roadmap		-0.060		0.070		-0.014		-0.112		0.014
		(-0.63)		(0.51)		(-0.10)		(-0.70)		(0.07)
Has Named Artist		-0.043		-0.032		-0.066		0.451***		-0.088
		(-0.44)		(-0.24)		(-0.37)		(2.68)		(-0.33)
Named Artist Has Twitter/Website		0.149		0.097		0.371**		0.014		0.615**
		(1.20)		(0.61)		(2.02)		(0.08)		(2.45)
Other GC-Level Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.078	0.228	0.044	0.134	0.076	0.195	0.086	0.168	0.079	0.183
N	429	429	477	477	461	461	438	438	404	404

Given this view, we are also interested in understanding what collection-level characteristics are associated with experienced investor involvement. To assess this question, we run cross-sectional specifications in which the dependent variable is our measure of experienced investor involvement in (6) and the explanatory variables include only the collection-level characteristics known prior to the minting period. We present these results in Appendix Table A.4. We find that experienced investors are less likely to participate in the primary market sales of GCs that have a roadmap, advertise rare items, or are a derivative of the CryptoPunks collection. On the other hand, they more likely to participate in the sales for projects associated with an artist with a web presence independent of the NFT collection.

4.2.2 Fees and returns

The findings in Tables 6 and 7 appear to show that experienced investors are more skilled at picking successful GCs. However, Column (6) of Table 5 shows that experienced investors actually achieve *lower* returns on average compared to inexperienced investors after controlling for buy-date and sell-date fixed effects. This relationship also shows up in aggregate statistics. If we simply calculate aggregate returns from only mint transactions, experienced investors achieved 147.7% while inexperienced investors made 266.7% (Appendix Figure A.7). Thus, while mints were extremely profitable on average, inexperienced investors did substantially better than experienced investors on mints.

To examine the drivers of experienced investors' underperformance during mints, we regress $r^{realized}_{i,j,c,t,\tau}$ and $r^{realized,nofees}_{i,j,c,t,\tau}$ on a dummy for seller experience for the sample of mints, with various fixed effects:

$$r_{i,j,c,t,\tau} = \beta \times Experienced\ Seller\ Dummy_i + \gamma X_{i,j,c,t,\tau} + \epsilon_{i,j,c,t,\tau}. \tag{8}$$

We present the results in in Table 8. Columns (1) to (3) show results for returns ignoring fees. Column (1) shows that experienced sellers achieve around 12% higher before-fee returns than inexperienced investors, which is consistent with the idea that experienced sellers pick collections that are more likely to succeed. Our estimate of β decreases substantially when controlling for GC or GC-buydate-selldate fixed effects, further supporting the idea that experienced sellers' excess returns come from their ability to pick successful collections.

In Columns (4) to (6), we show results for returns inclusive of fees. Column (4), which is identical to Column (6) of Table 5, shows that experienced sellers achieve approximately 6.2% *lower* returns than inexperienced investors after accounting for transaction fees. Our estimate of β remains negative when controlling for GC and buydate-selldate-GC fixed effects, implying that, conditional on purchasing items from the same collection, experienced investors pay higher fees.

4.2.3 Mint vs sale prices

Next, we test whether experienced sellers over- or under-perform relative to collection-level average returns. Suppose a trader mints an NFT and sells it at date t. The trader's total

Table 8: Experience and Realized Returns for Mint Transactions

Notes. In this table, we report the results from estimates of specification (8) in which we regress realized mint returns for each NFT on an experienced seller dummy, the log of the holding period, and various fixed effects. We only include realized return values where the purchase price was 0.01 ETH or more and these values are further truncated at the 99th percentile level. We also only include returns from trades in which the sale leg of the trade only involved a single NFT. Holding period is the fractional number of days the position was held. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Return from Mint Before Fees			Return from Mint Including Fees		
	(1)	(2)	(3)	(4)	(5)	(6)
Experienced Seller Dummy	0.120***	-0.015*	0.042***	-0.062***	-0.081***	-0.009*
	(11.93)	(-1.76)	(5.40)	(-9.14)	(-13.36)	(-1.67)
BuyDate-SellDate FE	Yes	Yes	No	Yes	Yes	No
GC FE	No	Yes	No	No	Yes	No
BuyDate-SellDate-GC FE	No	No	Yes	No	No	Yes
R^2	0.376	0.572	0.711	0.406	0.542	0.692
N	1,193,796	1,193,791	1,153,082	1,193,796	1,193,791	1,153,082

return can be broken down into four components: the average collection-level return; the amount by which the trader can mint at a price below the average mint price; the gas fee paid; and the amount by which the trader can sell at a price above the average collection sale price. We proceed to test whether experienced traders are able to "buy low" or "sell high" relative to the collections they purchase, by estimating the following specifications:

$$\log(Y_{i,j,c,t}) = \beta \times Experienced \quad Seller \quad Dummy_i + X_{i,j,c,t}\gamma + \epsilon_{i,j,c,t} \quad (9)$$

where $Y_{i,j,c,t}$ is either the mint price, the gas fee paid at mint, the sale price, or the fees paid upon sale. We control for various combinations of GC and date fixed effects.

The results are shown in Table 9 and the different specifications allow us to decompose returns into the four separate components. Columns (1) and (2) show results using $\log\left(Mint\ Price_{i,j,c,t}\right)$ as the dependent variable. The coefficients are significant and negative but also small, indicating that experienced investors pay approximately 10 basis points lower mint prices. Given that mint prices are fixed and set by the collection creator, this finding implies that experienced investors are more likely on average to take advantage of the bulk mint discounts when available.[19] Column (3) shows that experienced investors pay

[19] Recall from the discussion of primary market sales in Section 2.1 and Section 3.3 that many collections choose to set a schedule of mint prices depending on the number of NFTs purchased. For this reason, we use

approximately 7.8% higher gas prices for the same GCs. After controlling for GC-buydate fixed effects in Column (4), this decreases to 2.8%, suggesting that experienced sellers' higher gas fees are mostly due to the timing of their purchases. Column (5) shows that experienced sellers in fact sell items from the same GC at 4.1% *lower* prices than inexperienced sellers. However, column (6) shows that, after controlling for sell date, the price difference becomes very small (around 30 basis points). Thus, the results in Table 9 suggest that, controlling for entry and exit date, experienced sellers purchase and sell NFTs within a collection at similar prices to inexperienced sellers, but pay substantially higher gas fees. Columns (7) and (8) show that experienced sellers appear to pay lower fees upon sale, but these differences are mostly due to the fact that the sale prices are lower (Columns (5) and (6)) and fees upon sale are proportional. However, Column (8) shows that this difference decreases substantially when we control for GC-selldate fixed effects, suggesting that some component of this arises from experienced investors' ability to sell when sale gas fees are low.

Taken all together, our findings in this section suggest that experienced sellers enter mints late, when collections are close to minting out. As a result, experienced investors tend to purchase NFTs from collections with successful mints. However, experienced investors' trade execution within these collections is poor. Compared to inexperienced sellers, they pay higher gas fees upon minting the NFTs and they also achieve worse prices when they ultimately sell. The net effect is that experienced sellers' mint trades are actually less profitable on average than inexperienced sellers' mints.

Table 9: Experience, Mint Prices, Gas Fees, and Sale Prices

Notes. In this table, we report the results from estimates of specifications (9), where we regress log mint prices, gas fees, and sale prices on an experienced seller dummy and various fixed effects. We only include observations in which the purchase price was 0.01 ETH or more. We also only include trades in which the sale leg of the trade only involved a single NFT. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	ln(Mint Price)		ln(Gas from Mint)		ln(Sale Price)		ln(Fees from Sale)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experienced Seller Dummy	-0.001***	-0.001***	0.078***	0.028***	-0.041***	-0.003**	-0.048***	-0.009***
	(-4.60)	(-9.04)	(72.11)	(31.88)	(-24.15)	(-2.20)	(-28.41)	(-7.96)
GC FE	Yes	No	Yes	No	Yes	No	Yes	No
GC-BuyDate FE	No	Yes	No	Yes	No	No	No	No
GC-SellDate FE	No	No	No	No	No	Yes	No	Yes
R^2	0.963	0.981	0.804	0.883	0.553	0.819	0.569	0.831
N	1,200,493	1,199,269	1,200,291	1,199,067	1,200,493	1,185,253	1,200,493	1,185,253

the weighted average mint price as the representative collection-level mint price throughout our empirical analysis.

4.3 Secondary market returns

Next, we analyze the sources of experienced investors' outperformance in secondary markets. We regress $r^{realized}_{i,j,c,t,\tau}$ and $r^{realized,nofees}_{i,j,c,t,\tau}$ on a dummy for seller experience for the sample of secondary market trades, with various fixed effects:

$$r_{i,j,c,t,\tau} = \beta \times Experienced\ Seller\ Dummy_i + \gamma X_{i,j,c,t,\tau} + \epsilon_{i,j,c,t,\tau} \tag{10}$$

The results are shown in Table 10. The first few columns consider returns after accounting for fees with Columns (2) and (3) adding GC and buydate-selldate-GC fixed effects, respectively. The similar estimates for β across these specifications suggest that experienced investors' outperformance does not largely arise from picking good collections, or market timing within collections. Rather, experienced investors' excess returns in secondary markets appear to arise largely from better trade execution, controlling for collection, buy date, and sell date. Columns (4) to (6) consider returns after accounting for fees with Column (4) being identical to Column (7) of Table 5. The estimates for β decline suggesting that experienced investors pay slightly more than inexperienced investors in fees in secondary markets, decreasing their excess returns somewhat.

Table 10: Experience and Realized Returns for Secondary Market Transactions

Notes. In this table, we report the results from estimates of specification (10), where we regress realized secondary market returns on an experienced seller dummy and various fixed effects. The dependent variable is $r^{realized}_{i,j,c,t,\tau}$ in Columns (1)–(3), and $r^{realized,nofees}_{i,j,c,t,\tau}$ in Columns (4)–(6). We only include realized return values where the purchase price was 0.01 ETH or more and these values are further truncated at the 99th percentile level. We also only include returns from trades in which the both legs of the trade only involved the single NFT. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Return from Secondary Before Fees			Return from Secondary Including Fees		
	(1)	(2)	(3)	(4)	(5)	(6)
Experienced Seller Dummy	0.061***	0.082***	0.059***	0.044***	0.065***	0.048***
	(8.31)	(11.62)	(9.99)	(7.79)	(12.20)	(10.74)
BuyDate-SellDate FE	Yes	Yes	No	Yes	Yes	No
GC FE	No	Yes	No	No	Yes	No
BuyDate-SellDate-GC FE	No	No	Yes	No	No	Yes
R^2	0.307	0.382	0.784	0.323	0.408	0.799
N	928,453	928,415	713,369	928,453	928,415	713,369

The results in Table 10 show that, even after accounting for GC-buydate-selldate fixed effects, experienced sellers outperform inexperienced sellers. This implies that experienced sellers must be attaining either better buy prices, or better sell prices. To further test this, for each GC trade in our dataset, we construct the following sets of "synthetic returns":

$$\frac{Sold}{Paid}, \frac{Sold}{Index}, \frac{Index}{Paid}, \frac{Index}{Index} \tag{11}$$

The variable $\frac{Sold}{Paid}$ is the raw return. $\frac{Sold}{Index}$ calculates returns by using the actual sale price, and replacing the buy price with the GC index price on the buy date; $\frac{Index}{Paid}$ uses the actual buy price, and replaces the sale price with the index price; and $\frac{Index}{Index}$ uses indices for both the buy and sell prices. We then estimate the specification in Column (6) of Table 10, using each of the four synthetic returns as the dependent variable. These synthetic returns allow us break down whether experienced sellers' excess returns are largely coming from buying low or selling high. For example, the $\frac{Sold}{Index}$ replaces all buy prices by index prices, thus eliminating any difference in buy prices between experienced and inexperienced sellers. If experienced sellers continue to outperform under the $\frac{Sold}{Index}$, experienced sellers' outperformance must be driven by selling at high prices, rather than buying at low prices.

The results are shown in Table 11. The first column is identical to Column (6) of Table 10. Columns (2) and (3) show that the $\frac{Sold}{Index}$ return is slightly higher than the actual return, whereas the $\frac{Index}{Paid}$ return is actually negative. In words, in a counterfactual world where all experienced sellers bought at GC-level average prices, but sold at their realized sale prices, experienced sellers would in fact do 5.3% better on each trade on average. Conversely, if experienced sellers bought at their realized prices, but sold at the index, experienced sellers would actually *underperform* inexperienced sellers by 1.6%. Thus, experienced sellers' outperformance comes from the fact that they buy NFTs within a collection at slightly higher prices than inexperienced sellers, but sell at even higher prices.

As a simple sanity check of our methodology, Column (4) uses $\frac{Index}{Index}$ as the dependent variable. Since our GC indexes are daily, the coefficient on seller experience should be 0 with buydate-selldate-GC fixed effects, which we confirm empirically. Columns (5), (6), and (7) directly use the log of sale prices, buy prices, and gas fees paid as dependent variables, with GC-date fixed effects. Confirming the results in Columns (1) to (3), we find that experienced sellers sell for higher prices, buy for similar prices, and pay higher gas fees.

Note that, in Appendix B.1, we show that experienced investors underperform inexperienced investors for unrealized secondary market trades – that is, NFTs purchased in secondary markets which are held until the end of the sample. When we pool realized and unrealized returns, we find that experienced investors do slightly worse on average than inexperienced investors. Hence, it is not clear that experienced investors outperform after accounting for unrealized trades, though this conclusion may be somewhat sensitive to the way that unrealized returns are calculated, that is, how NFT valuations are imputed for NFTs held until the end of our sample period.

Table 11: Experience and Secondary Market Trading Execution

Notes. In Columns (1)–(4) of this table, we report the results from estimates of specification (10), where the dependent variable is a synthetic return, as defined in (11). In Columns (5)–(8), the dependent variable is the log sale price before fees, the log fees from the sale, the log purchase price, and the log gas paid. We only include realized return values where the purchase price was 0.01 ETH or more and these values are further truncated at the 99th percentile level. We also only include returns from trades in which the both legs of the trade only involved the single NFT. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1) Sold/Paid	(2) Sold/Index	(3) Index/Paid	(4) Index/Index	(5) ln(Sold b4 Fees)	(6) ln(Fees in Sale)	(7) ln(Paid b4 Fees)	(8) ln(Gas in Purchase)
Experienced Seller Dummy	0.048***	0.058***	-0.006**	-0.000	0.020***	0.010***	0.001	0.024***
	(10.74)	(10.13)	(-2.35)	(-0.00)	(12.77)	(6.34)	(0.48)	(27.30)
BuyDate-GC FE	No	No	No	No	Yes	Yes	No	No
SellDate-GC FE	No	No	No	No	No	No	Yes	Yes
BuyDate-SellDate-GC FE	Yes	Yes	Yes	Yes	No	No	No	No
R^2	0.799	0.984	0.872	1.000	0.854	0.848	0.871	0.741
N	713,369	713,369	713,369	713,369	924,728	924,728	927,519	927,519

5 Conclusion

In this paper, we analyzed the outperformance of experienced investors in the NFT market. After controlling for holding periods, experienced investors make 8.6 percentage points more per trade. This outperformance is mostly explained by the fact that experienced investors tend to mint more than inexperienced investors, and returns are higher for mints than secondary-market trades. Conditional on minting, experienced investors underperform inexperienced investors slightly due to paying higher gas fees. In secondary markets, experienced investors outperform slightly, by buying relatively high-priced NFTs within a collection, and selling for even higher prices. Our results push against hypotheses that the NFT market is "rigged" towards a small group of experienced investors; rather, experienced investors' returns appear to arise from good trade execution, and the simple strategy of minting more often.

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Appendix

A Supplementary Material for Section 2

This section describes additional details of our data and cleaning steps.

A.1 Data Sources and GC Sample Overview

Our primary data source is a transaction-level dataset scraped from Etherscan.io, which is a website that captures and displays data from the Ethereum blockchain. Our data include all on-chain transactions for the GCs in our sample between April 10, 2019, and March 31, 2022 at midnight UTC. Within the transaction-level data, we extract the following variables: transaction hash, which is a unique identifier on the Ethereum blockchain; transaction date and time; collection-level contract address; item ID, which is a number that identifies an item within a collection; the wallet addresses of the seller and buyer; transaction value in ETH, which is the price paid by the buyer; and gas fee paid in ETH. The GC-filtered dataset has over 6 million transactions of which approximately 48% are mints and the remainder are secondary market transactions (Table 1).

We compute a transaction price variable based on the transaction value as follows. First, we convert the transaction value from Wei to ETH by dividing it by 10^{18}. Wei is simply the smallest denomination of ETH, the native digital asset on the Ethereum blockchain. Next, we divide the ETH values by the number of items reported with the same transaction hash. We do this because the value provided is for the whole group when there are multiple items in the same transaction. We would therefore be necessarily overstating the true (but unobserved) prices for each item if we do not adjust for the number of items. By dividing the value equally, we are assuming that each item in a transaction has the same implied price.

A.2 Defining Generative Collections

As we discuss in Subsection 2.2, we restrict attention to generative collections. The specific set of filters we use to select collections is as follows.

1. **Each item corresponds to a unique piece of digital art.** Technically, all NFTs are unique in the sense that they have unique identifiers on the blockchain, hence their "non-fungible" nature. However, some NFT collections will include multiple items that

refer to the same digital art file, which would be like an artist creating multiple copies of the same painting.

2. **Items are variations on the same object/theme.** This condition ensures a degree of consistency across the items in a collection. It is admittedly a subjective feature that we determine during our data collection process.

3. **There exists a collection-level ERC-721 smart contract.** This collection-level smart contract not only formally ties together the items on the blockchain, but plays a crucial role in the initial crowdsale and governance of a GC as we describe later in this section. This condition also effectively restricts our sample to GCs on the Ethereum blockchain. Note that "ERC-721" refers to a "free, open standard that describes how to build non-fungible or unique tokens on the Ethereum blockchain."[20]

4. **Predetermined and fixed initial supply of items.** In these cases, this initial supply is common referred to as the "genesis supply." In addition to characterizing the contents of a collection, this condition provides a predetermined tangible goal that the creator is trying to attain in the initial crowdsale.

5. **Items in the genesis supply are sold on the primary market through a public sale.** This condition excludes collections in which the creator generates all the items on the blockchain and then sells them through the secondary market.

6. **Investors in the initial public sale receive a random item.** This condition further restricts the nature of the public sale, although it is quite common within the set of collections that meet the above conditions. It ensures that primary market investors are buying into the collection more broadly, not an individual item of interest.

We construct our sample of GCs, and implement these filters, through the following process. First, we scraped the rankings tables on the website OpenSea.io ("OpenSea"), the most popular NFT marketplace. This step, which we performed on a few dates in October 2021, generated an initial list of 7,987 NFT collections. We consider this set to represent the universe of NFT collections created until that time given the popularity of OpenSea. Moreover, we are not concerned about survivorship bias because we observe so many NFT collections in this sample that effectively failed (i.e., no secondary market activity and prices close to zero).[21]

[20] See http://erc721.org/.

[21] We cannot conclusively say that all failed NFT collections remain on the blockchain and continue to maintain an OpenSea collection page. However, we assume the extent to which any collections were removed from OpenSea was very small at most for two reasons. The first is the aforementioned high observed rate of failures in our sample. The second is that we are not aware of any driving mechanisms in practice

Second, we visually assessed the items in each collection to determine whether they met our GC criteria in terms of being (i) unique and (ii) variations on the same object/theme.[22] We are left with 2,545 potential GCs after this step. Third, we check each collection for whether or not there exists a central ERC-721 smart contract, which further restricts our list to 1,376 potential GCs. This step drops both Ethereum-based NFT collections without a central contract and also those on non-Ethereum blockchains. The latter group must ultimately be dropped regardless of our GC definition because the transaction-level data described in the next section only includes NFT collections on Ethereum.

In the final step of creating our list of GCs, we apply a few data filters that are both consistent with our GC criteria and necessary for our empirical analysis. The main filter is that the NFT collection must have a predetermined genesis supply. We manually gather this piece of information from a collection's OpenSea page, website, Twitter account, and Discord channel, as available. This variable is important to define a key measure of initial GC success: the number of items minted divided by genesis supply. In addition, we keep only GCs for which we have their primary market transaction data, which are required for computing many of our GC-level variables. Finally, we only keep collections for which at least 5% of the items sold in their primary sale were done so at a nonzero price. This filter captures our notion that a GC must have a public sale.

In aggregate, GCs raised the equivalent of $0.51 billion through primary market sales over the sample period, which represents nearly half of the total for all Ethereum-based NFT collections (Figure A.5). We compute the denominator in this figure using a transaction-level dataset from Moonstream, which contains all on-chain transactions for the universe of Ethereum-based NFT collections between April 1, 2021, and September 25, 2021.[23] Primary market sales represent inflows of capital into the NFT asset class and thus we document that GCs are a particularly attractive form of NFT collection to investors.

to remove stale ERC-721 smart contracts from the Ethereum blockchain or unsuccessful NFT collections from the OpenSea website. As an example, we note that the OpenSea collection page for Evolved Apes Inc remains active on OpenSea as of this manuscript date despite it being a well-documented scam in which the creator disappeared in October 2021 with $2.7 million in funds raised from investors (see, e.g., https://finance.yahoo.com/news/another-nft-rug-pull-evolved-084902519.html).

[22]In many cases, the collection description includes the term "generative" but we do not consider this a sufficient condition to be a GC.

[23]See Moonstream (2021) and `https://github.com/bugout-dev/moonstream/tree/main/datasets/nfts`.

A.3 Gathering Collection-Level Variables

We collect other information on GCs from project-specific websites. Summary statistics for these characteristics are listed in Table A.1. We gather data on whether a GC has a Twitter account, an independent website, and a Discord channel.[24] We gather data on whether each GC provides a "roadmap," which is a document that outlines planned future steps for the GC; and whether a GC highlights that certain items in their collection are rare, which is true for roughly one third of GCs. We collect data on whether the artist who created the art is explicitly named on the project's website or roadmap. If an artist is named, we further check whether they have a professional web presence (e.g., Twitter account or website) independent of the NFT project.

We manually evaluate whether the art in the NFT pictures is 3D, animated, and has music. We evaluate subjectively whether the art is "cute". A number of NFT collections are "derivatives" which clearly build off three popular projects: CryptoPunks, Bored Ape Yacht Club, and Loot. We label collections if they are clearly derivatives of these three projects.

A.4 Defining Collection-Level Variables

A.4.1 Fraction Minted by Experienced Investors

For an explicit measure of experienced investor involvement in each GC, we propose the share of experienced investor wallets that participate in the GC's primary market sale:

$$Frac.\,Minted\,by\,Experienced = \frac{NFTs\,Minted\,by\,Experienced}{All\,NFTs\,Minted}. \tag{12}$$

We need to be careful, however, about how we identify experienced wallets for this type of measure. A potential concern if we use the exact definition in Section 3.4 is that our measure would incorporate ex post information from the perspective of any given GC because both the thresholds and levels of trading activity would be based on the full sample. To mitigate this concern, we rely on ex ante indicators for identifying experienced wallets when computing the measure in (12).

To serve as the benchmark for comparison, we first compute the measure proposed in (12) using the GC activity thresholds based on the full sample as described in Section 3.4. Specifically, we define a wallet as corresponding to an experienced investor if it both

[24] Discord is a chat application, where community members can chat in different groups or "channels" with each other, and there are often private channels which are restricted to verified owners of NFTs within a collection.

minted from at least 6 GCs and traded within at least 11 GCs during our full sample. The corresponding indicators are used to compute the numerator in (12).

The ex ante version of (12) that we use in our analysis follows the same approach to identify experienced investors for the full sample as described above but with two key differences. The first is that the designation of an investor's experienced status is updated each date of the sample to make it an ex ante indicator. The second is that we impose the thresholds must be at least 2 distinct GCs for minting and trading. These minimum requirements make sure that we do not designate a large fraction of wallets as experienced early in the sample when the corresponding thresholds can be 0 or 1.

B Supplementary Material for Section 4

B.1 Unrealized Returns

Our analysis in the main text focuses on realized returns. However, many NFTs are held to the end of our sample; our results may simply reflect some selection bias, from the fact that experienced and inexperienced investors may have different propensities to hold NFTs that are performing well. To account for this possibility, we approximate unrealized returns using our collection-level price indexes (see Section 3.2). For NFTs which are held until the end of our sample, we assign a value equal to the price index at the end of our sample. Specifically, we compute the end-of-sample price index as the median price of the trades observed between March 25 and March 31, 2022. We require at least 5 trades in this period as with our daily price index. If we are not able to compute a price index for any day during this period due to a lack of trades, we consider the price index to be zero for the purposes of the unrealized gain calculation. The reason for this assumption is that some NFT collections essentially "die out", having zero or close-to-zero volume; we assume that these NFT collections are essentially worthless. After filling in these estimated values for unrealized trades, we can calculate unrealized returns for every NFT held until the end of our sample period, as:

$$r^{unrealized}_{i,j,c,T,\tau} \equiv \frac{(1 - RoyaltyRate_c - 2.5\%) \times PriceIndex_{c,T}}{Price^{Purch}_{i,j,c,\tau} + Gas_{i,j,c,\tau}} - 1 \tag{13}$$

where T is the end of our sample.

First, we show that accounting for unrealized returns does not change our headline conclusion that experienced investors outperform inexperienced investors. In Appendix Figure A.8, we calculate total returns by investor type. Experienced investors tend to outperform inexperienced investors on average based on this figure.

We then estimate versions of our main specification, (4), including unrealized returns. The results are shown in Table A.7. In the first four columns, we show the results focusing only on unrealized returns, for all trades, mints only, and secondary market trades only. Surprisingly, we find that experienced investors actually substantially underperform inexperienced investors. This is true when combining mints and secondary market purchases, when we control for whether the trade was a mint, and when we analyze mints and secondary market transactions separately.

To check whether this changes our conclusion that experienced investors outperform, in Columns (5) to (8), we combine realized and unrealized returns, and estimate (4) in the pooled sample. We find that experienced investors' outperformance persists in the pooled sample. Comparing the results to Column (3) of Table 4 in the main text, our estimate of β decreases by a few percentage points. However, the basic patterns we discuss in the main text largely persist: experienced investors outperform overall, a large fraction of outperformance is explained by a higher propensity to mint, and experienced investors underperform in mints. One difference from the main text is that experienced investors also slightly underperform in secondary markets after accounting for unrealized returns (Column (8)).

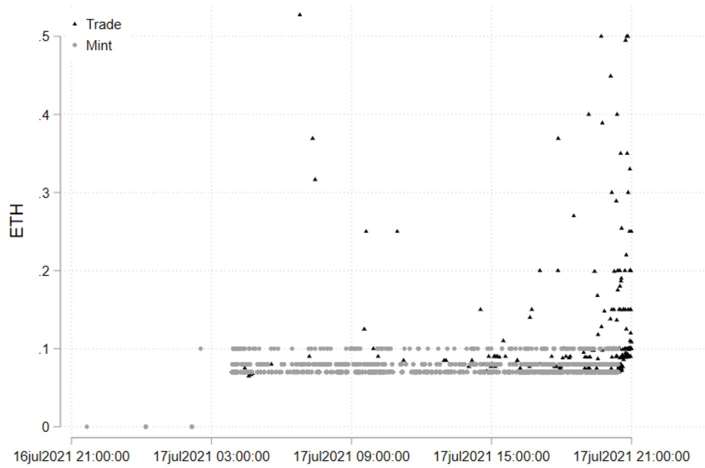

Figure A.1: SupDucks Primary Market Sale

Notes. This figure shows all transactions that occurred within the SupDucks primary market sale period through 9pm UTC on July 17, 2021. the aggregate transaction fees paid for positions that were ultimately closed as realized returns divided by the total amount spent obtaining those positions (transaction prices plus gas). The figure also breaks down the fees into royalties paid back to the creator during the sale, transaction fees paid to OpenSea, and the total gas paid by the investor who realized the return.

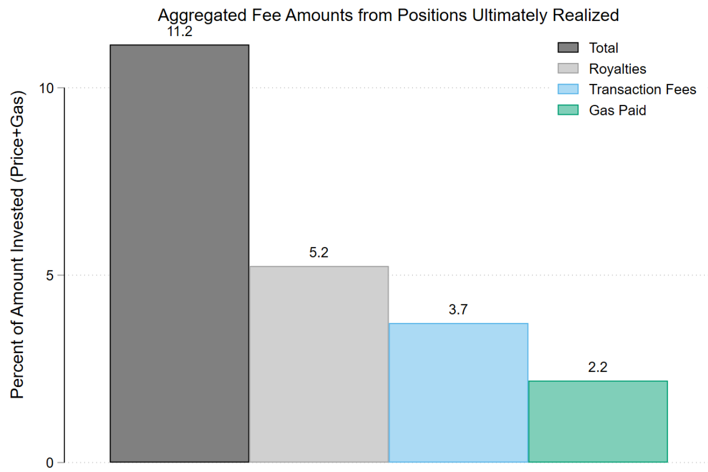

Figure A.2: Transaction Fees

Notes. This figure reports the aggregate transaction fees paid for positions that were ultimately closed as realized returns divided by the total amount spent obtaining those positions (transaction prices plus gas). The figure also breaks down the fees into royalties paid back to the creator during the sale, transaction fees paid to OpenSea, and the total gas paid by the investor who realized the return.

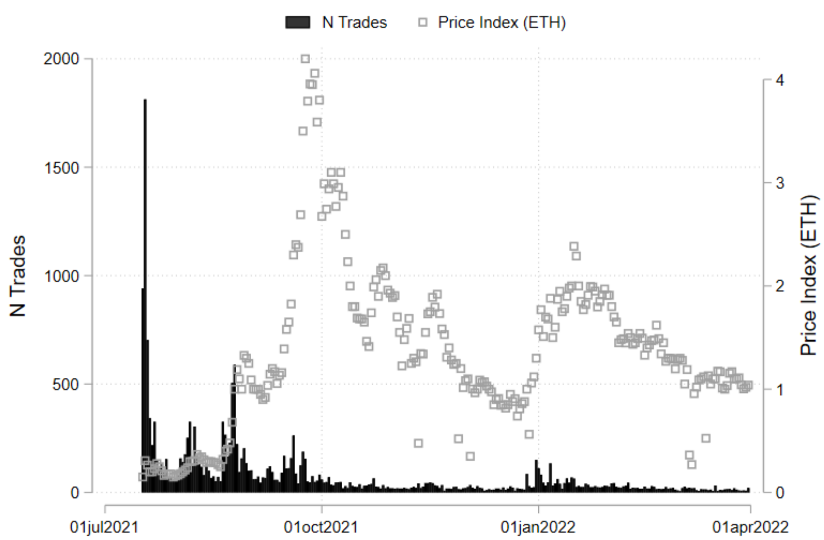

Figure A.3: SupDucks Example: Post-Mint Trading Period

Notes. This figure shows the daily trade volume and price index for the SupDucks GC since its initial primary market sale beginning on July 16, 2021. See Section 3.2 for a description of our price index construction.

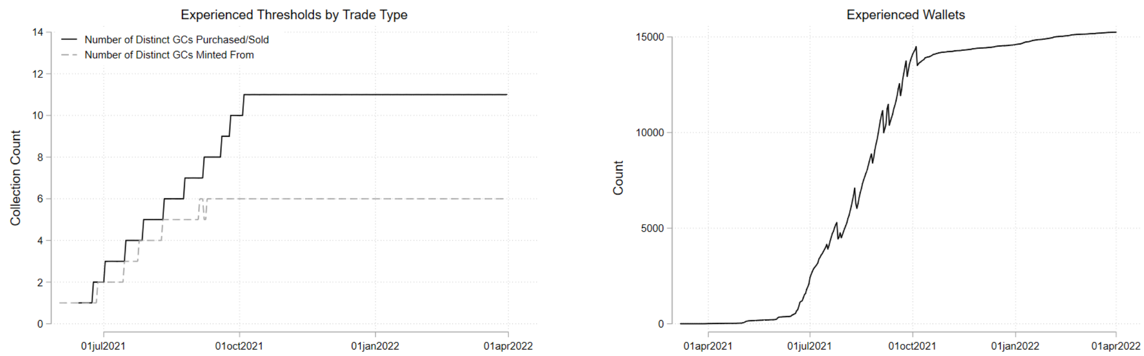

Figure A.4: Experienced Investor Thresholds and Counts Over the Sample Period

Notes. This figure reports the experienced investor minimum thresholds (left panel) and number of experienced investors (right panel) throughout our sample period. In order to be considered experienced, an investor must satisfy both activity-based thresholds using only their activity prior to the given date.

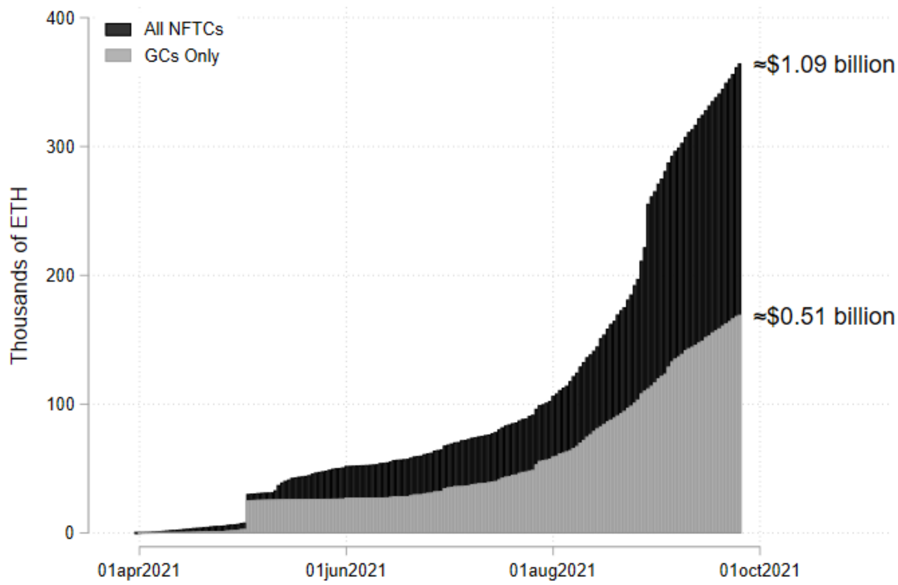

Figure A.5: Cumulative Funds Raised Through Primary Market Sales

Notes. This figure shows the accumulated amount of funds raised through the primary sales by our sample of GCs using our manually collected transaction-level data and amount raised by the full sample of NFT collections in the Moonstream data (see description in text). Dollar estimates are based on an exchange rate of $3,000 per ETH, which was the approximate ETH-USD exchange rate at the end of September 2021. In determining the full sample of NFT collections within the Moonstream data, we exclude a few collections that appear to be related to decentralized finance protocols. We do so because they are both large and do not represent NFT art collections. The specific collection-level contract addresses we exclude are the following: 0xC36442b4a4522E871399CD717aBDD847Ab11FE88 (Uniswap V3 Positions), 0x58A3c68e2D3aAf316239c003779F71aCb870Ee47 (Curve SynthSwap), 0xb9ed94c6d594b2517c4296e24A8c517FF133fb6d (Hegic ETH ATM Calls Pool), and 0x3AFF7B16489Fcc59483DE44e96Bd9Ec533915924 (BiFi Position).

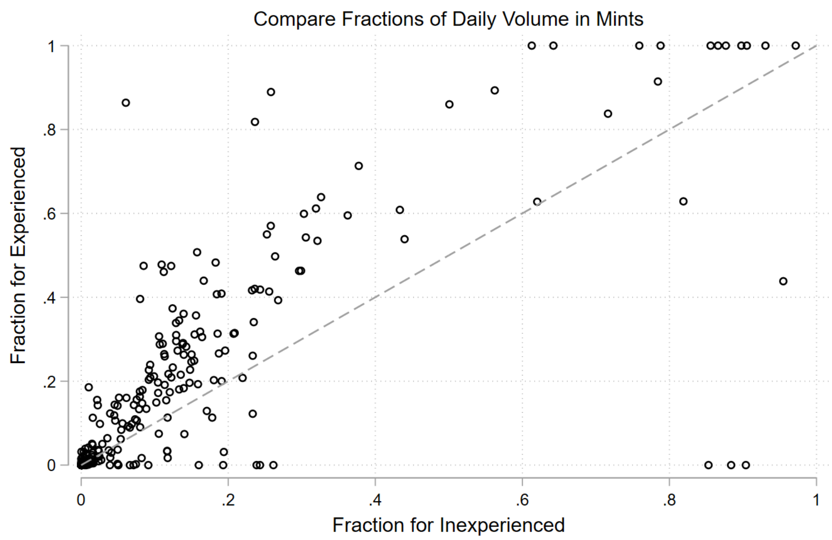

Figure A.6: Relative Minting Activity by Investor Group

Notes. Each circle in this figure represents a date within our sample. The x-axis value is the fraction of mints by inexperienced investors relative to their total number of trades (mints and secondary market transactions). The y-axis value is the same measure but for experienced investors. Experienced investors minted relatively more on a given date if the circle market lies above the dashed $y = x$ line.

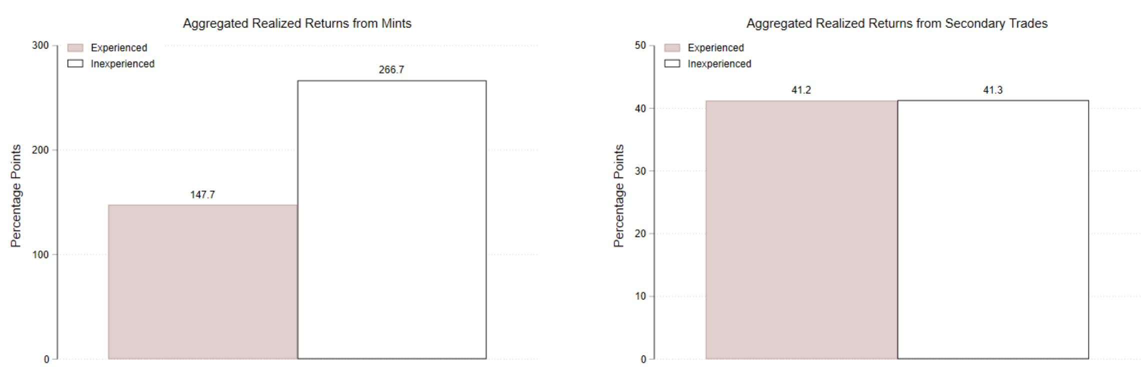

Figure A.7: Realized Returns by Investor Type: Mints and Secondary Market Trades

Notes. Realized returns after fees are computed as in (2). Investor type is assigned to each trade based on the investor's experienced status as of the purchase date (see Section 3.4 for details). The panels report aggregate returns after fees for mints and secondary market trades, respectively. Aggregate returns are computed as weighted averages of the trade-level returns. We only use returns from trades in which the both legs of the trade only involved the single NFT with the exception that the prior trade can involve multiple NFTs if it was a mint.

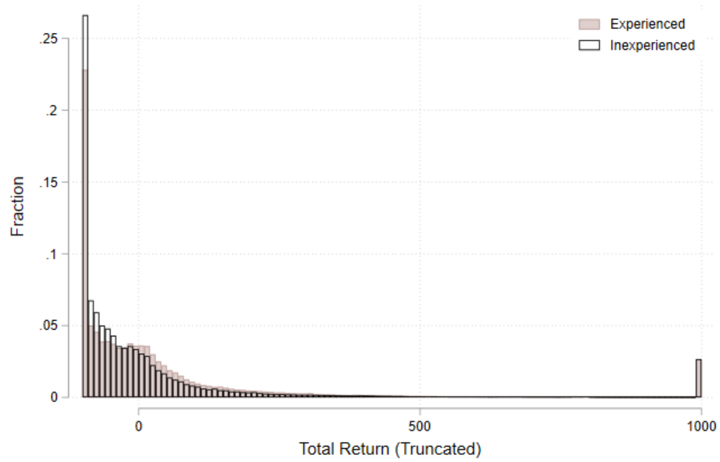

Figure A.8: Total Returns by Investor Type

Notes. This figure reports the distribution of total returns after fees at the trade level by investor type. Total returns include both realized returns after fees are computed as in (2) and unrealized returns after fees as in (13). Investor type is assigned to each trade based on the investor's experienced status as of the purchase date (see Section 3.4 for details). We only use returns from trades in which the both legs of the trade only involved the single NFT with the exception that the prior trade can involve multiple NFTs if it was a mint. For the top panel, we further restrict our sample to those in which the purchase price as at least 0.01 ETH.

Table A.1: Overview of GC Characteristics

Notes. In this table, we summarize the dummy variables that we created for each GC in our sample based on manually gathered data. The sources for our manual data gathering efforts are GC-specific webpages including but not limited to their OpenSea webpage. "Has Website" refers only to independent websites (e.g., an OpenSea webpage does not count). A "roadmap" is a document provided by a GC creator that outlines their planned future steps for the GC. "Has Charity Description" is true as long as the GC claims that at least part of its proceeds will go to a specified charity. The determination of the art characteristics are subjective based on our review.

	N	Count	Mean
Has Twitter	692	670	0.97
Has Website	692	663	0.96
Has Discord	692	593	0.86
Has Roadmap	692	404	0.58
Advertises Rare Items	692	235	0.34
Has Charity Description	692	116	0.17
Has Named Artist	692	296	0.43
Named Artist Has Twitter	692	136	0.20
Named Artist Has Website	692	35	0.05
Art is 3-D	692	221	0.32
Art is Animated	692	65	0.09
Art Has Music	692	14	0.02
Art Is Cute	692	40	0.06
Art Is Punk Derivative	692	22	0.03
Art Is BAYC Derivative	692	17	0.02
Art Is Loot Derivative	692	11	0.02

Table A.2: Top 10 GCs by Implied Collection Value as of Sep. 25, 2021

Notes. In this table, we report the top 10 GCs according to their price-index-implied valuation as of September 25, 2021. Mint price is the weighted average value (i.e., total amount of ETH raised in mint transactions divided by the total number of items minted). See Section 3.2 for a description of our price index construction. Return is the price index divided by the mint price minus 1. Implied value in USD computed as the price index times the number of items times $3,000 per ETH, which was the approximate ETH-USD exchange rate at the end of September 2021.

Rank	Name	First Mint Date	Mint Price ETH	Price Index ETH	Return %	N Items	Implied Value USD Mlns
1	Bored Ape Yacht Club	04/22/21	0.08	39.20	49,047	10,000	1,176.0
2	Meebits	05/03/21	1.10	4.46	304	20,000	267.8
3	Cool Cats NFT	06/27/21	0.02	8.60	40,221	9,933	256.3
4	SupDucks	07/16/21	0.07	4.10	5,627	10,001	123.0
5	World of Women	07/27/21	0.07	2.80	3,982	10,000	84.0
6	Sneaky Vampire Syndicate	09/09/21	0.08	2.39	2,918	8,888	63.7
7	Pudgy Penguins	07/22/21	0.03	2.20	7,229	8,888	58.7
8	0N1 Force	08/15/21	0.08	2.24	2,808	7,777	52.3
9	The Doge Pound	07/12/21	0.07	1.65	2,395	10,000	49.5
10	Rumble Kong League	07/27/21	0.08	1.53	1,819	10,000	45.9

Table A.3: Summary Statistics by GC Investor Type

Notes. In this table, we summarize investor-level variables separately for experienced and inexperienced GC investors. Inexperienced investors that never engaged in a transaction with a non-zero price are excluded. See Section 4.1 for a description of how we measure realized returns. We only compute investor-level realized returns for those that purchased at least 0.01 ETH worth of items to avoid capturing large but economically insignificant return values. See Section B.1 for a description of how we measure unrealized gains and returns. As with realized returns, we only compute unrealized returns for those that purchased at least 0.01 ETH worth of items to avoid capturing large but economically insignificant return values.

Panel A. Experienced

	N	Mean	SD	Min	10%	50%	90%	Max
ETH Minted	11,847	6.04	16.96	0	0.69	2.48	13.17	1,130
ETH Traded, Sold	11,847	27.31	67.09	0	1.79	10.84	65.10	4,085
ETH Traded, Purchased	11,847	16.48	40.43	0	1.09	6.53	36.39	1,320
N Positions Realized	11,847	70.32	132.40	0	7.00	33.00	158.00	4,844
Realized Gross Profit (ETH)	11,847	17.00	54.85	-93	0.64	5.77	40.70	3,626
Realized Gross Return (%)	11,652	244.52	592.46	-88	35.57	133.99	466.60	26,775
N Positions Still Unrealized	11,847	71.32	189.29	0	8.00	35.00	147.00	7,492
ETH Spent Positions Still Unrealized	11,847	11.53	33.17	0	0.66	4.48	24.60	1,327
Unrealized Gain Return (%)	11,764	78.92	311.07	-100	-53.63	3.64	257.95	13,150

Panel B. Inexperienced

	N	Mean	SD	Min	10%	50%	90%	Max
ETH Minted	280,026	0.35	3.18	0	0.00	0.07	0.63	639
ETH Traded, Sold	280,026	1.38	13.41	0	0.00	0.00	1.80	2,473
ETH Traded, Purchased	280,026	1.89	14.17	0	0.00	0.10	3.04	2,448
N Positions Realized	280,026	2.01	9.31	0	0.00	0.00	5.00	1,136
Realized Gross Profit (ETH)	280,026	0.80	10.01	-481	0.00	0.00	0.97	2,853
Realized Gross Return (%)	84,051	344.84	1624.38	-100	-15.11	97.87	735.86	245,855
N Positions Still Unrealized	280,026	6.41	20.96	0	1.00	2.00	14.00	3,517
ETH Spent Positions Still Unrealized	280,026	1.63	12.17	0	0.00	0.20	2.69	1,819
Unrealized Gain Return (%)	245,084	65.59	790.05	-100	-84.66	-22.22	156.42	138,615

Table A.4: Predicting Experienced Investor Involvement

Notes. In this table, we report the results from the cross-sectional regressions where the dependent variable is the collection-level measure of experienced investor involvement as defined in (6). See Section 2 for variable descriptions. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Frac. Minted by Experienced (Ex Ante)		Frac. Minted by Experienced (Full Sample)	
	(1)	(2)	(3)	(4)
Has Roadmap	-0.063***	-0.062***	-0.067***	-0.070***
	(-3.70)	(-4.05)	(-4.83)	(-5.70)
Advertises Rare Items	-0.030**	-0.027*	-0.024**	-0.023**
	(-2.03)	(-1.83)	(-2.13)	(-2.05)
Named Artist Has Twitter/Website	0.052**	0.056***	0.052***	0.050***
	(2.57)	(3.00)	(3.06)	(3.12)
Art Is Punk Derivative	-0.114***	-0.111***	-0.082***	-0.077***
	(-3.20)	(-3.13)	(-2.89)	(-2.70)
Other GC-Level Controls	Yes	No	Yes	No
Week FE	Yes	Yes	Yes	Yes
R^2	0.253	0.233	0.226	0.212
N	687	687	686	686

Table A.5: Predicting Minting Period Success

Notes. In this table, we report the results from the cross-sectional regression specified in (7) where the dependent variable is a minting period outcome for a GC. The key explanatory variable is our collection-level measure of experienced investor involvement as defined in (6). GC-level controls include the fraction of NFTs minted at a positive price, the largest value for the fraction of NFTs minted by a single wallet, the log of the weighted average mint price, the average number of items minted per wallet, the royalty rate, and all of the dummy variables shown in Appendix Table A.1. See Section 2 and Appendix Section A for more detailed variable descriptions. Standard errors are heteroskedasticity-consistent. *t*-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Dummy Minted All Genesis		N Items Minted / Genesis Supply		ln(Days to Mint Full)	
	(1)	(2)	(3)	(4)	(5)	(6)
Frac. Minted by Experienced (Ex Ante)	1.199***	1.006***	0.966***	0.741***	-6.569***	-7.162***
	(10.03)	(7.46)	(9.31)	(6.40)	(-7.31)	(-10.09)
Frac. Minted at Price > 0		0.354***		0.158		-1.005
		(2.98)		(1.58)		(-1.32)
Max Frac. Items Minted by Wallet		-0.586***		-0.818***		1.178
		(-2.64)		(-3.95)		(0.69)
Average Items Minted per Wallet		0.000**		0.000***		0.001***
		(1.99)		(2.78)		(2.88)
Has Twitter		0.127		0.033		1.928**
		(1.04)		(0.32)		(2.48)
Has Website		0.057		0.100		0.102
		(0.56)		(1.07)		(0.21)
Has Discord		0.036		0.045		-0.236
		(0.69)		(0.99)		(-0.70)
Has Roadmap		-0.075*		-0.090**		0.295
		(-1.77)		(-2.55)		(1.22)
Has Charity Description		-0.024		-0.018		-0.072
		(-0.50)		(-0.43)		(-0.31)
Advertises Rare Items		0.044		0.044		-0.101
		(1.14)		(1.38)		(-0.45)
ln(Weighted Average Mint Price)		-0.001		0.010		-0.171
		(-0.03)		(0.50)		(-1.40)
Royalty Rate		-0.614		-0.070		-9.615**
		(-0.84)		(-0.11)		(-2.20)
Has Named Artist		0.011		0.002		0.172
		(0.23)		(0.06)		(0.68)
Named Artist Has Twitter/Website		0.115**		0.088**		0.138
		(2.15)		(1.99)		(0.48)
Art is 3-D		0.046		0.052		0.205
		(1.15)		(1.57)		(1.02)
Art is Animated		-0.017		0.012		0.723**
		(-0.23)		(0.21)		(2.22)
Art Has Music		-0.014		-0.091		-0.761
		(-0.11)		(-0.85)		(-1.05)
Art Is Cute		-0.015		-0.045		-0.224
		(-0.21)		(-0.72)		(-0.58)
Art Is Punk Derivative		-0.002		-0.041		0.362
		(-0.02)		(-0.52)		(0.71)
Art Is BAYC Derivative		0.096		0.078		-0.183
		(0.86)		(0.81)		(-0.40)
Art Is Loot Derivative		-0.033		-0.108		-1.015
		(-0.23)		(-0.78)		(-1.40)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.165	0.240	0.155	0.256	0.331	0.418
N	686	686	686	686	342	342

Table A.6: Predicting Post-Minting-Period Price Index Returns

Notes. In this table, we report the results from the cross-sectional regression specified in (7) where the dependent variable is the post-minting-period price index return for a GC relative to its weighted average mint price. The key explanatory variable is our collection-level measure of experienced investor involvement as defined in (6). GC-level controls include the fraction of NFTs minted at a positive price, the largest value for the fraction of NFTs minted by a single wallet, the average number of items minted per wallet, the royalty rate, and all of the dummy variables shown in Appendix Table A.1. See Section 2 and Appendix Section A for more detailed variable descriptions. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	1 Day		7 Days		14 Days		21 Days		28 Days	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Frac. Minted by Experienced (Ex Ante)	0.989***	0.841**	0.793**	0.818**	1.505***	1.408***	1.741***	1.602***	1.965***	1.521***
	(2.91)	(2.54)	(2.31)	(2.16)	(3.85)	(3.47)	(4.26)	(3.46)	(4.24)	(2.93)
Frac. Minted at Price > 0		-1.855***		-0.987**		-1.402***		-1.409**		-1.130*
		(-5.49)		(-2.30)		(-3.22)		(-2.50)		(-1.79)
Max Frac. Items Minted by Wallet		-0.757		-0.163		0.641		-1.275*		-1.038
		(-1.50)		(-0.12)		(0.74)		(-1.68)		(-1.19)
Average Items Minted per Wallet		0.000**		0.000		-0.000		0.000		0.000
		(2.04)		(0.56)		(-0.45)		(1.08)		(0.62)
Has Twitter		0.359		0.355		1.042***		1.227*		2.677***
		(0.93)		(1.26)		(3.08)		(1.74)		(4.77)
Has Website		-0.163		0.099		0.458		0.160		0.335
		(-0.50)		(0.39)		(1.43)		(0.51)		(0.71)
Has Discord		0.044		0.435*		0.376		0.371		0.624
		(0.30)		(1.93)		(1.64)		(1.39)		(1.35)
Has Roadmap		-0.060		0.070		-0.014		-0.112		0.014
		(-0.63)		(0.51)		(-0.10)		(-0.70)		(0.07)
Has Charity Description		-0.067		0.054		-0.220		-0.233		-0.323
		(-0.56)		(0.39)		(-1.39)		(-1.22)		(-1.57)
Advertises Rare Items		0.002		0.022		-0.290**		-0.122		-0.392*
		(0.02)		(0.19)		(-2.21)		(-0.87)		(-1.94)
Royalty Rate		1.999		4.595**		0.993		0.760		0.391
		(1.04)		(2.01)		(0.37)		(0.26)		(0.08)
Has Named Artist		-0.043		-0.032		-0.066		0.451***		-0.088
		(-0.44)		(-0.24)		(-0.37)		(2.68)		(-0.33)
Named Artist Has Twitter/Website		0.149		0.097		0.371**		0.014		0.615**
		(1.20)		(0.61)		(2.02)		(0.08)		(2.45)
Art is 3-D		0.077		0.013		0.088		-0.126		-0.046
		(0.78)		(0.11)		(0.67)		(-0.83)		(-0.29)
Art is Animated		-0.281*		-0.034		0.006		0.303		0.329
		(-1.72)		(-0.19)		(0.03)		(1.26)		(1.61)
Art Has Music		0.123		0.295		0.387		0.659		0.328
		(0.68)		(0.87)		(0.55)		(1.14)		(0.64)
Art Is Cute		0.038		0.085		0.531**		0.199		0.660**
		(0.26)		(0.41)		(2.15)		(0.54)		(2.33)
Art Is Punk Derivative		-0.064		-0.230		-0.057		-0.366		-0.556
		(-0.40)		(-0.92)		(-0.19)		(-1.14)		(-1.21)
Art Is BAYC Derivative		0.115		0.307		0.551**		0.501*		0.598**
		(0.57)		(1.38)		(2.00)		(1.93)		(2.06)
Art Is Loot Derivative		-0.361		2.910***		-1.226		0.786		0.215
		(-0.60)		(4.47)		(-0.70)		(1.38)		(0.21)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.078	0.228	0.044	0.134	0.076	0.195	0.086	0.168	0.079	0.183
N	429	429	477	477	461	461	438	438	404	404

Table A.7: Regressions at Trade Level: Realized and Unrealized Returns

Notes. In this table, we report the results from estimates of specification (4), in which we regress realized and unrealized returns for each NFT on an experienced seller dummy, the log of the holding period, and buydate-selldate fixed effects. The sample consists of only unrealized returns in the first four columns, and realized and unrealized returns in the last four columns. We only include realized return values where the purchase price was 0.01 ETH or more, and these values are further winsorized at the 1st and 99th percentile level. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Unrealized Returns Only				Both Realized and Unrealized Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	All	Mints	Secondary	All	All	Mints	Secondary
Experienced Dummy	-0.048***	-0.044***	-0.033***	-0.059***	0.020***	-0.033***	-0.048***	-0.009**
	(-17.07)	(-15.82)	(-9.18)	(-14.14)	(7.27)	(-11.98)	(-12.40)	(-2.46)
BuyDate-SellDate FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BuyDate-SellDate-IsMint FE	No	Yes	No	No	No	Yes	No	No
R^2	0.183	0.226	0.276	0.145	0.340	0.405	0.434	0.293
N	2,607,575	2,607,574	1,357,128	1,250,446	4,736,011	4,729,893	2,550,954	2,178,939