Market Manipulation in Non-Fungible Token Markets*

Sebeom Oh†

July 30, 2024

Abstract

This study investigates wash trading and insider trading in the Non-Fungible Token (NFT) market using transaction data from 557 Ethereum blockchain collections. Despite over 422 million USD in wash trading, its impact on market outcomes is minimal. As cryptocurrency rewards from some marketplaces are proportional to trading volume, the rewards hypothesis partially explains wash trading, while no evidence supports using wash trading to obtain verification marks on the dominant marketplace. Insider purchases, involving wallets receiving free items in the primary market, significantly predict future price increases. Non-insiders with strong community ties can also predict future returns, underscoring the importance of community-based information. These findings highlight the utility of public blockchain data in understanding market manipulations.

Keywords: Speculative Market; Market Manipulation; Transparency; Blockchain

JEL Classifications: G12, G14

*I'm grateful to J.H. John Kim, Samuel Rosen, Oleg Rytchkov, Kanghyun Cho, Jongsub Lee (discussant), Donghoon Kim (discussant), Dongwha Shin (discussant), De-Rong Kong (discussant), Xin Tong (discussant), and Justin Mohr (discussant) for their invaluable feedback and discussions that greatly contributed to this paper. Thanks also to participants of various conferences, including Temple University, 2023 AKFA, APAD, CFEA, Shanghai-Edinburgh-UCL Fintech Conference, SFA, Boca-ECGI Corporate Finance and Governance Conference, AFBC, and 2024 EasternFA Conference for their constructive comments. This work was supported by the 25th Young Scholars Interdisciplinary Funds at Temple University. All errors are my own, and further feedback is welcome.

†Temple University Fox School of Business. Contact: sebeom.oh@temple.edu.

1 Introduction

Can investors detect manipulative behaviors from publicly available transaction-level data and avoid market-wide manipulations? This paper aims to answer these questions within the context of non-fungible token (NFT) markets by using blockchain data to explore market integrity and investor behavior. NFTs, which are digital assets like profile pictures, leverage blockchain technology for fundraising. Each NFT is finite, unique, and indivisible, which makes it ideal for tracking ownership and fraudulent trading behaviors. This unique structure provides a novel perspective for studying market misconduct, which was not possible in traditional finance research.

Although this paper does not primarily focus on defining NFTs, a brief introduction is necessary. An NFT is a digital proof of ownership recorded on the blockchain, often part of a themed collection. For example, an apartment company (NFT creator) might raise funds for a new complex (NFT collection) by pre-selling units (NFT items). Investors can track the transaction history of each NFT item. NFTs are traded for various reasons, such as being status symbols or membership tokens. NFTs can act as Veblen goods like art or wine, offering aesthetic appeal and potentially granting voting rights or unique privileges in digital realms such as games or metaverses (see Oh, Rosen, and Zhang (2023)). For investors seeking significant returns, NFTs might offer substantial economic value. For instance, an NFT sold for 190 USD in the primary market was later sold for around 2.9 million USD. NFT creators raise funds by offering their collections to early investors, similar to equity crowdfunding, initial coin offerings, or initial public offerings, and earn fees from secondary market sales.

NFT markets gained significant traction during the cryptocurrency bubble between 2021 and early 2022. In 2022, NFT transactions reached 2.4 billion USD, surpassing the 1.08 billion USD in the crowdfunding market[1]. However, the unregulated nature of these markets poses significant challenges. Often, anonymous NFT creators abandon projects if

[1]See the data from Statista for crowdfunding (https://www.statista.com/outlook/dmo/fintech/digital-capital-raising/crowdfunding/worldwide) and for NFT (https://www.statista.com/outlook/dmo/fintech/digital-assets/nft/worldwide).

they are unsuccessful or commit fraud by raising funds and then disappearing[2].

Even successful NFT projects face scrutiny due to potential insider trading and wash trading, with several instances voluntarily reported by the community[3] similar to cryptocurrency markets (Cong, Li, Tang, and Yang, 2023b; Aloosh and Li, 2023). Wash trading manipulates prices and volumes by creating fake trading activity to attract investors. Despite the transparency of the blockchain, concrete evidence of these behaviors is limited. The distinct characteristics of NFT markets, such as a finite number of unique items, theoretically enable easier on-chain analysis compared to equity or cryptocurrency markets.

In this paper, I first examine the impact of wash trades on future price index returns and volume changes for 557 NFT projects that successfully minted (i.e., sold) all items in the primary market from March 2021 to December 2021 and traded until February 2023. According to the U.S. Internal Revenue Service (IRS), wash trades are defined as three types of transactions: (1) identity trades, where the seller and buyer are the same wallet, (2) 1-1 trades, where a seller repurchases the same item within 7 days after selling, and (3) matched orders, where three wallets are involved in trading and all trades occur within 7 days. Surprisingly, wash trades do not significantly impact future market outcomes. Their ineffectiveness persists in same-day market outcomes, long-term market outcomes, and during both bubble and crash periods.

In the sample, wash trades make up only 0.3% of 3.6 million secondary market transactions but account for over 422 million dollars. Related literature suggests that a monopolistic environment, like the NFT market dominated by OpenSea, leads to ineffective market outcomes (e.g., Aloosh and Li (2023)), whereas competitive markets may see boosted platform activity rankings through wash trading (e.g., Cong et al. (2023b)). This paper tests the rewards and labeling hypotheses. One possible motive for wash trading is cryptocurrency rewards from marketplaces with low platform fees and reward distributions proportional to transaction value (e.g., Morgia, Mei, Mongardini, and Nemmi (2023)). About half of the

[2]The NFT community calls this a rug pull, with examples like Frosties and Evolved Apes. The Frosties founders were arrested, but such cases are rare.

[3]See articles from Chainalysis (https://blog.chainalysis.com/reports/2022-crypto-crime-report-preview-nft-wash-trading-money-laundering/) and Decrypt (https://decrypt.co/91510/looksrare-has-reportedly-generated-8b-ethereum-nft-wash-trading), or @hildobby_ (https://community.dune.com/blog/nft-wash-trading-on-ethereum) for examples.

wash traders who claimed rewards earned positive profits, some even millions of dollars, partially explaining their motives. Additionally, creators might wash trade to get a verified mark on OpenSea for collections traded over 75 ETH. However, the McCrary density test found no evidence of manipulation around this cutoff, suggesting no statistical support for creators' involvement in artificially boosting trading volume at non-reward distributing and monopolistic marketplaces.

This paper also examines whether insider trading exists in the NFT market by using on-chain transaction data. Insiders are defined as wallets that have received free items from creators in the primary market, with a focus on their purchase activity to minimize frequent trading noise. Insiders constitute 4.9% of the total wallets that participated in the primary market. The results indicate that insider buying activity strongly predicts future daily price index returns. A one standard deviation increase in insider buying activity leads to approximately a two percentage point increase in future daily median price returns, suggesting that insiders exploit information asymmetry in NFT markets. Further analysis reveals that online communities serve as significant information channels. Both insiders and non-insiders with substantial ties to these communities can accurately forecast future returns on their purchases.

One might question the utility of focusing on NFT markets, given their speculative nature and the possibility that they may not endure beyond the next five years. However, the structural parallels between NFT markets and established collectible markets–such as those for housing, art, or wine–distinguished by blockchain's transparent transaction data, underscore the significance of this study. This transparency enables a level of market analysis previously unattainable, offering insights into market behaviors, regulatory needs, and investor strategies across a broad spectrum of assets (See Jiang and Li (2024) for a detailed survey). Exploring NFT markets, therefore, not only enriches our understanding of digital assets but also sheds light on the dynamics in traditional collectibles and social goods markets through the lens of transparency.

This paper makes two main contributions. Firstly, it discusses the use of blockchain technology as a forensic finance tool to detect insider and wash trading in a recent crypto asset. The market structure of NFTs provides an opportunity to study manipulative behaviors more precisely compared to equity or cryptocurrency markets. Secondly, this paper demonstrates certain types of manipulations given the limited amount of information volume and the transparency even in a speculative market. By addressing these aspects, our research directly responds to the opening inquiries, demonstrating how blockchain technology and the granular data it provides enable a profound understanding of market dynamics and investor strategies against manipulations.

This paper explores market misconduct, focusing on insider trading and wash trading. Previous research has examined the spread of insider information through personal networks (e.g., Anderson, Reeb, and Zhao (2012); Sun and Yin (2017); Ahern (2017)) and differentiated types of insider trades (e.g., Cohen, Malloy, and Pomorski (2012)). Extending these insights, this study adapts traditional analysis to semi-anonymized crypto assets using public blockchain transaction data, identifying indicators of insider trading in the crypto space. This approach demonstrates that transaction data is a valuable tool for market analysis, highlighting blockchain data's potential in advancing our understanding of market dynamics and integrity.

Insiders can be manipulators. Aggarwal and Wu (2006) showed that market manipulation occurred in small and illiquid OTC markets, with insiders and brokers potentially being the manipulators. Massoud, Ullah, and Scholnick (2016) discussed the price and liquidity effects of hiring undisclosed promoters for publicly traded firms. Manipulation is often associated with high-frequency and deceptive trading activities, such as spoofing or pump-and-dump schemes, which do not result in actual ownership changes. While these activities have been explored in stock markets (e.g., Kyle and Viswanathan (2008); Aitken, Cumming, and Zhan (2015)), they have also been discussed in the crypto space (e.g., Li, Shin, and Wang (2022)).

Wash trading, which is another form of fake trading, has been the focus of many studies. Although investors and scholars commonly refer to it as wash trading, the U.S. Internal Revenue Service (IRS) has formally defines it as non-tax-deductible trades due to the absence of a change in ownership (see e.g. Grinblatt and Keloharju (2004); Cong, Landsman, Maydew, and Rabetti (2023a) for tax-related research), while the U.S. Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC) consider wash trading as a violation of regulations[4]. Wash trading can mislead investors because daily trading volume is often used as a prominent market attention measure.

Detecting wash trades presents significant challenges in financial research due to the general inaccessibility of account-level transaction data. Traditional methods have ranged from direct detection using graph theory algorithms (Cao, Li, Coleman, Belatreche, and McGinnity, 2016), analysis of leaked information from Bitcoin exchanges (Gandal, Hamrick, Moore, and Oberman, 2018; Aloosh and Li, 2023), to statistical indirect estimation techniques (Cong et al., 2023b). In contrast, the NFT market, characterized by direct transactions between unique buyer and seller pairs and the immutable record-keeping of public blockchains, offers a unique advantage for detecting such trades. This direct trading model necessitates a specific counterpart wallet for wash trades, a requirement not found in stock or cryptocurrency wash trading. Wachter, Jensen, Regner, and Ross (2022) analyzed 52 NFT collections through graph theory and revealed wash trades constituted approximately 2% of sample transactions. Similarly, Morgia et al. (2023) using direct detection algorithms, suggested that the motive behind NFT wash trading might lean more towards exploiting token reward systems rather than inflating NFT values. Despite these advancements, finance research has yet to fully grasp the extent and impact of wash trading within the NFT space. This paper aims to bridge this gap by conducting a comprehensive economic analysis of wash trading, highlighting how blockchain's inherent transparency might revolutionize data governance, as explored by Jiang and Li (2024).

This paper contributes to the growing literature on NFT markets, specifically addressing market structure and the potential for manipulation. For a discussion of NFT markets from a finance perspective, see Kräussl and Tugnetti (2023) for a detailed survey, Veblen goods nature (e.g., Oh, Rosen, and Zhang (2023)), herding behaviors (e.g., Bao, Ma, and Wen (2023)), market index construction (e.g., Borri, Liu, and Tsyvinski (2022); Kong and Lin (2022)), and media coverage (e.g., Wilkoff and Yildiz (2023)).

[4]The IRS's concern with wash sales primarily revolves around their tax implications, rather than the legality of the trades themselves. According to the CFTC, entering into transactions, or purporting to do so, to give the appearance that purchases and sales have been made without incurring market risk or changing the trader's market position, is defined as wash trading and is prohibited. See also 17 CFR 38.152.

2 NFT Markets, Measures, and Predictions

2.1 Backgrounds

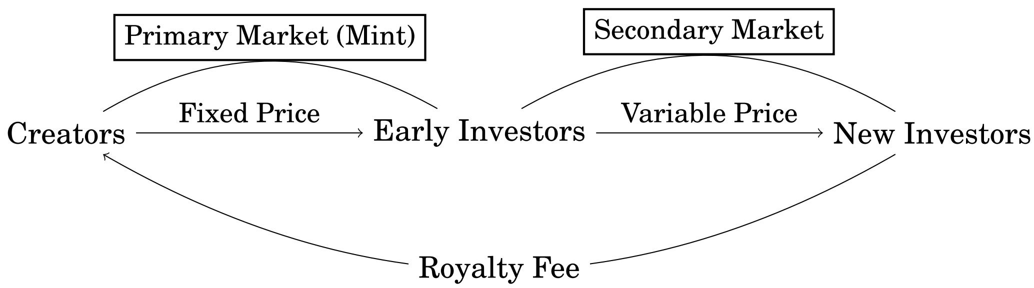

Figure 1. Overview of NFT Markets
Notes. The figure above shows the simplified NFT market. Creators sell NFT items at fixed price to initial investors and then initial investors trade items in secondary market. Creators receive royalty fee on every realized trades.

Before describing the data and summary statistics, it is essential to clearly explain the terminologies and background using Figure 1. An *NFT collection* is a set of NFTs based on the same theme and launched by an NFT creator team, while an *NFT* is an individual item within that collection. An NFT can be considered a single picture, whereas an NFT collection represents a set or brand of pictures. For example, the right picture of Figure 2 is an NFT, and the left picture represents an NFT collection. The *primary market* is where NFT creators sell NFTs directly to early investors at fixed prices[5]. This process is also known as *minting* or *mint*. NFT creators promote their minting process through various online communication channels, such as X (formerly Twitter), Discord, and Reddit. Early investors can sell their minted items to other investors, and some investors buy and sell items on the *secondary market*. In addition to raising funds on the primary market, creators earn a percentage *royalty fee* on every secondary market sale. Consequently, creators continue updating their development process and promoting sales to potential investors and NFT holders even after the primary market sales. It is important to note that successfully

[5] Some NFT collections offer different sets of fixed prices depending on the number of mints. When an investor buys more items, the mint price for each NFT becomes cheaper. However, there is a limit on the maximum amount one can mint, set by creators.

minting all NFTs is crucial for subsequent secondary market sales, as new entrants can buy NFTs at a fixed price from creators at any time if there are unsold items.

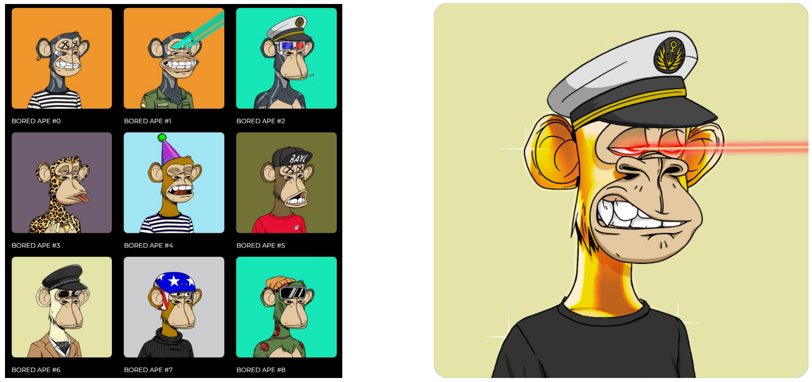

Figure 2. Example of NFT collection and NFT item
Notes. The left picture shows an NFT collection which is a set of pictures on the same theme under the same brand name called the *Bored Ape Yacht Club*. The right figure is an item (#3749) of *Bored Ape Yacht Club* that is sold at record price, 740 ETH (2.9 million USD) at September 6th, 2021.

This paper focuses on NFT collections based on the Ethereum (ETH) blockchain system, one of the most popular cryptocurrencies. It is important to note that buyers and sellers do not need to trade using ETH cryptocurrency. While transaction data is recorded on the ETH blockchain, participants can also pay using alternative cryptocurrencies like USDC, USDT, or ApeCoin. Traders using the Ethereum system must pay the *ETH transaction fee* or *gas fee* to blockchain miners for transaction verification in every NFT trade, including mints. This fee varies depending on the complexity of the Ethereum network. In late 2021, when the cost of transactions on ETH became high due to increased demand for trading ETH itself or crypto-based NFTs, some NFT creators launched their collections on other blockchain systems, such as Polygon. Nevertheless, the vast majority of NFTs are still based on the Ethereum ecosystem, so this study restricts the sample to Ethereum-based NFT collections. Furthermore, the fixed supply of NFT items plays a crucial role in defining the scarcity and limited access of the NFT market[6], making it possible to apply economic principles applicable to other traditional asset classes such as equity, housing, or the arts,

[6]Some famous NFTs like CryptoKitties do not have a supply limit as their cyber-cats repeatedly generate kittens, potentially leading to an infinite number of items.

as discussed by Oh, Rosen, and Zhang (2023).

2.2 Wash Traders in NFT Markets

According to the U.S. IRS, if one sells securities at a loss and buys substantially identical securities within 30 days before or after the sale, with no change in beneficial ownership, it is classified as a wash sale. When a related third party is involved, it is called a matched order. Losses from wash trades are not tax deductible.

Table 1. Example of Wash Trades in NFT Markets
Notes. This table presents an example of manipulative trading records on a single item. This collection is named "The Wonder Quest" with its unique contract address 0x08bEBEB5f042CCbaEb128582DA560cb25a5dB7e9. It is easily noticeable that investor 0x70e09... (marked as red) and 0x40c39... (marked as blue) buy and sell the identical item #1320 frequently on February 4th, 2022. Moreover, their transaction prices from wash trades (bolded) are significantly higher than the previous transaction price.

Item #	Trading Time	Seller	Buyer	Price (ETH)	Notes
1320	2021-07-26 20:12:29	0x0000000000000000000000000000000000000000	0x31992b19c40f2e472da5d39b167dc6fe952d3777	0.088800	Mint
1320	2021-08-12 03:39:03	0x31992b19c40f2e472da5d39b167dc6fe952d3777	0x3dcba64c3596aa254ad41502d8e15f9b54aa6e61	0.077000	-
1320	2022-02-02 01:10:17	0x3dcba64c3596aa254ad41502d8e15f9b54aa6e61	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	0.020000	-
1320	2022-02-02 02:21:49	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	0x40c398c0a3def59757683c82659f64678595f2de	0.045318	Wash
1320	2022-02-04 05:23:42	0x40c398c0a3def59757683c82659f64678595f2de	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	**36.812552**	Wash
1320	2022-02-04 05:48:57	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	0x40c398c0a3def59757683c82659f64678595f2de	**34.646000**	Wash
1320	2022-02-04 05:57:23	0x40c398c0a3def59757683c82659f64678595f2de	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	**33.953000**	Wash
1320	2022-02-04 06:09:45	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	0x40c398c0a3def59757683c82659f64678595f2de	**31.950000**	Wash
1320	2022-02-04 06:13:11	0x40c398c0a3def59757683c82659f64678595f2de	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	**31.316000**	Wash
1320	2022-02-04 06:31:15	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	0x40c398c0a3def59757683c82659f64678595f2de	**29.479841**	Wash
1320	2022-02-04 06:38:10	0x40c398c0a3def59757683c82659f64678595f2de	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	**28.890749**	Wash
1320	2022-02-04 06:50:57	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	0x40c398c0a3def59757683c82659f64678595f2de	**27.188134**	Wash
1320	2022-02-04 06:54:59	0x40c398c0a3def59757683c82659f64678595f2de	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	**26.648171**	Wash
1320	2022-02-04 07:01:16	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	0x40c398c0a3def59757683c82659f64678595f2de	**25.081046**	Wash
1320	2022-02-04 07:09:42	0x40c398c0a3def59757683c82659f64678595f2de	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	**24.579425**	Wash
1320	2022-02-04 07:15:45	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	0x40c398c0a3def59757683c82659f64678595f2de	**23.133958**	Wash
1320	2022-02-04 17:43:29	0x40c398c0a3def59757683c82659f64678595f2de	0x70e09c770c8bb76ed309db5ad9eab63a89a93788	**35.000000**	Wash

Wash trades, characterized by repetitive buying and selling of assets, create a misleading impression of market activity. While the SEC and CFTC consider such practices manipulative and thus prohibited, unlike the IRS, they do not publicly share their criteria or methods for detecting wash trades. Investors often view sudden spikes in trading volume or price as indicators of heightened market interest. However, two investors can exploit this by engaging in wash trades, artificially inflating the price of an NFT through coordinated buying and selling at elevated prices. This strategy can deceive new investors, as demonstrated in Table 1, leading them to overpay based on the distorted market signals reflected in the aggregate price index and trading volume.

The exploration of manipulative trading practices such as wash trades has been hampered by the general unavailability of detailed transaction data to researchers. The NFT market, with its blockchain data, offers a unique environment for such analysis. Each NFT possesses a unique identifier, and pseudo-anonymous wallet addresses involved in transactions are known, eliminating the need for data from proprietary exchanges. This transparency diminishes the plausibility of normal trade claims when identical items are bought and sold repetitively by the same parties within a collection, as demonstrated in Table 1. Previous work like Wachter et al. (2022) and Morgia et al. (2023) has utilized graph theory algorithms for direct detection of wash sales in NFT markets. Concurrently, the NFT community has adopted similar analytical methods, such as those devised by Dune Analytics[7], indicating a collaborative effort toward transparency and integrity in market transactions.

Table 2. Logic of Wash Trades Detection

Type	Wash Type (1)	Wash Type (2)	Wash Type (3)
Name	Identity Trade	1-1 Trade	Matched Order
Transactions	A Sell → A Buy	A Sell → B Buy B Sell → A Buy	A Sell → B Buy B Sell → C Buy C Sell → A Buy
Time Span	-	Within 7 days	Within 7 days
Observations	346	10408	1183

This paper adopts a wash trade definition akin to that used by the IRS, albeit with a narrower timeframe to better suit the rapid pace of NFT and cryptocurrency markets. Initial purchases at standard prices set the stage for identifying subsequent wash sales. As delineated in Table 2, a transaction is flagged as a wash sale under any of three conditions: (1) the same entity sells and repurchases the item concurrently, (2) a previous seller reacquires the item within a 7-day window, or (3) a series of trades involving three distinct wallets transpires within a 7-day period, qualifying as a matched order. The standard 30-day period designated by the IRS for traditional markets is reduced here, reflecting the accelerated transaction dynamics in NFT markets, as exemplified in Table 1. Analysis con-

[7]Refer to this online community posting (https://community.dune.com/blog/nft-wash-trading-on-ethereum) for their algorithm.

firms that even shorter intervals, such as 3 or 5 days, yield significant instances of 1-1 trades (8564 and 8705 observations, respectively). Utilizing this streamlined definition (detailed algorithms are available in Appendix B), the study identifies 10166 (0.3%) potential wash trades out of 3.6 million secondary market transactions. Remarkably, 43% of the 557 collections examined harbored at least one such trade, despite an average wash trade incidence of merely 0.3% per collection. Comprehensive summary statistics are provided in Table A.1.

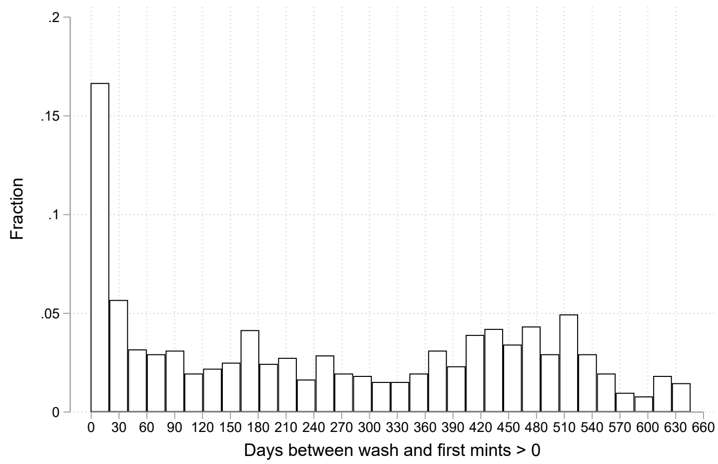

Figure 3. Timing of Wash Trade in Secondary Market
Notes. This figure reports the distribution of wash trade ratio out of secondary market trade in collection-wise. Collections that do not have wash trades are omitted in the figure.

Another noteworthy aspect of wash trades is their timing. Figure 3 illustrates the histogram of elapsed days from the first mint sales to wash trades in each collection. More than 20% of wash trades occurred within 60 days after mints but more mature collections also had wash trades. Combining with around half of collection have at least one wash trades, wash trades may be market-wide phenomena. The idea in this subsection can be summed up with the following prediction.

Prediction 1: Wash trading activities could potentially impact the future price returns of NFT collections. Investors, possibly unaware of such trades, may be misled by artificially inflated prices, influenced by the perceived surge in market interest. This complexity of information, even when available, might overwhelm investors, hindering their ability to digest detailed data on transactions and collection nuances, a scenario highlighted by Banerjee, Davis, and Gondhi (2018).

Yet, this prediction might not universally apply due to the vigilant self-policing nature of the NFT community, which actively shares and reports suspicions on social platforms like X. Additionally, the granularity of available information limits the depth of transaction analysis to the individual item level, allowing for more straightforward identification of manipulation within specific collections or items. This aspect is somewhat akin to the real estate market, where broad trends in property prices are observable, but detailed scrutiny is possible for individual unit transactions, particularly when anomalous price increases arise.

Prediction 1A: The influence of wash trading on future price returns of collections might be negligible as investors discern and disregard such manipulative signals. The ability of investors to sift through a manageable volume of data suggests they can sidestep the pitfalls of distorted pricing induced by wash trading.

2.3 Insiders in NFT Markets

Another valuable thing that might be inferred from on-chain transaction data is insider trading. A distinctive characteristic of the NFT market is the concurrent online communication system facilitated via platforms like X and Discord. In Discord, each NFT project has two types of chat rooms. The first chat room is open to everyone, including aspiring investors who do not yet hold an NFT, while the second is exclusively for current NFT holders[8]. Through the automated verification system, NFT owners can establish their ownership, and all they need to do is show their verified ownership to Discord managers, who are NFT creators and their communication teams. Thus, access to member-only chat rooms is restricted to NFT owners, as creators and their communication teams use these rooms to engage with members of their community.

Insider trading in a public firm refers to the stock trading behavior of managers who hold more than a certain amount of shares. Insiders of public companies are required to report their trading records to the U.S. SEC. Unlike the stock market, there is no regulation requiring insiders in the NFT market to report their trading records. Furthermore, the

[8] The Bored Ape Yacht Club does not have a community for potential investors, but has exclusive member-only community.

personal identity of each wallet is not revealed unless the owner of the wallet chooses to disclose it. Therefore, insiders can only be inferred from transaction records unless tracking wallet identity using other databases as in Makarov and Schoar (2021). Without legal consequences for insider trading, those with information advantages in a speculative market are more likely to exploit their information advantage for trading purposes.

In this study, insiders are identified as wallets receiving free items (*Free Minters*), likely privy to insider information. Research, including Anderson, Reeb, and Zhao (2012), Sun and Yin (2017), and Ahern (2017), illustrates that personal connections can serve as conduits for information dissemination. Similarly, Pourghannad, Kong, and Debo (2020) showed that early crowdfunding investors often have social ties with project creators, gaining informational benefits. In the NFT realm, used for launching projects and fundraising, *Free Minters* are potentially the creators themselves, those with close social ties to the creators, or recipients of promotional giveaways[9].

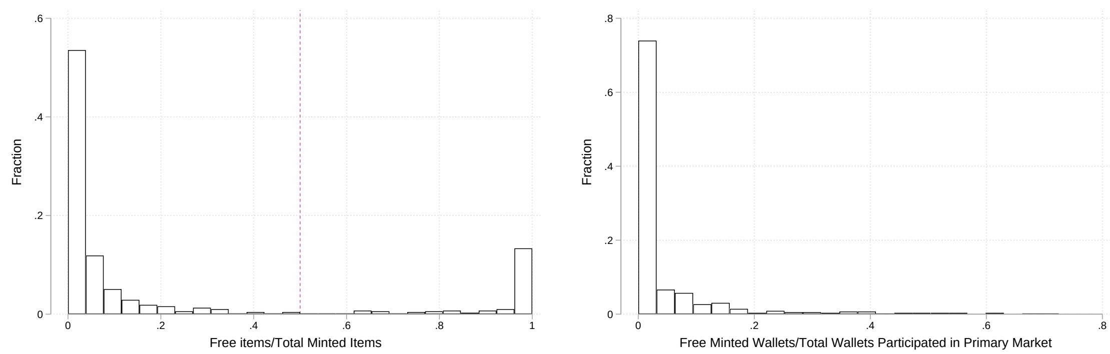

Figure 4. Distribution of Insiders in Primary Market
Notes. These figures report the distribution of potential insiders in collection-wise primary market. The left figure shows the distribution of free items out of total items including collections that are omitted in the sample selection process. In the analysis, NFT collections on the right side of red dotted line are deleted. Potential insiders are defined as wallets that received free items in primary market. The right figure describes the distribution of such insiders out of total wallets involved in primary market.

Figure 4 presents the distribution of insiders from two perspectives. The left figure is

[9]Promotional giveaways, or airdrops, are limited due to the fixed supply of NFT items. This study does not differentiate between airdrops and free mints, as both are determined by creators for purposes such as marketing. These giveaways often target active community members or those promoting the NFT project on platforms like X.

the histogram of items using full sample, and it is not difficult to see most NFT collections does not give most items freely. Ad hocly, I omitted 131 collections for further analysis that distributed more than 50% of their items without any cost (right side of red dotted line) as they have higher probability of being derivatives for already successful main projects and they are less likely to be fundraising projects. The right figure depicts the distribution of wallets in the final sample. On average, 4.9% of wallets were classified as insiders on the primary market. Other relevant summary statistics are present in Table A.1. The following testable prediction summarizes the concept and explanation in this subsection.

Prediction 2: Behaviors of insiders who are defined as wallets that received NFT items freely will strongly predict future returns since insiders may use internal information through online community. Specifically, insider purchase will predict higher future price returns. Insider selling will predict negative future returns but it may not be strong or the sign can be flipped since the market is upward-trending and speculative.

The variance in predictive power between insider buying and selling behaviors can be attributed to the unique membership identity associated with NFTs. Purchasing additional illiquid items, especially when already possessing some, is likely indicative of an insider's informational advantage and their positive outlook on the collection's future success. This is informed by their unique position within the community, which provides access to privileged information. Conversely, insider selling could be motivated by knowledge of forthcoming negative developments not yet publicized to the wider community. While such sales might logically predict negative future returns, the actual predictive power of selling behavior could be diluted or even reversed. This is due to the speculative nature of the market, which complicates the timing of sales based on insider information. Therefore, while insider selling may indeed be informed by adverse insider knowledge, pinpointing the precise timing for such trades remains a significant challenge in the highly speculative and volatile NFT market.

2.4 Free-Minting for Insiders

One might question why insiders participate in the NFT community through smart contracts, which are often rephrased as vending machines that give a random item in a collection. However, for NFT creators, avoiding the negative impression of being short-lived pump-and-dump manipulators is crucial, especially since success in the primary market is a necessary precursor for continued success in secondary markets.

The most successful NFT collection, Bored Ape Yacht Club (BAYC), is a good example for understanding how creators are involved in the community. After a media report revealed some creators' identity in February 2023, four founders publicly disclosed their identities and their NFT profile pictures on X (former Twitter)[10]. According to the reports, of the 10,000 items starting from number 0 to number 9999, four creators held one item each: number 1, 2, 3, and 30. With BAYC included in the sample, it prompts an analysis of this representative collection.

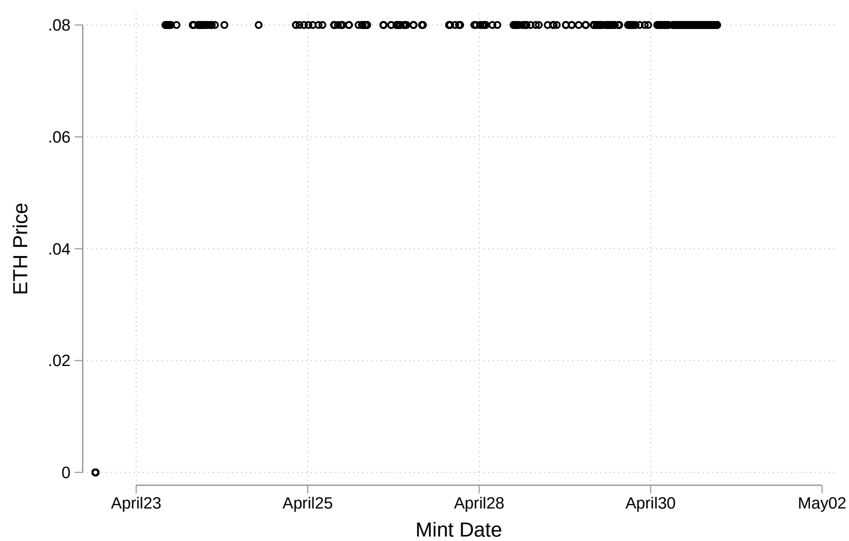

Figure 5. Example of Mint Transactions
Notes. This figure displays the mint price of Bored Ape Yacht Club (BAYC). 30 NFT items were minted at 0 ETH and 9970 NFT items at 0.8 ETH between April 22, 2021 and May 1, 2021.

Figure 5 illustrates the primary market transactions. Initially, smart contracts sold 30 items (numbers 0 – 29) to BAYC deployer wallet[11]. This wallet basically funtion as an official account for the collection. This deployer wallet later transferred 30 items to

[10]See these news articles on identity leaks (https://www.buzzfeednews.com/article/katienotopoulos/bored-ape-nft-founder-identity) and creators' response (https://www.cryptotimes.io/bored-ape-yacht-club-founders/).
[11]See this transaction record for details (Etherscan Link).

individual wallets, including three creators, at zero price. Simple wallet tracking reveals that creator A holds items #0 and #30, B holds item #1, C has item #2 and #121, and D has item #3. Therefore, all creators participated in the community with at least one free item. This indicates that the minting process is not entirely random for insiders, as they can select and receive their NFT items at no cost in the early stage of minting.

However, unreported subsample analysis on primary markets shows that when controlled for mint price with fixed effects, there is no statistical difference in item-level rarity scores between insiders and non-insiders[12]. This is because NFT items are generated randomly, and thus it is hard to pre-allocate specific rare items to multiple insiders. In conclusion, free minters are highly likely to be creators themselves, their family, friends, and early supporters.

3 Data

The list of NFT collections was manually compiled in October 2021 from the "Top Collectibles NFT rankings" on OpenSea, the largest NFT trading platform. This list extends the sample in Oh, Rosen, and Zhang (2023) by including newly launched projects between October 2021 and December 2021. After selecting collections that successfully minted all items, the final sample consists of 557 ERC-721 NFT collections traded on the Ethereum blockchain. Transaction data is primarily obtained from Dune Analytics, a commercial data company, and cross-checked with Etherscan, one of the largest free blockchain data websites. Indirect trades involving DeFi platforms such as Uniswap and Sushiswap are excluded, while direct ERC-1155 trades are included[13]. The number of mint transactions is 3.6 million, and the number of secondary transactions is also 3.6 million. To eliminate unusual near 0 ETH transactions, only secondary market trades of at least 0.01 ETH are considered in the sample. All return variables discussed in Table 3 are further winsorized at the 1/99 percentile level. The sample covers the period from February 17th, 2021, to February 14th,

[12]Item level rarity scores can be obtained from https://rarity.tools/. This website tries to score NFT items on selected samples.

[13]ERC-1155 allows for batch transfers, i.e., multiple trades in a single transaction hash. In ERC-721, one NFT item is traded under one transaction hash, thus ERC-1155 reduces a significant amount of transaction cost.

2023, allowing for the incorporation of the crypto winter in 2022.

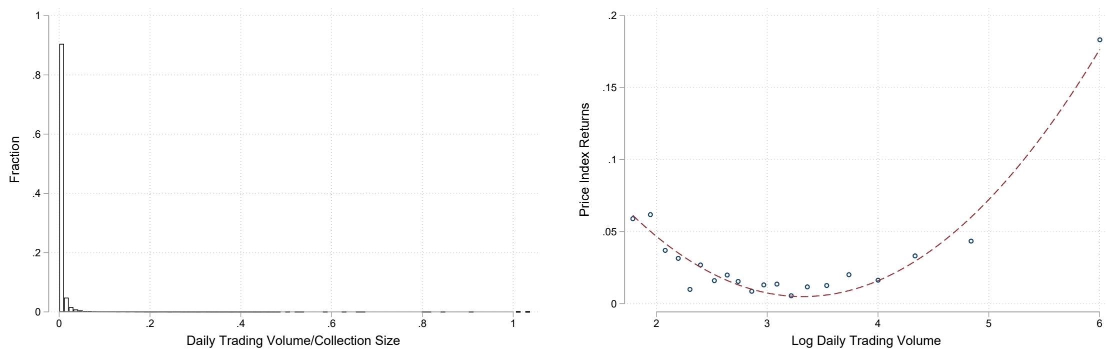

Figure 6. Trading volume and Median Price of NFT

Notes. The left figure shows the daily secondary market trading volume divided by each collection's supply. The plot on the right depicts the square-root relationship between logged daily median price and logged daily secondary market trading volume.

Figure 6 illustrates the illiquidity of NFT markets. The left figure shows the daily secondary market trading volume divided by each collection's minted items, highlighting the rarity of transactions compared to the number of issued items. The right plot shows a positive square-root relation between daily median price and daily trading volume, similar to the traditional price-volume relationship observed in finance. This suggests that investors pay close attention to a collection's trading volume, given the overall market illiquidity. This implies that increased investor attention and the introduction of new information can significantly drive up prices (Wilkoff and Yildiz, 2023). Therefore, it is logical to expect that information advantages, such as insider trading and false investor attention from wash trading, may contribute to a collection's investment return and longevity.

The variables used in the analysis are aggregated at the collection-date level, as shown in Table 3. The dependent variables are the rate of median price and trading volume change, with and without wash trades. The daily median price is used as the price index since most NFT items are homogeneous, and the most common items in the collection are traded around a similar price (Oh, Rosen, and Zhang, 2023). Wash trades can distort the representative market price and trading volume of NFTs; therefore, it is more appropriate to consider values that account for wash sales, which are prevalent in the experiences of most

Table 3. Variable Definitions
Notes. This table defines the variables used in this paper. Only secondary market trades of at least 0.01 ETH are considered in the sample. Variables marked with † are further winsorized at the 1/99 percentile level. Daily transaction volumes of less than 5 are omitted from the data. Note that dependent variables are leads.

Variables	**Description**
Dependent Variables	
†Price Return	Rate of median price change from day t to $t+1$
†Price Return nowash	Rate of median price change from day t to $t+1$, omitting all wash sales
†Volume Change	Rate of trading volume change from day t to $t+1$
†Volume Change nowash	Rate of trading volume change from day t to $t+1$, omitting all wash sales
Independent Variables	
InsiderBuy Activity	Free minters' buying volume at day t scaled by the number of total minted items
InsiderSell Activity	Free minters' selling volume at day t scaled by the number of total minted items
Wash Activity	Wash sales volume at day t scaled by the number of total minted items
Control Variables	
Log(1+Days after mints)	Log(1 + number of days past after first mint)
Past Volume	Log(1 + non-wash trade volume) at day $t-1$
†Past Day Returns	Rate of median price change from day $t-2$ to $t-1$
†Past Week Returns	Rate of median price change from day $t-7$ to $t-2$
Log Market Value of Collection	Log(median price at day t × mint volume)

novice traders. While investors typically focus on the floor price, which is the minimum available list price at that time, the median price is the best possible measure for the price index due to data constraints.

The independent variables are insider buy volume, insider sell volume, and wash trade volume at day t, both scaled by the total minted amount in each collection. The return variables are winsorized at 1/99 percentile level. Summary statistics of the variables are presented in Table 4. Note that the number of observations of dependent variables is not equal. This indicates there are cases where all transactions in a whole day involve wash trades. Secondary market trading volume, daily median price in USD, and daily median price in USD without wash sales are not winsorized in the Table 4.

Table 4. Summary Statistics

Notes. This table shows the summary statistics of variables defined in Table 3. Only secondary market trades of at least 0.01 ETH are considered in the sample. Variables marked with † are further winsorized at the 1/99 percentile level. Daily transaction volumes of less than 5 are also omitted from the data. Secondary market trading volume, daily median price in USD, and daily median price in USD omitting wash sales are not winsorized.

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) p50	(6) max
†Price Return	58,126	0.0326	0.260	-0.544	0.000464	1.258
†Price Return nowash	58,133	0.0329	0.261	-0.544	0.000466	1.274
†Volume Change nowash	58,132	0.245	1.097	-0.833	-0.0363	6.500
†Volume Change	58,139	0.245	1.097	-0.833	-0.0357	6.500
InsiderBuy Activity	75,268	0.000106	0.000940	0	0	0.0775
InsiderSell Activity	75,268	0.000128	0.00193	0	0	0.249
Wash Activity	75,268	0.154	4.274	0	0	387
Wash Dummy	75,268	0.0218	0.146	0	0	1
# of Wash Sales	75,268	0.154	4.274	0	0	387
Days between wash and first mint sales	75,268	174.2	143.1	-0.960	137.4	689.2
Market Value of Collection (Million)	75,268	22.59	175.0	0	2.302	5,675
Positive Priced Secondary Market Trading Volume	75,268	47.15	177.2	5	13	7,995
median price in USD	75,268	2,408	17,566	0	283.8	567,495
median price in USD omitting wash sales	75,268	2,346	16,733	0	283.4	465,646

4 Wash Trade Analysis

4.1 Impact of Wash Trade

This subsection analyzes the impact of wash trades on market outcomes. Transaction data is aggregated into daily panel data, and this approach is particularly relevant as simple values, such as index price and trading volume, are not only easily accessible but also crucial market signals for investors. For a collection c and day t, the regression model is as follows:

$$DV_{c,t+1} = \beta WashActivity_{c,t} + \gamma X_{c,t} + CollectionFE + DateFE + u_{c,t+1} \tag{1}$$

where $DV_{c,t+1}$ is the rate of change in the index price or trading volume from day t to $t+1$, $Wash\ Activity_{c,t}$ is the daily wash trade volume scaled by the total mint amount, and $X_{c,t}$ includes control variables.

For the choice of control variables, I assume that investors focus on the past day price index return from day $t-2$ to $t-1$ and past week return from day $t-7$ to $t-2$ as momentum factor. The natural logarithm of non-wash trading volume at day $t-1$, and log of the market value of the collection, which is the median price multiplied by the total minted volume, is considered. To mitigate unreported confounding effects, collection fixed and date fixed effects are included. The appendix includes regression tables detailing all control variables.

Note that the daily price index and trading volume can be measured in two ways. The first, which is what most investors observe on trading platforms, is the total or nominal value, including wash trades. The other is the true or real value, which excludes wash trades since they distort the price and trading volume. I present estimated results on price returns using real values and volume change using real values, but the distinction between nominal and real values does not alter the results.

Column (1) of Table 5 shows that there is insignificant association between wash activity and future price returns. The results from Column (2) show that one percentage point increase in daily wash trade activity leads to 0.42 percentage points decrease in future volume change. This value is economically insignificant, suggesting that wash trades do not

Table 5. Impact of Wash Trade on Future Market Outcomes
Notes. This table reports the results from estimates of specification (1), regressing future median price index returns or future change in trading volume on daily wash trade activity for collection c as of day t. Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$.

	All		Bubble		Crash	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Price	Volume	Price	Volume	Price	Volume
Wash Activity	4.94e-05	-0.00423***	-3.70e-05	-0.00469***	-2.34e-05	-0.00297
	(0.136)	(-3.239)	(-0.0793)	(-2.985)	(-0.0324)	(-0.560)
Log(1+Days after mints)	0.00438	-0.0493***	0.00572	-0.0556***	-0.105	-0.311*
	(0.534)	(-2.796)	(0.695)	(-2.637)	(-0.675)	(-1.685)
Past Volume (Real)	0.00773***	-0.152***	0.0116***	-0.155***	0.00283	-0.159***
	(3.148)	(-18.75)	(3.957)	(-16.07)	(0.567)	(-8.700)
Past Day Returns	-0.0140	-0.00788	-0.0193**	0.00536	0.0238	-0.0450
	(-1.563)	(-0.247)	(-2.004)	(0.149)	(1.058)	(-0.587)
Past Week Returns	-0.00245	0.0239*	-0.00137	0.0201	0.0146	0.0745*
	(-0.667)	(1.798)	(-0.333)	(1.389)	(1.228)	(1.863)
Log Market Value of Collection	-0.0788***	-0.0388***	-0.0910***	-0.0626***	-0.153***	0.0352
	(-12.37)	(-3.504)	(-12.79)	(-4.810)	(-7.190)	(1.123)
Observations	33,725	33,725	26,995	26,995	6,709	6,709
Collection FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Within Adj R-squared	0.0426	0.0150	0.0487	0.0173	0.0731	0.00966
Adj R-squared	0.0886	0.0306	0.0929	0.0318	0.130	0.0262

generate any meaningful market outcomes. Results are similar in one standard deviation increase in daily wash activity. With fixed effects and controls, one standard deviation increase shows insignificant change in future price returns and 1.8 percentage point decrease in future real volume change. The insignificant result holds in subsample periods: market bubble (before May 3rd, 2022) and crash period (after May 3rd, 2022).

However, these results are somewhat puzzling, given that wash trades are typically executed at high ETH prices and can distort the market price, as illustrated in Table 1. It is unclear whether most investors recognize the unusual market outcomes associated with wash trading, despite the availability of detailed transaction records on free websites. It seems possible that wash trades exert temporary effects on market outcomes, not extending beyond a single day.

To explore this possibility, I employed a modified version of Equation 1 at Table 6, where I regress the real index price return in USD from day $t-1$ to day t (i.e., same-day return) and real change of trading volume on the same day, on daily wash trade activity for collection c as of day t. The control variables remain consistent with previous estimations.

Table 6. Impact of Wash Trade on Same Day Market Outcomes
Notes. This table reports results from regression estimates, regressing current median price index returns or current change in trading volume on daily wash trade activity for collection c as of day t. Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	All		Bubble		Crash	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Price	Volume	Price	Volume	Price	Volume
Wash Activity	6.42e-05	0.0161***	0.000341	0.0135***	-0.00112	0.0515***
	(0.0582)	(4.653)	(0.269)	(4.065)	(-1.049)	(3.949)
Log(1+Days after mints)	0.0621***	-0.378***	0.0642***	-0.394***	0.162	-0.108
	(7.819)	(-10.94)	(7.619)	(-10.83)	(0.805)	(-0.285)
Past Volume (Real)	0.0368***	-0.555***	0.0369***	-0.560***	0.0183***	-0.698***
	(12.40)	(-39.28)	(10.47)	(-35.48)	(3.739)	(-22.73)
Past Day Returns	-0.296***	0.175***	-0.289***	0.167***	-0.415***	0.194***
	(-25.60)	(6.482)	(-23.62)	(5.788)	(-20.61)	(3.151)
Past Week Returns	-0.0702***	0.110***	-0.0721***	0.0984***	-0.133***	0.136***
	(-14.78)	(7.700)	(-14.34)	(6.802)	(-9.980)	(2.840)
Log Market Value of Collection	0.0591***	0.188***	0.0697***	0.207***	0.187***	0.236***
	(7.807)	(10.53)	(8.356)	(9.816)	(7.536)	(3.968)
Observations	42,861	42,861	35,034	35,034	7,806	7,806
Collection FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Within Adj R-squared	0.114	0.125	0.115	0.126	0.246	0.165
Adj R-squared	0.155	0.140	0.155	0.141	0.300	0.181

The findings in Table 6 continue to support the argument that wash trades have a negligible impact on market outcomes. The coefficients of *Wash Activity* remain economically insignificant or statistically insignificant. The current real price return remains unaffected, while the real trading volume change increases by around 1.6 percentage points for one percentage point increase in wash activity. Given the negligible magnitude and lack of statistical strength, these findings further reinforce the conclusion that wash trades do not significantly influence NFT returns; otherwise, a significant effect on same-day returns would be expected.

Long-term Impact of Wash Trade. Now I investigate whether investors refrain from trading other NFT items within the same collection following wash trades. Specifically, the model examines any notable long-term changes in collection-level trading volume or price index after wash trades, over extended periods such as 2, 3, 5, 7, or 14 days post day t.

Table 7. Long-term Impact of Wash Trade on Market Outcomes
Notes. This table presents results from estimates of specification (3) in which future median price returns and future trading volume changes are regressed on daily activities of wash trading for collection c as of day t. Panel A's dependent variable is the long-term median price change in USD from day t to days $t+1, t+2, t+3, t+5, t+7$ and $t+14$, excluding all trades classified as wash trades. Panel B's dependent variable is the trading volume change from day t to days $t+1, t+2, t+3, t+5, t+7$ and $t+14$, also excluding all wash trades. Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Price Returns	1 Day	2 Day	3 Day	5 Day	7 Day	14 Day
Wash Activity	0.000300	-1.25e-05	0.000128	-0.000772	0.000216	0.00393
	(0.597)	(-0.0155)	(0.127)	(-1.459)	(0.102)	(1.376)
Observations	39,757	39,258	38,924	38,426	37,870	36,266
Collection FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Within Adj R-squared	0.0448	0.0582	0.0718	0.0921	0.110	0.158
Adj R-squared	0.0901	0.139	0.170	0.230	0.267	0.361
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Volume Change	1 Day	2 Day	3 Day	5 Day	7 Day	14 Day
Wash Activity	-0.00378***	-0.00304*	-0.00265	-0.00569**	-0.000233	-0.00619
	(-2.786)	(-1.797)	(-1.231)	(-2.555)	(-0.0874)	(-1.520)
Observations	39,757	39,258	38,924	38,426	37,870	36,266
Collection FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Within Adj R-squared	0.0141	0.0180	0.0233	0.0311	0.0402	0.0497
Adj R-squared	0.0322	0.0451	0.0584	0.0771	0.0948	0.127

Panel A of Table 7 assesses the impact of wash activity on long-term price index returns. Column (1), for reference, is replicated from Table 5. Columns (2) through (6) demonstrate that the long-term effect is statistically insignificant, signifying no meaningful future median price change after wash trades. Panel B of Table 7 explores the impact on long-term real volume change. Results from Columns (2) through (6) indicate that coefficients are economically insignificant or statistically insignificant.

In summary, wash trades do not have a significant impact on the NFT returns and trading volume. Consequently, it appears that investors are not influenced by wash traders. This further suggests that investors do not typically avoid engaging in transactions involving collections associated with wash trades. In both the short and long term, the market does not appear to be trapped or penalize collections with a history of wash trading, in terms of either volume or price. Items with abnormal prices tend to be ignored by investors.

4.2 Purpose of Wash Trading

The wash trades identified in this study involve a total of 422 million USD. Despite the significant amounts, these trades seemingly fail to attract investors, underscoring the need to explore the underlying mechanisms. Previous literature on cryptocurrency wash trading offers some baseline explanations, such as exchange ranking boosting measured by total trading volume in competitive environments (Cong et al., 2023b) and negligible effects in monopolistic environments (Aloosh and Li, 2023).

Wash trades may not solely target market manipulation. Discussions around cryptocurrency rewards in NFT marketplaces have surfaced (Morgia et al., 2023), highlighted by the case of LooksRare and its reported 8 billion USD in NFT wash trading[14]. Therefore, it is important to examine the distribution of wash trades across various marketplaces. Table 8 presents a two-way frequency table of wash trades and NFT marketplaces, showing that OpenSea is the largest and leading NFT marketplace during the sample period. Additionally, numerous marketplaces have policies where marketplace fees are compensated with marketplace coins or offer near-zero percent fees compared to OpenSea. Marketplaces like X2Y2, Blur, and LooksRare have token reward systems for investors, collecting fees from all transactions and distributing them proportionally to one's NFT transaction amount. This is referred to as the *rewards hypothesis*.

The NFT market, mirroring a monopolistic environment similar to the Mt. Gox case

[14] See this article about suspicious trading on LooksRare (https://decrypt.co/91510/looksrare-has-reportedly-generated-8b-ethereum-nft-wash-trading). However, the trading reward system was discontinued at LooksRare in September 2023.

Table 8. Wash Trades and NFT Marketplaces
Notes. Table 8 presents descriptive statistics for NFT marketplaces and their associated wash trades, based on our sample of 557 secondary market trades. The marketplace fee policy data is as of March 5th, 2023. Foundation and Zora are omitted from the following analysis due to their small number of observations.

NFT Marketplaces	Not Wash Trade	Wash Trade	Total	Related Policy
Blur	39124	1460	40584	0% fee
	(96.40)	(3.60)	(100.00)	Receive token when traders pay full royalty to creators
Element	625	123	748	0.5% fee
	(83.56)	(16.44)	(100.00)	
Foundation	2	0	2	5% fee
	(100.00)	(0.00)	(100.00)	
LooksRare	10542	176	10718	2% fee. Token stakers earn 75~100% of the trading fees
	(98.36)	(1.64)	(100.00)	
OpenSea	3590664	1573	3592237	2.5% platform fee (temporarily 0% after the sample period)
	(99.96)	(0.04)	(100.00)	
Sudoswap	8589	205	8794	0.5% fee
	(97.67)	(2.33)	(100.00)	
X2Y2	24436	6628	31064	0.5% fee. Fees are rewarded to X2Y2 stakers
	(78.66)	(21.34)	(100.00)	
Zora	18	1	19	0% fee
	(94.74)	(5.26)	(100.00)	
Total	3674000	10166	3684166	
	(99.72)	(0.28)	(100.00)	

(Aloosh and Li, 2023), is dominated by OpenSea, which accounts for over 97.5% of transactions in the sample (see Table 8). Additionally, the information volume in NFT markets is finite, in contrast to cryptocurrency or equity markets, due to limited and fixed supply.

Furthermore, Aggarwal and Wu (2006) and Massoud, Ullah, and Scholnick (2016) have explored the potential involvement of insiders in manipulative trades in traditional finance markets. Creators and insiders may be motivated to engage in trades that garner attention, given the potential to create upward price momentum via pump-and-dump schemes (Li, Shin, and Wang, 2022). Creating artificial attention might be more appealing to them during and right after the minting process since collections are either successfully minted or failed to mint (Oh, Rosen, and Zhang, 2023). More specifically, OpenSea, the dominant marketplace, gives a "verified" mark for a collection whose total traded volume reaches 75 ETH[15]. Obtaining a verified mark at a monopolistic marketplace will generate better mar-

[15] Additionally it requires a profile picture, banner image, connected Twitter/Discord/Instagram account, logo image, and all NFT items in a collection should be minted or revealed. See this page for details

ket attention for a newly minted collection. Investors cannot easily predict the success of each NFT collection in secondary markets, and it is likely that such verification marks can be a key factor for attracting investors' attention. This is referred to as the *labeling hypothesis*.

Rewards Hypothesis. To understand how marketplace rewards can drive wash trading, consider the case presented in Table 1, where transactions flagged as wash trades actually occurred on LooksRare. Wash traders generated an artificial trading volume of 388.66 ETH (or 1.16 million USD). For simplicity, assume their portion is one-tenth of the total daily trading volume on LooksRare. Consequently, wash traders would be able to claim 10% of the predetermined daily LOOKS cryptocurrency rewards a day later. They would pay a 2% marketplace platform fee on 388.66 ETH, equating to 7.77 ETH (or approximately 23,000 USD at the time), and a gas fee of around 700 USD.

It's important to note that wash traders don't earn rewards right after trades. Instead, they gain the right to claim marketplace cryptocurrencies, analogous to a call option structure without an expiration date[16]. Their payoff increases when they receive more cryptocurrency rewards based on their portion in the marketplace or when the price of the marketplace cryptocurrencies increases, at least for the next day[17]. In more formal terms, the payoff for wash trader i at marketplace m on day t can be defined as:

$$Payoff_{i,m,t} = k \times \frac{Wash\ amount_{i,m,t}}{Total\ amount_{m,t}} \times \widetilde{Rate_{t+\tau}} - Gas\ fee_{i,m,t} - Marketplace\ fee_{i,m,t} \tag{2}$$

where k represents the pre-defined reward amount for the time interval t, and $\widetilde{Rate_{t+\tau}}$ is the future exchange rate from the reward token to USD at time $t+\tau$.

In simpler terms, a wash trader's payoff equals the reward earned from their share of the total trading volume, adjusted by the exchange rate of the cryptocurrency, minus the costs of gas fees and marketplace fees. The pre-defined reward amount k varies across different periods. On LooksRare, for the first 30 days after the marketplace launch, 2,866,500

(https://support.opensea.io/en/articles/8867072-what-is-a-verified-account-or-badged-collection).

[16]See the official documents for LooksRare (https://docs.looksrare.org/about/rewards/trading-rewards) and X2Y2 (https://docs.x2y2.io/tokens/rewards/trading-rewards).

[17]Traders can claim their rewards anytime after rewards are calculated.

LOOKS tokens are distributed daily, 1,361,587.50 LOOKS for the next 90 days, 537,465.75 LOOKS for the next 240 days, and then 286,650 LOOKS for the following 361 days, although this reward system has been discontinued since September 2023. Similarly, on X2Y2 and Blur, proportional cryptocurrencies are distributed to traders.

Revisiting the scenario in Table 1, suppose the predefined reward k is 2,866,500 LOOKS. Then, the hypothetical wash traders' profit is $286,650$ LOOKS $- 23,700$ USD. In reality, on February 5th, 2022, 1 LOOKS was equal to around 3.95 USD, and the wash traders' break-even point was 5,925 LOOKS, or only 0.02% of the total volume in the emerging marketplace.

Empirically, Morgia et al. (2023) analyzed claimed rewards on the blockchain for all Ethereum-based ERC-721 NFTs until January 18th, 2022. They found that wash traders should call rewards to particular smart contracts[18]. Following their approach, wallet addresses that distribute token rewards can be identified[19]. However, one empirical issue in rewards tracking persists – the timing of claims is arbitrary, making it difficult to distinguish between rewards from wash trades and rewards from ordinary trades. Given that the dollar value of wash trades is significantly larger than that of ordinary trades, as shown in Table 1, I assume rewards from ordinary trades are negligible.

Table 9 shows reward claims during the sample period from buyer wallets identified as involved in wash trades. The minute-level dollar value of each token is obtained from Dune Analytics, and for missing values, the estimated value on the day of transfer is used from Etherscan. During the sample period, 2,770 claims were performed by 285 wallets. After subtracting gas fees for claims, the average rewards were around 60,000 USD, with the top five wallets receiving 6.62 million, 1.84 million, 1.59 million, 1.26 million, and 0.9 million USD from the three marketplaces. The highest claim occurred at X2Y2 with 3.87 million USD, while the other top four transactions, each over 3 million USD, were recorded at LooksRare in early 2022.

Additionally, 617 wallets paid three associated fees - gas fees to process blockchain

[18] 0x453c1208B400fE47aCF275315F14E8F9F9fbC3cD for LooksRare.

[19] 0x453c1208B400fE47aCF275315F14E8F9F9fbC3cD and 0x0554f068365eD43dcC98dcd7Fd7A8208a5638C72 for LooksRare, 0xeC2432a227440139DDF1044c3feA7Ae03203933E for Blur, and 0xc8c3cc5be962b6d281e4a53dbcce1359f76a1b85 for X2Y2.

Table 9. Claimed Marketplace Rewards
Notes. This table shows wallet-level descriptive statistics for reward claims and associated fees on LooksRare, X2Y2, and Blur. All values have been converted to USD at the time of transaction.

	count	mean	std	min	p25	p50	p75	max
Reward Claims								
Token Value	285	59,298.50	429,885.31	0.14	1.18	320.84	6,301.24	6,625,162.74
Gas for Claims	285	100.80	214.65	0.00	7.53	28.37	87.37	2,168.73
Profit from Claims	285	59,197.70	429,816.23	-482.25	-10.80	280.83	6,214.58	6,624,804.83
Cost on Wash Trades								
Gas Fee	617	2,961.39	26,122.20	0.00	5.82	15.84	62.43	358,381.55
Marketplace Fee	617	738.10	6506.11	0.00	0.00	0.00	0.00	105,330.15
Royalty Fee	617	79.83	556.87	0.00	0.00	0.00	5.89	11,927.99
Realized Profit	285	53,333.21	431,262.24	-358,390.55	-75.66	-9.31	4,785.46	6,624,772.64

transactions, marketplace fees to each marketplace, and royalty fees to creators - on wash trades. The average gas fee for wash traders was around 3,000 USD, but the top two wallets paid more than 350,000 USD while not making (or claiming) enough rewards to cover the cost. These two wallets interacted as counterparts and artificially traded NFT items 873 times for a particular collection[20] at X2Y2. On average, wash traders earned a realized profit of 53,000 USD, but the negative median value indicates that most did not make profits. This suggests that while some wash traders earn substantial profits from marketplace reward tokens, rewards may not be the primary motive for other wash traders.

Labeling Hypothesis. While the rewards hypothesis can partially explain the motivations behind wash trades in reward-giving marketplaces, it does not account for wash trades in marketplaces without reward systems, such as OpenSea, Sudoswap, and Element. Additionally, the motivations of wash traders who incur negative profits remain less understood.

Collection creators might engage in wash trades to attract market attention. OpenSea awards a mark to collections that meet specific criteria, aiming to "build trust in the NFT ecosystem by helping the community identify authentic creators and recognize their content." Specifically, a key criterion for receiving this mark is whether an NFT collection has been traded for over 75 ETH (approximately 225,000 USD) in the secondary market. If

[20]Cute Pig Club 0x9336888c4fc4adae3c7ced55be2b54884c052d59.

creators were artificially generating wash trades to meet this threshold, we would expect a reduction in wash trades after their collections exceed 75 ETH in trading volume due to reduced incentives.

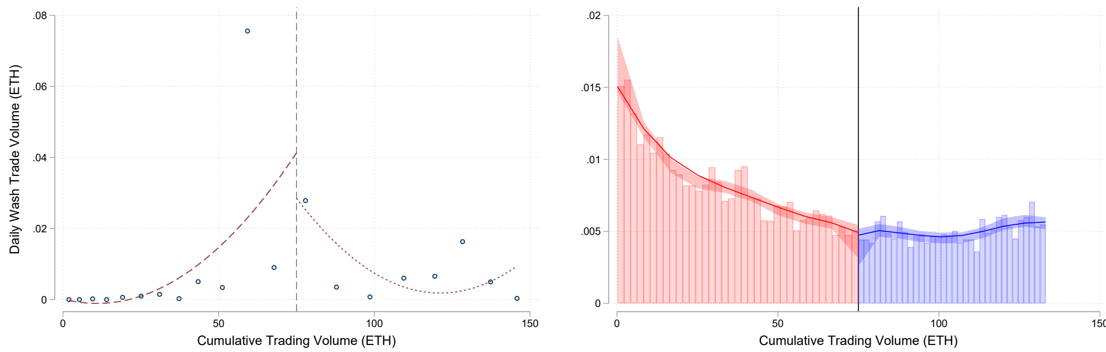

Figure 7. Cumulative Trading Volume and OpenSea Cutoff
Notes. The left figure shows daily wash trade volume in ETH until collections reach 150 ETH cumulative trading volume. The black dotted line indicates the 75 ETH cutoff for marked collections on OpenSea. The right figure shows the density function of the McCrary test.

The left panel of Figure 7 describes the binscatter plot of daily wash trade volume from the start of secondary market sales to 150 ETH cumulative sales. It seems that daily wash trade volume increases as cumulative trading volume approaches 75 ETH. After exceeding 75 ETH cumulative trading volume, wash trade volume appears to decrease. However, it is possible that this binscatter plot could be influenced by random variation.

In regression discontinuity design, the McCrary density test is commonly used to detect manipulation of the running variable around the cutoff point (McCrary, 2008). It tests whether the marginal density of the running variable (cumulative trading volume) is continuous without a jump. If there is a jump in the density, it suggests potential manipulation around the cutoff. In this study, this test is applicable since the cutoff is known in advance, and creators could strategically manipulate the cumulative trading volume to be above the cutoff. The right panel of Figure 7 shows no jump in the density function. The unreported estimation result also shows a t-statistic of -0.44 and a p-value of 0.65, suggesting there is no statistically significant evidence of manipulation at the cutoff point of 75 ETH. In other words, there is no strong evidence that creators are artificially boosting trading volume to receive the verified mark. It is important to note that this does not rule out the possibility that creators may engage in wash trading for other reasons.

Overall, this paper explored two primary hypotheses behind wash trading: the rewards hypothesis and the labeling hypothesis. The rewards hypothesis provides a partial explanation, as some wash traders indeed earn substantial profits from marketplace reward tokens. However, the labeling hypothesis, tested through the McCrary density test, found no significant evidence of creators artificially boosting trading volume to receive a verified mark on OpenSea. While marketplace rewards can drive some wash trading behaviors, the labeling incentive does not appear to be a significant motivator.

4.3 Investor Response to Wash Traded Item

Beyond understanding the motivations behind wash trades, it is crucial to examine whether NFT investors actively process the available information. Do NFT investors review transaction data, heed wash trade warnings on platforms like X (formerly Twitter), and engage with collections through Discord and other social channels? If so, do they subsequently avoid purchasing suspicious collections and items during the NFT boom? An affirmative answer would support the notion of rational investor behavior in the blockchain economy.

This subsection explores this question by examining manipulative trades. Specifically, I analyze whether investors disengage from items with a history of wash trades and if such items' return profiles significantly differ from those without a wash trade history. A key consideration is whether investors penalize items with a wash trade history, similar to Table 7, but using *transaction-level* data. This would suggest that investors can understand and act on public transaction-level data if they are neither trapped by wash traders nor significantly influenced by artificial prices.

To investigate this, an analysis of NFT items at the individual level is conducted. The realized return of an NFT item is examined based on its wash trade history. For a collection c and item i, purchased at time τ and sold at time t, the realized return is defined as $Price_{c,i,t}/Price_{c,i,\tau} - 1$. This calculation excludes gas fees, royalties, and marketplace fees, and returns are winsorized at the 1/99 percentile level for robustness. The key variable of interest, *Dummy previous is wash*, indicates whether the item's most recent transaction was a wash trade, ensuring the current transaction is not and that the previous buyer is now the seller. This binary variable thus distinguishes between items that are being traded normally after being part of a wash trade and those that are not.

Table 10. Realized Returns After Wash Trades
Notes. This table presents estimates regressing realized returns against a past wash trade history. The independent variable is *Dummy previous is wash*, set to 1 if a previous trade for the same collection c, item i was a wash trade, the current trade is not, and the previous buyer is the seller in the current trade. Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) Realized Return	(2) Realized Return	(3) Realized Return	(4) Realized Return
Dummy Previous Is Wash	-1.845***	-0.293**	-3.495***	-0.209
	(-9.649)	(-2.074)	(-5.258)	(-1.621)
Log(1+Holding Period)			0.0393	0.465***
			(0.784)	(4.457)
Log(NFT Price)			1.537***	1.550***
			(18.58)	(17.64)
Observations	3,296,355	2,310,561	3,296,355	2,310,561
Collection FE	NO	YES	NO	YES
Item FE	NO	YES	NO	YES
Date FE	NO	YES	NO	YES
Within Adj R-squared	5.00e-05	2.34e-06	0.156	0.0673
Adj R-squared	5.00e-05	0.0551	0.156	0.119

The regression results are in Table 10 where Columns (1) and (2) excludes collection, item, and date fixed effects and controls, and (3) and (4) includes fixed effects and control variables. Item fixed effects are included to control unspecified item-level characteristics such as rarity. Coefficients in Columns (1) and (2) are negative, indicating lower returns for items previously involved in wash trades, yet when controlled for fixed effects, the significance of this relationship disappears. This indicates investors do not systematically penalize items with a history of wash trades.

Although constructing a treatment-control group is impossible, three external shocks that might affect investors' perception or information processing ability are used to examine post-event effects. These shocks potentially shift investor perceptions and market dynamics, influencing how wash-traded NFTs are valued. First, on May 22nd, 2022, OpenSea adopted a new trading protocol, Seaport[21]. This new protocol allows more efficient trading strategies and options such as detailed listings and counteroffers, bidding and auction systems, and tipping. Second, on June 1st, 2022, the SEC charged a former OpenSea employee who used and leaked information about routine Top 100 ranking updates. He used this information to purchase NFT items that were to be included in future Top 100 lists in advance. This may serve as a warning signal to potential manipulators. Lastly, on August 30th, 2022, OpenSea, which mainly used ETH, incorporated the popular cryptocurrency Polygon into their system. This broadens investors' accessibility to the NFT market and lowers gas fees, one of the biggest issues with using ETH.

Table 11. Post-Event Realized Returns
Notes. This table presents estimates regressing realized returns against a past wash trade history and events that affect investors' perception or information processing ability. The main interest variable is terms interacted by *Dummy previous is wash*. Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) Realized Return	(2) Realized Return	(3) Realized Return	(4) Realized Return	(5) Realized Return	(6) Realized Return
Dummy Previous Is Wash	-2.508***	-0.746**	-2.509***	-0.719**	-2.408***	-0.634**
	(-6.108)	(-2.279)	(-6.072)	(-2.210)	(-6.434)	(-2.219)
policy_seaport	-0.898**					
	(-2.555)					
previous_is_wash×policy_seaport	-0.483	0.739**				
	(-0.718)	(2.140)				
opensea_insider			-0.920***			
			(-2.658)			
Dummy Previous Is Wash×opensea_insider			-0.453	0.700**		
			(-0.673)	(2.043)		
opensea_polygon					-0.887**	
					(-2.390)	
Dummy Previous Is Wash×opensea_polygon					-0.734	0.619**
					(-1.092)	(2.019)
Log(1+Holding Period)	0.0717	0.465***	0.0751	0.465***	0.0581	0.465***
	(1.273)	(4.457)	(1.320)	(4.457)	(1.089)	(4.457)
Log(NFT Price)	1.509***	1.550***	1.507***	1.550***	1.519***	1.550***
	(17.80)	(17.64)	(17.77)	(17.64)	(18.08)	(17.64)
Observations	3,296,355	2,310,561	3,296,355	2,310,561	3,296,355	2,310,561
Collection FE	NO	YES	NO	YES	NO	YES
Item FE	NO	YES	NO	YES	NO	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.157	0.0673	0.158	0.0673	0.157	0.0673
Adj R-squared	0.157	0.119	0.158	0.119	0.157	0.119

Table 11 shows post-event effects of external shocks. Odd-numbered Columns are without fixed effects, and even-numbered Columns are with fixed effects. Columns (2), (4), and (6) describe post-event effects which is an intersection term is positive. More specifi-

[21]Technical details can be found at https://docs.opensea.io/docs/seaport.

cally, interaction terms offset negative coefficients in *Dummy Previous Is Wash*. This can be interpreted as these events or policies offset negative realized returns from wash trade history by giving confidence to the NFT ecosystem and its transparency.

5 Insider Trading Analysis

5.1 Impact of Insider Trading

As mentioned in subsection 2.3 and subsection 2.4, it is possible to infer NFT insiders from on-chain transaction data without knowing their exact identities. Moreover, this inference aligns with known cases. In this section, I examine the impact of information-based trades on two aggregated market outcomes using predictive regressions: the rate of daily price index changes and daily trading volume changes. Transaction data is aggregated into daily panel data as in section 4. The baseline regression model for a collection c and day t is similar to subsection 4.1:

$$DV_{c,t+1} = \beta InsiderActivity_{c,t} + \gamma X_{c,t} + CollectionFE + DateFE + u_{c,t+1} \tag{3}$$

where $DV_{c,t+1}$ represents the rate of change in the real index price, or the rate of change in real trading volume from day t to $t+1$, as defined in Table 3. The main independent variable is either insider buy volume or insider sell volume for collection c at day t, divided by the total minted amount of collection c. $X_{c,t}$ represents a matrix of control variables at day t. Standard errors are clustered by collection and date.

The estimated results are shown at Table 12. Column (1) shows regression the result of insider buying activity on real future price index returns, and Column (2) represents the result of insider selling activity. Similarly, Column (3) explains the impact of insider buy activity on real future volume change, and Column (4) is for insider sell activity. All columns include date and collection fixed effects. Columns (1) and (2) display positive coefficients that are statistically significant. Given the large coefficients, interpreting the increase in standard deviations might be more straightforward. A one standard deviation increase in *InsiderBuy Activity* leads to 2.7 percentage point increase in future daily index returns

Table 12. Impact of Insider Activity on Future Market Outcomes
Notes. This table reports the results from the estimates of specification (3), where I regress future median price index returns (Columns (1) and (2)) or future changes in trading volume (Columns (5) and (6)) against the daily purchase activity of insiders for collection c as of day t. Price index regressed on daily insider sell activity is in Columns (5) and (6), and volume is in Columns (7) and (8). Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) Price	(2) Price	(3) Volume	(4) Volume
InsiderBuy Activity	26.86***		-147.7***	
	(5.929)		(-7.229)	
InsiderSell Activity		7.650***		-20.46
		(3.653)		(-1.411)
Log(1+Days after mints)	0.00710	0.00484	-0.0651***	-0.0515***
	(0.875)	(0.597)	(-3.611)	(-2.904)
Past Volume (Real)	0.00736***	0.00732***	-0.151***	-0.152***
	(3.007)	(2.988)	(-18.68)	(-18.54)
Past Day Returns	-0.0145	-0.0152*	-0.00499	-0.00469
	(-1.604)	(-1.687)	(-0.157)	(-0.147)
Past Week Returns	-0.00252	-0.00289	0.0245*	0.0253*
	(-0.694)	(-0.810)	(1.790)	(1.892)
Log Market Value of Collection	-0.0790***	-0.0791***	-0.0383***	-0.0385***
	(-12.42)	(-12.39)	(-3.456)	(-3.474)
Observations	33,725	33,725	33,725	33,725
Collection FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Within Adj R-squared	0.0448	0.0438	0.0179	0.0153
Adj R-squared	0.0908	0.0898	0.0335	0.0309

when controls are applied. For a standard deviation increase in *InsiderSell Activity* lead to 1.6 percentage points increase in future daily index returns. This suggests that insiders buy before the price increase and also sell before the price increase, yet the implications for insider selling are less straightforward.

As previously discussed, achieving optimal market timing by selling at high prices in a speculative market is challenging, largely due to the price dependency on other investors' demand (Oh, Rosen, and Zhang, 2023) and prevailing sentiment (Wilkoff and Yildiz, 2023). In contrast, purchases can be more directly attributed to information asymmetry. This notion aligns with the positive coefficients observed for insider purchase behavior, paralleling the findings in Cohen, Malloy, and Pomorski (2012). However, in contrast to the superior market timing patterns of insiders noted in Cohen, Malloy, and Pomorski (2012), the coefficients for insider selling behavior do not exhibit a negative value.

This raises a question: Is a fundamental mechanism at play here? If insider activity does not meaningfully alter the trading volume, then it cannot be merely a simple more demand–higher price, or less demand–lower price relationship in illiquid market. Column (3) shows that the estimated β is negative, implying that insider purchase decreases future trading volume. Specifically, a one standard deviation increase in *InsiderBuy Activity* results in an approximate decrease of 14 percentage points in daily trading volume. However, given the low liquidity–where the average trading volume is 47 and the median is 13–the actual economic significance is marginal. In Column (4), the coefficient is statistically and economically insignificant. Consequently, measured insider activity behavior does not capture trivial demand and price mechanism. This suggests that insiders effectively leverage their informational advantage in purchasing activities but might not apply the same strategy when selling.

5.2 Online Community as Information Channel

To further underscore insiders' information advantage, this subsection explores the heterogeneity of insiders' behavior by examining their holding patterns alongside their purchase and sale activities. Insider buying behavior can be categorized into two distinct types: purchases made while already holding other NFTs in their collection, and those made when no NFTs are held, typically following previous sales. Similarly, selling behavior can be split into insiders selling while still retaining other NFTs in a collection, and those who completely divest their NFT holdings, effectively exiting the collection.

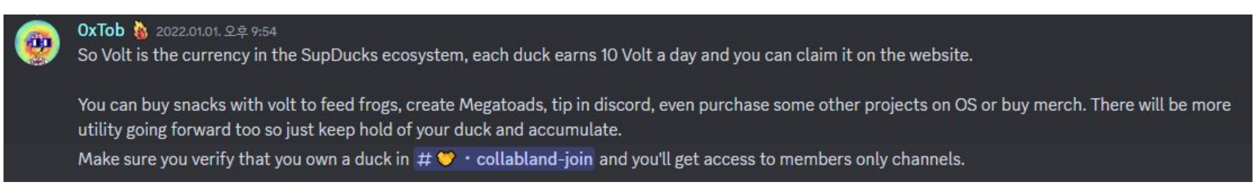

Figure 8. Example of Member-only Chatrooms
Notes. This screenshot illustrates a members-only chatroom with exclusive content from *Supducks*, facilitated by an automatic ownership verification system. This figure does not imply or suggest any misconduct or inappropriate behavior associated with *Supducks*.

Insiders maintaining their NFT holdings might have an additional advantage by utilizing information from members-only chat rooms to guide their buying or selling decisions. As depicted in Figure 8, these chat rooms offer exclusive content to verified members. In essence, by retaining their NFTs, insiders preserve access to community-specific knowledge linked to their collection. For example, future planned collaborations with other famous collections or celebrities, gatherings with creators and like-minded people, or updates on their development processes are spread in the chatroom. The variable *InsiderBuy Activity* × *With Access* quantifies the additional purchasing behavior of insiders when they already hold at least one different NFT within their collection. Similarly, *InsiderSell Activity* × *With Access* denotes the insiders' additional selling behavior when they already possess at least one different NFT.

In contrast, insider wallets that do not have any NFTs lack access to these exclusive communities and their benefits. The variable *InsiderBuy Activity* × *No Access* captures insiders' trading behavior when they do not have any NFTs in their collection, indicating a purchase without information advantage. Such behavior could indicate attempts to re-enter the collection without prior access. *InsiderSell Activity* × *No Access* reflects the departure of insiders, possibly due to negative insights about the collection, or simply as a decision to realize their investment profits by liquidating their NFTs.

Table 13 presents results from a regression analysis using a similar specification to Equation 3. Columns (1) and (2) follow the findings from Columns (1) through (4) of Table 12, but with insider buy and sell in the same equation. Even if the magnitude of sell behavior becomes smaller, implications do not change. Columns (3) and (4) reveal that *InsiderBuy Activity* × *With Access* is statistically significant, whereas *InsiderBuy Activity* × *No Access* is not significant. This suggests that not all insiders gain an information advantage; rather, only those with community access do. The magnitude of coefficients, 2.2 and 2.6 percentage points per a standard deviation increase, are consistent with those in Columns (1) and (2) in Table 12. For selling behavior, as shown in Columns (5) and (6), the *InsiderSell Activity* terms for insiders with access are not statistically significant, indicating that these insiders do not demonstrate poor timing in their selling decisions. Conversely, the positive and statistically significant coefficient in Column (6) suggests that insiders without informa-

Table 13. Heterogeneity in Insider Behavior
Notes. This table reports the results from regression analysis of heterogeneous insider activities. It examines future median price returns regressed on daily insider buy and sell activity, categorized into with and without community access, for collection c as of day t. Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) Price	(2) Price	(3) Price	(4) Price	(5) Price	(6) Price
InsiderBuy Activity	20.22***	24.12***				
	(4.571)	(5.178)				
InsiderBuy Activity x With Access			25.26***	29.74***		
			(5.647)	(6.612)		
InsiderBuy Activity x No Access			-26.41	-31.81		
			(-0.568)	(-0.732)		
InsiderSell Activity	3.958***	4.392***				
	(2.968)	(3.155)				
InsiderSell Activity x With Access					2.821	2.349
					(0.590)	(0.592)
InsiderSell Activity x No Access					39.56*	49.20***
					(1.874)	(2.840)
Observations	39,801	39,757	39,801	39,757	39,801	39,757
Collection FE	NO	YES	NO	YES	NO	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.0151	0.0476	0.0148	0.0473	0.0142	0.0465
Adj R-squared	0.0151	0.0927	0.0148	0.0925	0.0142	0.0918

tion access tend to sell their holdings just before an increase in the price index, potentially indicating less informed or poorly timed selling choices.

5.3 Extension to Informed Trading

This subsection explores whether non-insiders can engage in informed trading similar to insiders when internal information is disseminated through an online community[22]. Recall that insiders are identified as free-minters, and their purchase behaviors are categorized into informed and non-informed trading. Informed trading is characterized by making ad-

[22]Unfortunately, it is challenging to verify what types of information is spreading in the online community from the transaction data. Many Discord community of the sample have been closed or inactive during the crypto winter in 2022.

ditional purchases while holding at least one NFT item in the collection[23].

By assessing whether each wallet holds at least one item in a collection before purchasing another, we can detect not only insiders' informed trading but also non-insiders' informed trading. Informed buy is defined as the sum of insiders' purchases with community access and non-insiders' purchases with community access. Conversely, uninformed buying encompasses the sum of insiders' purchases without community access and non-insiders' purchases without community access.

Table 14. Heterogeneity in Informed Buying Trade
Notes. This table presents the results of regression analyses on informed and uninformed trading. Informed purchase is defined as the standardized purchase volume with community access at day t for collection c. Uninformed purchase is the remainder of the trading volume at day t for collection c. Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) Price	(2) Price	(3) Price	(4) Price	(5) Price	(6) Price
InsiderBuy Activity x With Access	25.26***	29.74***				
	(5.647)	(6.612)				
InsiderBuy Activity x No Access	-26.41	-31.81				
	(-0.568)	(-0.732)				
Non-insiderBuy Activity x With Access			3.537***	4.211***		
			(5.089)	(7.882)		
Non-insiderBuy Activity x No Access			0.203	-0.376		
			(0.243)	(-0.562)		
InformedBuy Activity					3.645***	4.339***
					(5.246)	(8.097)
UninformedBuy Activity					0.0546	-0.553
					(0.0650)	(-0.828)
Observations	39,801	39,757	39,801	39,757	39,801	39,757
Collection FE	NO	YES	NO	YES	NO	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.0148	0.0473	0.0257	0.0592	0.0260	0.0597
Adj R-squared	0.0148	0.0925	0.0257	0.104	0.0260	0.104

Table 14 shows the regression results on market outcomes. Columns (1) and (2) is copied from Columns (3) and (4) of Table 13 for readability. Columns (3) and (4) reveal that

[23]In exploring informed selling behaviors, distinguishing between the effects of genuinely informed trading and high-frequency flipped trading presents a significant challenge. The dynamics of the NFT market complicate the clear identification of trading based on information versus speculative flipping. This complexity limits the analysis into informed buying behaviors.

non-insiders with community access can also predict higher future returns, whereas non-insiders without community access do not demonstrate the ability to predict positive future returns. Informed purchase that is a mix of insider buy with access and non-insider buy with access in Columns (5) and (6) shows consistent result. One standard deviation increase in informed purchase leads to 4.9 or 5.8 percentage points increase while uninformed purchase is statistically insignificant. This suggests that being an insider is not a necessary condition for abnormal profits. Instead, information sharing within a community is key, enabling all informed traders in the community to predict future returns.

Long-term Impact of Informed Trading. If an information advantage exists, its effects should extend beyond a single day. This can be tested in the similar manner to the wash trade. The dependent variable is cumulative index price returns after 2, 3, 5, 7, and 14 days. Table 15 shows coefficients of informed buy activity is statistically and economically significant up to one week. Uninformed buy activity still remains statistically insignificant. This result further supports the notion that both insiders and non-insiders with access to member-only communities have an information advantage.

6 Conclusion

This paper provides a comprehensive examination of wash trading and insider trading within the NFT market, utilizing a rich dataset of transaction-level data from the Ethereum blockchain. By deploying a combination of empirical strategies, including predictive regressions and item-level analyses, the study sheds light on the nuanced behaviors of market participants and the impact of these behaviors on market outcomes.

The findings suggest that wash trading does not significantly impact future price returns or trading volumes, indicating that investors may recognize and discount the artificial signals generated by these trades. This lack of a meaningful long-term impact reinforces the perception that the NFT market, despite its speculative nature, is navigated by informed market participants.

The study also explores the incentives behind wash trading. Marketplaces offering cryptocurrency rewards proportional to daily trading volume incentivize traders to generate

Table 15. Long-term Impact of Informed and Uninformed Buying Trade
Notes. This table reports the results from regression analysis of informed and uninformed trading. Informed purchase is defined as the standardized purchase volume with community access at day t for collection c. Uninformed purchase is the remainder of the trading volume at day t for collection c. The dependent variable is the long-term median price change in USD from day t to days $t+1, t+2, t+3, t+5, t+7$ and $t+14$, excluding all trades classified as wash trades. Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$.

VARIABLES	(1) 1 Day	(2) 2 Day	(3) 3 Day	(4) 5 Day	(5) 7 Day	(6) 14 Day
InformedBuy Activity	4.339***	4.314***	4.515***	3.986***	3.648***	0.763
	(8.097)	(6.531)	(5.496)	(4.353)	(3.180)	(0.427)
UninformedBuy Activity	-0.553	-0.959	-1.864*	-1.724	-0.455	1.392
	(-0.828)	(-1.068)	(-1.952)	(-1.568)	(-0.323)	(0.666)
Log(1+Days after mints)	0.0199**	0.00854	0.00986	-0.00479	-0.00940	-0.0608
	(2.428)	(0.750)	(0.674)	(-0.236)	(-0.368)	(-1.508)
Past Volume (Real)	3.23e-05	-0.000632	0.00416	0.00580	0.00881	0.0169*
	(0.0138)	(-0.219)	(1.095)	(1.190)	(1.432)	(1.812)
Past Day Returns	-0.0345***	-0.0413***	-0.0487***	-0.0487***	-0.0414***	-0.0411***
	(-4.310)	(-4.453)	(-4.447)	(-4.411)	(-3.535)	(-2.643)
Past Week Returns	-0.0103***	-0.00722	-0.00524	-0.0146*	-0.0231**	-0.00659
	(-3.247)	(-1.388)	(-0.776)	(-1.754)	(-2.413)	(-0.510)
Log Market Value of Collection	-0.0841***	-0.116***	-0.146***	-0.193***	-0.243***	-0.390***
	(-12.75)	(-14.26)	(-15.05)	(-16.12)	(-15.97)	(-15.81)
Observations	39,757	39,258	38,924	38,426	37,870	36,266
Collection FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Within Adj R-squared	0.0597	0.0667	0.0774	0.0952	0.113	0.158
Adj R-squared	0.104	0.147	0.175	0.233	0.270	0.362

fake volume and artificial prices. Around half of the wash traders who claimed rewards at these marketplaces earned positive profits, some even millions of dollars, partially explaining the motivation behind wash trading. Conversely, OpenSea provides verification marks for collections exceeding 75 ETH in cumulative trading volume, potentially incentivizing wash trades. However, the McCrary density test suggests no manipulative attempts to surpass this cutoff. Additionally, further analysis of item-level transaction data reveals that NFT investors generally ignore the wash trade history of each item. Combined with the finding that wash trade activity does not predict future market outcomes, this indicates that investors can avoid being influenced by wash trading by checking blockchain data. The study also shows that events improving market transparency can offset negative realized returns from wash trade history.

Insider trading, particularly insider buying activities, significantly predicts future price returns, indicating an information advantage leveraged by insiders. Insider selling activities do not exhibit similar predictive power, highlighting the complexities of market timing in a speculative and illiquid market. The analysis also reveals that access to online community channels is crucial for both insiders and informed non-insiders to anticipate future market movements, underscoring the importance of social dynamics and digital communities in shaping market trends within the NFT ecosystem.

This paper contributes to the understanding of market integrity and investor behavior in the NFT market, highlighting the roles of information asymmetry, community engagement, and speculative trading strategies. By analyzing the interplay between insiders, wash traders, and the broader investor base, it offers valuable insights into this rapidly evolving market. Future research and regulatory frameworks should focus on ensuring transparency, fairness, and investor protection using public blockchain data.

References

Aggarwal, R. K., and G. Wu. 2006. Stock Market Manipulations. *Journal of Business* 79:1915–53.

Ahern, K. R. 2017. Information Networks: Evidence from Illegal Insider Trading Tips. *Journal of Financial Economics* 125:26–47.

Aitken, M., D. Cumming, and F. Zhan. 2015. High Frequency Trading and End-Of-Day Price Dislocation. *Journal of Banking & Finance* 59:330–49.

Aloosh, A., and J. Li. 2023. Direct Evidence of Bitcoin Wash Trading. *Management Science* .

Anderson, R. C., D. M. Reeb, and W. Zhao. 2012. Family-Controlled Firms and Informed Trading: Evidence from Short Sales. *Journal of Finance* 67:351–85.

Banerjee, S., J. Davis, and N. Gondhi. 2018. When Transparency Improves, Must Prices Reflect Fundamentals Better? *Review of Financial Studies* 31:2377–414.

Bao, T., M. Ma, and Y. Wen. 2023. Herding in the non-fungible token (NFT) market. *Journal of Behavioral and Experimental Finance* 39:100837–.

Borri, N., Y. Liu, and A. Tsyvinski. 2022. The Economics of Non-Fungible Tokens. Working paper.

Cao, Y., Y. Li, S. Coleman, A. Belatreche, and T. M. McGinnity. 2016. Detecting Wash Trade in Financial Market Using Digraphs and Dynamic Programming. *IEEE Transactions on Neural Networks and Learning Systems* 27:2351–63.

Cohen, L., C. Malloy, and L. Pomorski. 2012. Decoding Inside Information. *Journal of Finance* 67:1009–43.

Cong, L. W., W. Landsman, E. Maydew, and D. Rabetti. 2023a. Tax-Loss Harvesting with Cryptocurrencies. *Journal of Accounting and Economics* 76:101607–.

Cong, L. W., X. Li, K. Tang, and Y. Yang. 2023b. Crypto Wash Trading. *Management Science* 69:6427–54.

Gandal, N., J. Hamrick, T. Moore, and T. Oberman. 2018. Price Manipulation in the Bitcoin Ecosystem. *Journal of Monetary Economics* 95:86–96.

Grinblatt, M., and M. Keloharju. 2004. Tax-Loss Trading and Wash Sales. *Journal of Financial Economics* 71:51–76.

Jiang, W., and T. Li. 2024. Corporate Governance Meets Data and Technology. Working paper.

Kong, D.-R., and T.-C. Lin. 2022. Alternative Investments in the Fintech Era: The Risk and Return of Non-Fungible Token (NFT). Working paper.

Kräussl, R., and A. Tugnetti. 2023. Non-Fungible Tokens (NFTs): A Review of Pricing Determinants, Applications and Opportunities. *Journal of Economic Surveys* 38:555–74.

Kyle, A. S., and S. Viswanathan. 2008. How to Define Illegal Price Manipulation. *American Economic Review: Papers & Proceedings* 98:274–9.

Li, T., D. Shin, and B. Wang. 2022. Cryptocurrency Pump-and-Dump Schemes. Working paper.

Makarov, I., and A. Schoar. 2021. Blockchain Analysis of the Bitcoin Market. Working paper.

Massoud, N., S. Ullah, and B. Scholnick. 2016. Does It Help Firms to Secretly Pay for Stock Promoters? *Journal of Financial Stability* 26:45–61.

McCrary, J. 2008. Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test. *Journal of Econometrics* 142:698–714.

Morgia, M. L., A. Mei, A. M. Mongardini, and E. N. Nemmi. 2023. A Game of NFTs: Characterizing NFT Wash Trading in the Ethereum Blockchain. In *2023 IEEE 43rd International Conference on Distributed Computing Systems*.

Oh, S., S. Rosen, and A. L. Zhang. 2023. Digital Veblen Goods. Working paper.

Pourghannad, B., G. Kong, and L. Debo. 2020. Is Kindness the Magical Spell? The Role of Information and Reciprocity in Revenue-Sharing Crowdfunding. Working paper.

Sun, H., and S. Yin. 2017. Information Leakage in Family Firms: Evidence from Short Selling around Insider Sales. *Journal of Corporate Finance* 47:72–87.

Wachter, V. v., J. R. Jensen, F. Regner, and O. Ross. 2022. NFT Wash Trading: Quantifying Suspicious Behaviour in NFT Markets. Working paper.

Wilkoff, S., and S. Yildiz. 2023. The Behavior and Determinants of Illiquidity in the Non-Fungible Tokens (NFTs) Market. *Global Finance Journal* 55:100782–.

Appendix

A Supplementary Materials

Table A.1. Summary Statistics
Notes. This table presents the summary statistics for insiders and wash trades, as defined in subsection 2.3 and subsection 2.2. Insiders are identified as free minters who received NFTs at no cost from the creators. Wash trades are classified as either (1) identity trades, (2) 1-1 trades, or (3) matched orders. The observations in this table represent the aggregate measures for each collection-level variable.

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Panel A: Insider					
Trading_Volume	557	6,601	7,269	13	44,372
# of Minted Items	557	6,529	3,780	1,000	25,000
Insider Buying Volume	557	105.6	343.8	0	5,777
Insider Selling Volume	557	127.8	448.8	0	5,455
Insider Sell/# of Minted Items	557	0.0340	0.0837	0	0.580
Insider Buy/# of Minted Items	557	0.0324	0.0763	0	0.701
Insider Buying + Selling /# of Minted Items	557	0.0345	0.0824	0	0.905
Wallets in Primary Market	557	1,524	1,112	61	7,724
Potential Insider Wallets (Free Minted)	557	61.72	164.9	0	1,964
Insider Wallets/Total Wallets in Primary Market	557	0.0464	0.105	0	0.725
Panel B: Wash Trade					
Average # of Type 1 Wash Sales	557	0.621	3.620	0	67
Average # of Type 2 Wash Sales	557	18.68	170.1	0	3,416
Average # of Type 3 Wash Sales	557	2.120	15.88	0	297
Average # of Wash Sales	557	20.99	173.1	0	3,422
Collection Volume (Total # of Minted Items)	557	6,529	3,780	1,000	25,000
Average Type 1 Wash Sales Volume/Collection Volume	557	6.95e-05	0.000373	0	0.00670
Average Type 2 Wash Sales Volume/Collection Volume	557	0.00340	0.0490	0	1.139
Average Type 3 Wash Sales Volume/Collection Volumes	557	0.000238	0.00164	0	0.0297
Average Wash Sales Volume/Collection Volume	557	0.00366	0.0492	0	1.141
Has Type 1 Wash Sales	557	0.115	0.319	0	1
Has Type 2 Wash Sales	557	0.397	0.490	0	1
Has Type 3 Wash Sales	557	0.140	0.347	0	1
Has Wash Sales	557	0.431	0.496	0	1

Table A.2. Correlation Matrix

Notes. This table shows Pearson correlation coefficients of all variables used in Table 4. Each variables are (1) Price Return, (2) Price Return nowash, (3) Volume Change nowash, (4) Volume Change, (5) InsiderBuy Activity, (6) InsiderSell Activity (7) Wash Activity, (8) Days between wash and first mint sales, (9) Past Day Returns, (10) Past Week Returns, (11) Market Value of Collection. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	1.00										
(2)	1.00***	1.00									
(3)	0.13***	0.13***	1.00								
(4)	0.13***	0.13***	1.00***	1.00							
(5)	0.01*	0.01*	-0.04***	-0.04***	1.00						
(6)	0.02***	0.02***	-0.02***	-0.02***	0.37***	1.00					
(7)	-0.01*	-0.01*	-0.01*	-0.01**	0.00	0.00	1.00				
(8)	0.01*	0.01*	0.01	0.01	-0.08***	-0.05***	0.02***	1.00			
(9)	-0.01*	-0.01*	-0.02***	-0.02***	0.00	0.04***	0.01	-0.01	1.00		
(10)	-0.01	-0.00	-0.01**	-0.01**	0.02***	0.05***	-0.00	-0.03***	-0.14***	1.00	
(11)	-0.02***	-0.02***	-0.01**	-0.01*	-0.01**	-0.01	0.07***	0.08***	-0.00	0.00	1.00

Table A.3. Long-term Impact of Wash Trade on Market Outcomes (Panel A)
Notes. This table presents results from estimates of specification (3) in which future median price returns and future trading volume changes are regressed on daily activities of insider and wash trading for collection c as of day t. Panel A's dependent variable is the long-term median price change in USD from day t to days $t+1, t+2, t+3, t+5, t+7$ and $t+14$, excluding all trades classified as wash trades. Panel B's dependent variable is the trading volume change from day t to days $t+1, t+2, t+3, t+5, t+7$ and $t+14$, also excluding all wash trades. Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) 1 Day	(2) 2 Day	(3) 3 Day	(4) 5 Day	(5) 7 Day	(6) 14 Day
Wash Activity	0.000300	-1.25e-05	0.000128	-0.000772	0.000216	0.00393
	(0.597)	(-0.0155)	(0.127)	(-1.459)	(0.102)	(1.376)
Log(1+Days after mints)	0.00673	-0.00383	-0.00149	-0.0147	-0.0207	-0.0659
	(0.840)	(-0.339)	(-0.102)	(-0.720)	(-0.806)	(-1.630)
Past Volume (Real)	0.00987***	0.00851***	0.0124***	0.0130**	0.0171***	0.0210**
	(4.211)	(2.789)	(3.111)	(2.475)	(2.591)	(2.105)
Past Day Returns	-0.0238***	-0.0313***	-0.0403***	-0.0410***	-0.0312***	-0.0357**
	(-3.020)	(-3.343)	(-3.528)	(-3.669)	(-2.649)	(-2.233)
Past Week Returns	-0.00420	-0.00154	-0.000161	-0.0101	-0.0177*	-0.00411
	(-1.264)	(-0.288)	(-0.0235)	(-1.224)	(-1.871)	(-0.315)
Log Market Value of Collection	-0.0823***	-0.114***	-0.144***	-0.192***	-0.242***	-0.390***
	(-13.04)	(-14.39)	(-15.10)	(-16.06)	(-15.91)	(-15.80)
Observations	39,757	39,258	38,924	38,426	37,870	36,266
Collection FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Within Adj R-squared	0.0448	0.0582	0.0718	0.0921	0.110	0.158
Adj R-squared	0.0901	0.139	0.170	0.230	0.267	0.361

Table A.4. Long-term Impact of Wash Trade on Market Outcomes (Panel B)
Notes. This table presents results from estimates of specification (3) in which future median price returns and future trading volume changes are regressed on daily activities of insider and wash trading for collection c as of day t. Panel A's dependent variable is the long-term median price change in USD from day t to days $t+1, t+2, t+3, t+5, t+7$ and $t+14$, excluding all trades classified as wash trades. Panel B's dependent variable is the trading volume change from day t to days $t+1, t+2, t+3, t+5, t+7$ and $t+14$, also excluding all wash trades. Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) 1 Day	(2) 2 Day	(3) 3 Day	(4) 5 Day	(5) 7 Day	(6) 14 Day
Wash Activity	-0.00378***	-0.00304*	-0.00265	-0.00569**	-0.000233	-0.00619
	(-2.786)	(-1.797)	(-1.231)	(-2.555)	(-0.0874)	(-1.520)
Log(1+Days after mints)	-0.0550***	-0.0949***	-0.118***	-0.139***	-0.207***	-0.205***
	(-3.181)	(-3.079)	(-3.158)	(-2.902)	(-3.635)	(-3.124)
Past Volume (Real)	-0.146***	-0.200***	-0.256***	-0.297***	-0.348***	-0.412***
	(-18.80)	(-17.35)	(-19.61)	(-17.31)	(-18.15)	(-16.15)
Past Day Returns	-0.0195	0.00340	0.0696**	0.0367	0.0739**	0.165***
	(-0.643)	(0.0976)	(2.155)	(1.035)	(2.089)	(3.800)
Past Week Returns	0.0279**	0.0366*	0.0485**	0.00883	-0.00500	0.0485*
	(2.179)	(1.835)	(2.363)	(0.373)	(-0.211)	(1.712)
Log Market Value of Collection	-0.0503***	-0.0941***	-0.103***	-0.160***	-0.194***	-0.227***
	(-4.622)	(-5.576)	(-4.912)	(-6.338)	(-7.240)	(-6.395)
Observations	39,757	39,258	38,924	38,426	37,870	36,266
Collection FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Within Adj R-squared	0.0141	0.0180	0.0233	0.0311	0.0402	0.0497
Adj R-squared	0.0322	0.0451	0.0584	0.0771	0.0948	0.127

Table A.5. Heterogeneity in Insider Behavior

Notes. This table reports the results from regression analysis of heterogeneous insider activities. It examines future median price returns regressed on daily insider buy and sell activity, categorized into with and without community access, for collection c as of day t. Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) Price	(2) Price	(3) Price	(4) Price	(5) Price	(6) Price
InsiderBuy Activity	20.22***	24.12***				
	(4.571)	(5.178)				
InsiderBuy Activity x With Access			25.26***	29.74***		
			(5.647)	(6.612)		
InsiderBuy Activity x No Access			-26.41	-31.81		
			(-0.568)	(-0.732)		
InsiderSell Activity	3.958***	4.392***				
	(2.968)	(3.155)				
InsiderSell Activity x With Access					2.821	2.349
					(0.590)	(0.592)
InsiderSell Activity x No Access					39.56*	49.20***
					(1.874)	(2.840)
Log(1+Days after mints)	0.00368*	0.00940	0.00375*	0.00969	0.00308	0.00782
	(1.770)	(1.183)	(1.810)	(1.220)	(1.478)	(0.983)
Past Volume (Real)	-0.00219	0.00931***	-0.00205	0.00947***	-0.00196	0.00944***
	(-1.048)	(3.983)	(-0.981)	(4.062)	(-0.937)	(4.036)
Past Day Returns	-0.0154*	-0.0246***	-0.0149*	-0.0240***	-0.0158*	-0.0248***
	(-1.848)	(-3.100)	(-1.773)	(-3.027)	(-1.890)	(-3.122)
Past Week Returns	-0.00122	-0.00444	-0.000893	-0.00422	-0.00131	-0.00450
	(-0.302)	(-1.371)	(-0.219)	(-1.281)	(-0.325)	(-1.385)
Log Market Value of Collection	-0.0158***	-0.0826***	-0.0158***	-0.0825***	-0.0160***	-0.0826***
	(-5.767)	(-13.08)	(-5.770)	(-13.09)	(-5.789)	(-13.05)
Observations	39,801	39,757	39,801	39,757	39,801	39,757
Collection FE	NO	YES	NO	YES	NO	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.0151	0.0476	0.0148	0.0473	0.0142	0.0465
Adj R-squared	0.0151	0.0927	0.0148	0.0925	0.0142	0.0918

Table A.6. Heterogeneity in Informed Buying Trade

Notes. This table reports the results from regression analysis of informed and uninformed trading. Informed purchase is defined as the standardized purchase volume with community access at day t for collection c. Uninformed purchase is the remainder of the trading volume at day t for collection c. Standard errors are clustered by collection and date. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Price	Price	Price	Price	Price	Price
InsiderBuy Activity x With Access	25.26***	29.74***				
	(5.647)	(6.612)				
InsiderBuy Activity x No Access	-26.41	-31.81				
	(-0.568)	(-0.732)				
Non-insiderBuy Activity x With Access			3.537***	4.211***		
			(5.089)	(7.882)		
Non-insiderBuy Activity x No Access			0.203	-0.376		
			(0.243)	(-0.562)		
InformedBuy Activity					3.645***	4.339***
					(5.246)	(8.097)
UninformedBuy Activity					0.0546	-0.553
					(0.0650)	(-0.828)
Log(1+Days after mints)	0.00375*	0.00969	0.00542***	0.0194**	0.00558***	0.0199**
	(1.810)	(1.220)	(2.592)	(2.366)	(2.664)	(2.428)
Past Volume (Real)	-0.00205	0.00947***	-0.0125***	0.000131	-0.0126***	3.23e-05
	(-0.981)	(4.062)	(-5.995)	(0.0560)	(-6.050)	(0.0138)
Past Day Returns	-0.0149*	-0.0240***	-0.0244***	-0.0345***	-0.0244***	-0.0345***
	(-1.773)	(-3.027)	(-2.895)	(-4.318)	(-2.892)	(-4.310)
Past Week Returns	-0.000893	-0.00422	-0.00678*	-0.0103***	-0.00680*	-0.0103***
	(-0.219)	(-1.281)	(-1.734)	(-3.236)	(-1.740)	(-3.247)
Log Market Value of Collection	-0.0158***	-0.0825***	-0.0159***	-0.0841***	-0.0159***	-0.0841***
	(-5.770)	(-13.09)	(-5.757)	(-12.74)	(-5.748)	(-12.75)
Observations	39,801	39,757	39,801	39,757	39,801	39,757
Collection FE	NO	YES	NO	YES	NO	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.0148	0.0473	0.0257	0.0592	0.0260	0.0597
Adj R-squared	0.0148	0.0925	0.0257	0.104	0.0260	0.104

B Algorithms to Detect Wash Trades

This appendix section describes algorithms that I used to detect wash trades from transaction data. Note that the data has at least five columns: *nft_address*, *token_id*, *datetime*, *buyer*, and *seller*. In addition, since every NFT item is unique in item-level, we run algorithms in its unique collection-item level.

The first algorithm detects identity trades, a straightforward process. Grouping is done for each unique combination of *nft_address* and *token_id*. Within these groups, transaction records are arranged row-wise, representing specific item transactions. The algorithm checks each group for transactions where the seller and buyer are the same. Such transactions are flagged as *wash_type1*, indicating a potential wash trade where an entity trades with itself.

Algorithm 1 Flag wash trade type 1 (identity trade)

Require: DataFrame *df_secondary* with columns *nft_address*, *token_id*, *datetime*, *buyer*, and *seller*

Ensure: DataFrame *df_secondary* with updated column *wash_type1*

```
procedure FlagWashTypeOne(df_secondary)
    for each unique pair of nft_address and token_id in df_secondary do
        group ← all rows with the same nft_address and token_id
        for each row in group do
            if row.seller == row.buyer then
                row.wash_type1 ← 1
            else
                row.wash_type1 ← 0
            end if
        end for
    end for
end procedure
```

The second algorithm identifies 1-1 trades that occur within a 7-day window. This process involves two checks. First, it examines whether the buyer in a previous transaction is the seller in the current transaction, and vice versa. This reciprocal trade, occurring in a short span, signals a potential wash trade. Additionally, the algorithm assesses future transactions, checking if the current seller and buyer swap roles in a subsequent trade within the next seven days. Transactions meeting either of these criteria are flagged as *wash_type2*, highlighting a 1-1 trade pattern often indicative of wash trading. This approach effectively captures the entry and exit points of wash traders.

Algorithm 2 Flag wash trade type 2 (1-1 trade within 7 days)

Require: DataFrame *df_secondary* with columns *nft_address*, *token_id*, *datetime*, *buyer*, and *seller*
Ensure: DataFrame *df_secondary* with updated column *wash_type2*

```
procedure FlagWashTypeTwo(df_secondary)
    for each unique pair of nft_address and token_id in df_secondary do
        group ← all rows with the same nft_address and token_id
        for each row in group do
            past_criteria ← (row.previous_buyer == row.seller and row.previous_seller == row.buyer and row.time_diff_same_item ≤ 7 days)
            future_criteria ← (row.seller == row.future_buyer and row.buyer == row.future_seller and row.future_txn_diff ≤ 7 days)
            if past_criteria or future_criteria then
                row.wash_type2 ← 1
            else
                row.wash_type2 ← 0
            end if
        end for
    end for
end procedure
```

The third algorithm focuses on detecting triangle matched orders in wash trades. These sophisticated schemes involve three parties (A, B, and C) trading in a loop, where A sells to B, B sells to C, and C sells back to A. This form of wash trading creates an illusion of increased activity and demand without any actual change in ownership.

This algorithm operates on two fronts. First, it examines past transactions up to the current row. It checks if a past seller (A), who sold an item two transactions prior, is buying back the same item within seven days. This pattern indicates a potential loop in the trading chain.

Second, the algorithm inspects the subsequent two transaction records. If these transactions are flagged as wash trades and occur within seven days, and the current trade is flagged similarly, it indicates a continuation of the wash trade loop. Additionally, if a trade is sandwiched between two transactions marked as wash trades, it is also flagged as part of the wash trade sequence.

Employing this approach allows for the identification of intricate wash trading patterns that simple identity checks or 1-1 trade analyses may overlook. This contributes to a more nuanced understanding of market manipulation techniques within the NFT marketplace.

Algorithm 3 Flag wash trade type 3 (triangle matched trade within 7 days)

Require: DataFrame *df_secondary* with columns *nft_address*, *token_id*, *datetime*, *buyer*, and *seller*

Ensure: DataFrame *df_secondary* with updated column *wash_type3*

procedure FLAGWASHTYPETHREE($df\_secondary$)
    for each unique pair of *nft_address* and *token_id* in $df\_secondary$ **do**
        group ← all rows with the same *nft_address* and *token_id*
        for each row in *group* **do**
            if sum of time_diff_same_item for current and previous transaction ≤ 7 days **and** seller 2 transactions before == current buyer **then**
                row.wash_type3 ← 1
            end if
            if wash_type3 in 2 transactions ahead is 1 **and** sum of time_diff_same_item for current, next, and next-next transaction ≤ 7 days **then**
                row.wash_type3 ← 1
            end if
            if wash_type3 in next and previous transaction is 1 **and** sum of time_diff_same_item for current, next, and previous transaction ≤ 7 days **then**
                row.wash_type3 ← 1
            end if
        end for
    end for
end procedure