Market Manipulation in NFT Markets

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Abstract

Non-Fungible Tokens (NFTs) offer a unique opportunity to study market misconduct in an unregulated crowdfunding environment. This paper examines insider and wash trading in the NFT market using publicly accessible Ethereum blockchain data. Results reveal that insider purchases, particularly by those maintaining community ties, significantly predict future price returns. Despite over 422 million USD circulating in wash trades, their impact on market outcomes is negligible. This paper also highlights motivations behind wash trading, such as securing marketplace rewards or promoting emerging platforms.

Keywords: Blockchain, Market Manipulation, Insider Trading, Wash Trading

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1 Introduction

NFTs, or non-fungible tokens, are digital assets that utilize blockchain technology for fundraising. During 2021 and early 2022, the NFT market gained significant attention alongside the cryptocurrency bubble. News articles[1] reported single cartoon pictures selling for over $23 million. However, many people, including academics, often focus more on potential investment returns and the magnitude of the irrational market bubble, rather than the underlying purpose of NFT projects. Essentially, NFTs can be viewed as a form of equity crowdfunding in an unregulated environment.

Similar to crowdfunding, NFT creators raise funds for their projects by selling their NFT collections to initial investors in the primary market. To understand this better, imagine an apartment company (NFT creator) raising funds for an apartment-to-be-built (NFT collection) by pre-selling all the studios (a predetermined fixed number of similar NFT items). The main distinction between crowdfunding and NFTs lies in the fact that equity crowdfunding involves trading firm shares, while NFT creators raise funds by selling virtual items to investors. NFT items are often represented as virtual profile pictures (see Figure 2), but they actually function as membership tickets that may include voting rights in a secret community or unique characters in a game-in-development or metaverse (Oh, Rosen, and Zhang, 2022).

One of the critics NFT and the cryptocurrency community face is the unregulated or less regulated market environment. Since the creators of NFTs are anonymous in most cases, it is not uncommon for projects to be abandoned if they are not successful on the primary market. Some creators intentionally raised funds by selling NFTs and then disappeared[2]. In fact, even for successful NFT projects that have received considerable investor attention, it is difficult to verify whether there is insider trading based on asymmetric information as there is no obligation to report. In addition, the NFT community voluntarily has reported several cases of wash trading[3]. Wash trade in NFT markets is used as price and

[1] See articles from Forbes or Nasdaq. Both gives examples of expensive NFTs traded around 2022.

[2] NFT community calls this as a rug pull. Some examples are Frosties and Evolved Apes. The founders of Frosties were arrested in California but it is a rare case.

[3] See an article from Chainalysis, Decrypt, or @hildobby_ for example.

volume manipulation method to generate fake trading volume and index price to allure investors by repeating buying and selling behavior. However, there is still a lack of compelling evidence on how widespread these misconduct behaviors are in this new market and their consequence.

In this paper, I study whether there exists unrevealed insider trading and wash trading in the NFT market. Insiders are defined as investors who have received free items from creators in the primary market, and I focus on their purchase activity rather than their selling activity to eliminate frequent trading noise as much as possible. Wash trades are defined as three types of transactions: (1) identity trade, where the seller and buyer are the same wallet, (2) 1-1 trade, where a seller purchases the same item again within 7 days after selling, or (3) matched order, where three wallets are involved in trading and all trades occur within 7 days. In the NFT market, insiders are 4.9% of total wallets participated in primary market, and wash trades are 0.3% out of 3.6 million secondary market transaction.

I investigate the impact of these misconduct behaviors on market outcomes for 558 successful NFT projects that successfully minted (i.e., sold) all items in the primary market from March 2021 to January 2023 and traded until February 2023. There are two potential ways that unrevealed insider trading and wash trading can affect the market. First, unrevealed insiders may use their information on the NFT collection earlier than other investors since they can directly communicate with NFT creators. However, they may not be able to use their information effectively since they already hold an illiquid membership ticket. Second, while NFT wash traders may aim to draw investor attention by inflating trading volume and price, the effectiveness of such strategies is questionable as the NFT community actively exposes wash trades. Lastly, Banerjee, Davis, and Gondhi (2018) predicts that more information access can be harmful when speculative motives dominate in the market. The speculative motivation was the main driver of the NFT bubble in the sample period, and the blockchain technology guarantees high level of information access. Therefore it is an empirical problem that I can test the theory through data.

The results indicate that insider buying activity is a strong predictor of future daily price index returns. A one standard deviation increase in insider buying activity leads to around a four percentage point increase in future daily median price returns. While wash trading exhibits a negative effect on future price returns, the impact is economically negligible. Furthermore, neither insider purchases nor wash trades have a significant influence on the future change in trading volume. This suggests that unrevealed insiders take advantage of information asymmetry in NFT markets, but wash trading, which is often used as a manipulation method, is actually ineffective in manipulating market outcomes. Subsequent analysis reveals that insiders maintaining substantial ties with creators are the ones who can accurately forecast future returns on purchases. Moreover, the volume of USD transacted in wash trades surpasses 422 million in the sample. The intention behind wash trading might not be market manipulation.

Therefore, I analyzed the possible purpose of wash trades, and one answer could be the cryptocurrency reward from NFT marketplaces (i.e., NFT exchanges). Several marketplaces charge a platform fee close to zero percent and reward traders proportionally to the transaction value of traded items. Further analysis indicates that rewarding platforms are highly associated with the occurrence of wash sales, while insiders are not associated with wash sales. This suggests that some investors perform wash trades to generate artificial financial rewards or attract market attention to startup marketplaces to compete with the dominant marketplace, OpenSea.

The equity crowdfunding market is relatively well-known to investors and entrepreneurs even before the emergence of NFTs. With the help of the internet, early-stage companies and startups can raise relatively small funds from a large number of investors who are either interested in investing or in purchasing the company's products (Chemmanur and Fulghieri, 2014). Many researchers have discussed this new venture capital market so far (See e.g. Lukkarinen, Teich, Wallenius, and Wallenius (2016); Hornuf and Schwienbacher (2018); Gong, Krishnan, and Liang (2022)). However, the transaction amount in the worldwide crowdfunding market at 2022 is 1.08 billion USD, while the transaction amount is 2.4 billion USD in the NFT market[4]. This is a significant difference that has been largely overlooked, even after the crypto market downturn in 2022.

One might wonder why financial economists should care about a speculative market that may fade away within five years. However, this paper makes three contributions to the

[4]See Statistica for crowdfunding and for NFT.

literature. Firstly, it discusses the use of blockchain technology to detect unrevealed insider and manipulative trading in recent crypto assets. The market structure of NFTs provides an opportunity to study manipulative behaviors more precisely. Secondly, the findings are crucial for regulators and policymakers interested in ensuring fair and efficient markets. The study suggests that efforts should be made to increase transparency in the NFT market, particularly with regard to unrevealed insider trading practices. Additionally, the study highlights the importance of regulating reward systems in NFT marketplaces to prevent artificial price and volume manipulation through wash trading. Lastly, this paper demonstrates the direct application of blockchain in enhancing data governance and transparency in financial markets. Overall, this paper provides valuable insights into the functioning of the NFT market and sheds light on the extent and impact of misconduct behaviors in this emerging asset class.

I provide some technical background on the NFT space and how to measure insider and wash trades in section 2. Sample selection procedure and summary statistics are shown in section 3. In section 4, I examine the impact of insider and wash trading activities on market outcomes using predictive regression analysis. I investigate more on insider's information advantage in section 5. Additionally, I discuss potential purpose of wash trades and discuss the aftermath effect on wash-traded items in section 6. Finally, I present my conclusions in section 7.

Related Literature

This paper discusses various topics related to market misconduct, including unrevealed insider trading and manipulative trading. Several studies have examined the spread of unrevealed insider information through family connections (Anderson, Reeb, and Zhao, 2012; Sun and Yin, 2017). Other social ties, such as friends and geographic proximity, have also been explored as means of spreading inside information. Ahern (2017), for example, showed how these ties can be used to spread insider information. In the context of revenue-sharing crowdfunding, Pourghannad, Kong, and Debo (2020) found that early investors who have a social tie with the entrepreneur may be informed about the project. However, Cohen, Malloy, and Pomorski (2012) argued that not all insider trading involves the use of nonpublic information. They distinguished between routine and opportunistic insider trading based on past trading records, discovering that only opportunistic trades predict future returns. This paper contributes to the literature by positing that face-to-face interactions or exclusive online community ties could potentially serve as insider mechanisms within the context of cryptoassets.

Manipulative trading has also been the subject of research. Aggarwal and Wu (2006) showed that using SEC litigations from 1990 to 2001, market manipulation occurred in small and illiquid OTC markets, with insiders and brokers potentially being the manipulators. Kyle and Viswanathan (2008) identified various forms of illegal price manipulation, such as corners and squeezes, pump-and-dump, and not making required disclosures. Massoud, Ullah, and Scholnick (2016) discussed the price and liquidity effects of hiring undisclosed promoters for publicly traded firms, and Li, Shin, and Wang (2022) analyzed pump-and-dump schemes in the cryptocurrency market, finding that they produce abnormal short-term increments in price, volume, and volatility.

Manipulation is often associated with high-frequency and deceptive trading activities, known as spoofing, which do not result in ownership changes. Aitken, Cumming, and Zhan (2015) explored the relationship between high frequency trading and market manipulation in stock markets. Wash trading, which is another form of fake trading, has been a focal point of many studies. Although investors and scholars commonly refer to it as wash trading, the U.S. Internal Revenue Services (IRS) has formally defined it as non-tax deductible trades due to the absence of change in ownership (see e.g. Grinblatt and Keloharju (2004) for tax-related research). Wash trading can be misleading to investors as daily trading volume is often used as a prominent market attention measure. Most of the existing research on wash trading has concentrated on exchanges or brokers. Cao, Li, Coleman, Belatreche, and McGinnity (2016) utilized directed graph theory and dynamic programming to detect wash trading. In the context of the crypto space, Gandal, Hamrick, Moore, and Oberman (2018) and Aloosh and Li (2019) directly investigated manipulative behavior through bot trading, using leaked secret information from a Bitcoin exchange. Additionally, Cong, Li, Tang, and Yang (2022) indirectly estimated wash trading using Benford's law on regulated and unregulated crypto exchanges.

Detecting wash trades in the NFT space may be easier compared to traditional markets such as stocks or cryptocurrencies, as unique NFT items are traded directly between buyers and sellers. It requires a specific wash trade counterpart wallet or conspirator, which is not the case for stock or cryptocurrency wash trading. Additionally, the public blockchain enables tracking of manipulations. Furthermore, NFT creators and insiders may have an incentive to participate in wash trading as it generates fake abnormal liquidity and an unusually high price to attract investors as in Aggarwal and Wu (2006) or Massoud, Ullah, and Scholnick (2016). Wachter, Jensen, Regner, and Ross (2022) analyzed 52 NFT collections using graph theory and found that wash trades accounted for around 2% of total sale transactions. However, further research is needed to better understand the extent and impact of wash trading in the NFT market. This paper delves into the economic analysis of wash trading and underscores the potential of blockchain technology in data governance and transparency.

This paper adds to the existing literature on NFT markets and equity crowdfunding, specifically addressing market structure and the potential for manipulation. For a discussion of NFT markets from finance perspective, Kräussl and Tugnetti (2022) provided an overview of NFT markets and summarizes the pricing methods of other papers. Oh, Rosen, and Zhang (2022) compared the returns of experienced and inexperienced investors, Bao, Ma, and Wen (2022) examined herding behaviors and found inexperienced investors' entering can be a trigger of herding, Borri, Liu, and Tsyvinski (2022) and Kong and Lin (2022) attempted to construct market indices and conduct related analysis. Wilkoff and Yildiz (2023) examined the effect of media coverage on NFT market liquidity, and Falk, Tsoukalas, and Zhang (2022) discussed how NFT royalties to creators are determined. In the equity crowdfunding space, Meoli and Vismara (2021) investigated information manipulation, Cumming, Hornuf, Karami, and Schweizer (2021) analyzed the determinants of crowdfunding fraud using social media data, and Babich, Marinesi, and Tsoukalas (2021) demonstrated that crowdfunding can benefit entrepreneurs and investors but may also be theoretically harmful.

2 NFT Markets and Measures

2.1 Backgrounds

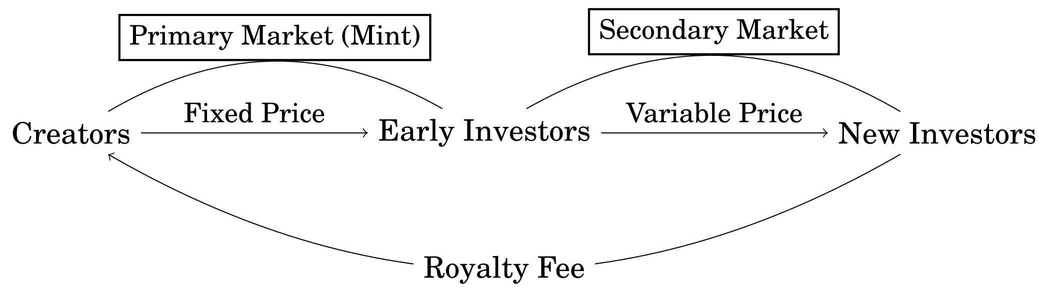

Figure 1. Overview of NFT Markets
Notes. The figure above shows the simplified NFT market. Creators sell NFT items at fixed price to initial investors and then initial investors trade items in secondary market. Creators receive royalty fee on every realized trades.

Before describing the data and summary statistics, it is necessary to clearly explain the terminologies and background with Figure 1. An *NFT collection* is a set of NFTs on the same theme and launched by an NFT creator team. An *NFT* is an individual item in an NFT collection. Alternatively, an NFT is a single picture, while an NFT collection is a set or brand of pictures. For example, the right picture of Figure 2 is an NFT, and the left picture is an NFT collection. The *primary market* is a market where NFT creators sell NFTs directly to early investors at fixed prices[5]. It is also called *minting* or *mint*. NFT creators promote their minting process through various online communication channels, such as Twitter, Discord, and Reddit. Early investors can sell their minted items to other investors, and some investors buy and sell items from others on the *secondary market*. As well as raising funds on the primary market, creators are paid a percentage *royalty fee* on every secondary market sale. As a result creators keep updating their development process and promoting sales to potential investors and NFT holders after the primary market sales. Note that successfully minting all NFTs is imperative in the subsequent secondary market

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

sales as new entrants can buy NFTs at a fixed price from creators anytime if there is an unsold item.

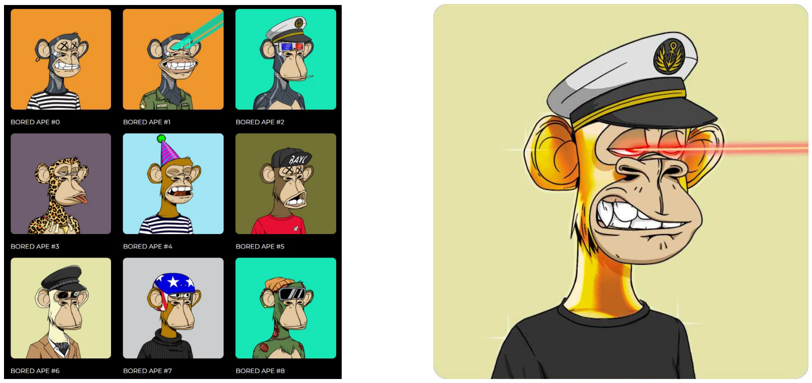

Figure 2. Example of NFT collection and NFT item
Notes. The left picture shows an NFT collection which is a set of pictures on the same theme under the same brand name called the *Bored Ape Yacht Club*. The right figure is an item (#3749) of *Bored Ape Yacht Club* that is sold at record price, 740 ETH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

The focus of this paper is on NFT collections based on the Ethereum (ETH) blockchain system, one of the most popular cryptocurrencies. Note that buyers and sellers do not need to trade in ETH cryptocurrency. While transaction data is recorded in the ETH blockchain, participants can also pay using alternative cryptocurrencies like USDC, USDT, or ApeCoin. Although it is not discussed in this paper, traders that use 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 depends 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 I restrict the sample to Ethereum-based NFT collections. Furthermore, the fixed supply[6] of NFT items plays a crucial role in defining the scarcity and limited access of the NFT market, making it possible to apply economic principles that are applicable to other traditional asset classes such as equity, housing, or

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

the arts as in the setting of Oh, Rosen, and Zhang (2022).

2.2 Insiders in NFT markets

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 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. Without legal consequences for insider trading, those with information advantages are more likely to exploit their information advantage for trading purposes.

A distinctive characteristic of the NFT market is the concurrent online communication system facilitated via platforms like Twitter 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. 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.

In the context of this paper, insiders are defined as wallets that receive free items (*Free Minters*), given their potential access to internal information. Anderson, Reeb, and Zhao (2012), Sun and Yin (2017), and Ahern (2017) discussed family and face-to-face connection can be a channel for information leakage. Pourghannad, Kong, and Debo (2020) found that early investors in crowdfunding is likely to have a social connection with the project creators and obtain benefits from internal information. Recall that NFTs are used to launch new projects and raise funds from investors. Free Minters are likely to be creators themselves, since creators need to join their NFT social communities, individuals who have social connections with project creators, or recipients of free giveaway events[7]. This give-

[7] These free giveaway items are sometimes called as airdrops. The amount of airdropped NFT items is

away event is mostly for marketing purposes, and creators usually give an item to someone who shares lots of tweets tagging NFT on Twitter or who already holds an NFT.

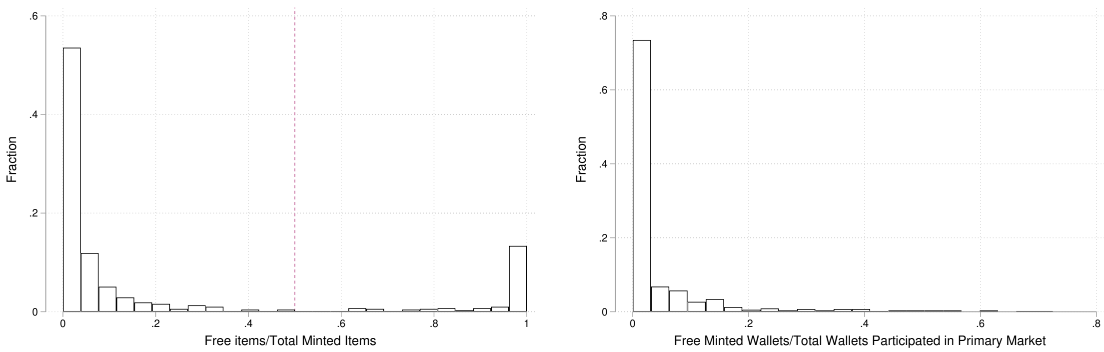

Figure 3. Distribution of Insiders in Primary Market
Notes. These figures report the distribution of potential insiders in collection-wise primary market. The left figure shows the distribution of free items out of total items including collections that are omitted in the sample selection process. In 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 3 presents the distribution of insiders from two perspectives. The left figure is 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.

2.3 Wash Traders in NFT Markets

By the U.S. IRS, if one sells securities at a loss and buys substantially identical securities within 30 days before or after the sale, and there is no change in beneficial ownership, it is classified as a wash sale. When there is a related third person or party, it is called a matched

limited as the supply of NFT items are fixed.

order. Loss from wash trades is not tax deductible, but the wash trade itself is permitted.

Table 1. Example of Wash Trades in NFT Markets
Notes. One of manipulative trading records on a single item is presented in this table. 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 identical item #1320 frequently on February 4th, 2022. Moreover their transaction prices from wash trades (bolded) are enormously higher than 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	-
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

Focusing on the repetition of buy and sell, a wash trade also refers to manipulative trading or behavior of providing false impression to market participants. Recall that in general, investors interpret significant changes in trading volume or price as the degree of market attention. Two investors can generate fake signals by buying and selling one NFT item at an unusually high price at the same time. This simple two participant wash sale model is shown in Table 1. By only looking at the overall price index and trading volume, a new investor would be trapped by wash traders and pay a significantly higher price.

The scholarly examination of this particular form of manipulative trading is limited due to the inaccessibility of micro-level transaction data for most academics. However, with the blockchain system, the NFT market structure is exceptionally useful to analyze wash trades since each item has a distinguishable number, and all wallet addresses are revealed, even without proprietary exchange data. Intuitively, it is less likely to argue that trades are normal if one sells and buys the exact same item again out of similar items in a collection. Wachter et al. (2022) suggested a graph theory-based algorithm that directly detects wash sales in the NFT market. On the NFT industry or community side, a method used by Dune Analytics[8] has been used so far.

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	8808	1183

In this paper, a wash trade is defined similar to Wachter et al. (2022) and Dune Analytics, a commercial company that reveals its detection algorithm, but time span is incorporated as in IRS definition. A wallet first buys an item at normal price as a preparation step. As shown at Table 2, trades are classified as wash sales if (1) an item is sold and purchased by exact same identity at the same time, (2) an item is purchased again by previous seller within 7 days, or (3) as a matched order, 3 wallets are involved in trading and all trades occurred within 7 days. Although IRS impose 30 days to define wash trades, it is too long period in NFT and cryptocurrency markets as we can check in Table 1. The result is consistent with shorter periods such as 3 or 5 days (8564 and 8705 observations each for 1-1 trade). Even with this simple definition, we can identify a total of 10166 (0.3%) suspicious wash trades out of 3.6 million secondary market transactions. Additionally, 44% of the 558 collections contained at least one suspicious wash trade, despite the average wash trade volume in each collection being just 0.3%. Detailed summary statistics are shown at Table A.1.

Another remarkable characteristic of wash trades to check is timing. The above plot of Figure 4 shows 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.

[8]See this online community posting for his algorithm.

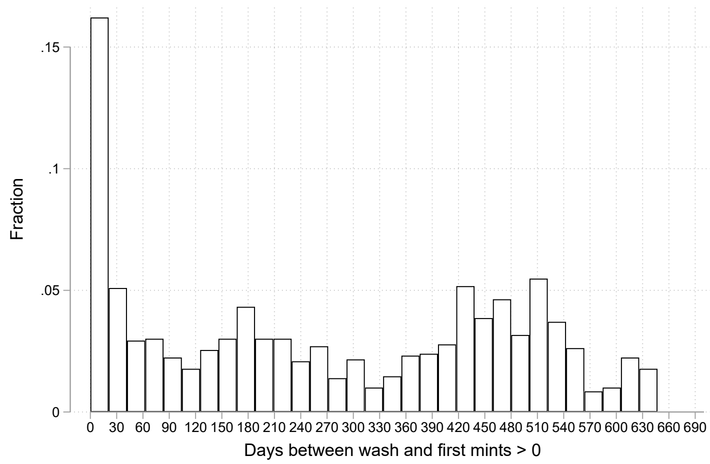

Figure 4. Timing of Wash Trade in Secondary Market
Notes. This figure reports the distribution of wash trade ratio out of secondary market trade in collection-wise. Collections that do not have wash trades are omitted in the figure.

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. The NFT list extends the sample in Oh, Rosen, and Zhang (2022) with some new successfully launched projects after October 2021 and before December 2021. After only selecting collections that successfully minted all items, the final sample consists of 558 ERC-721 NFT collections traded in the Ethereum blockchain system. Transaction data is primarily obtained from Dune Analytics, a commercial data company, but is also cross-checked at Etherscan, one of the biggest free websites. Indirect trades involving DeFi platforms such as Uniswap and Sushiswap are excluded, while direct ERC-1155 trades are included[9]. The number of mint transactions is 3.6 million, and the number of secondary transactions is 3.6 million as well. To eliminate extremely high-priced outliers and unusual near 0 ETH transactions, only secondary market trades of at least 0.01 ETH are considered in the sample, and all return variables that will be discussed in Table 3 are further winsorized at the 1/99 percentile

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

level. The sample covers the period from February 17th, 2021 to February 14th, 2023, which allows for the incorporation of the crypto winter in 2022.

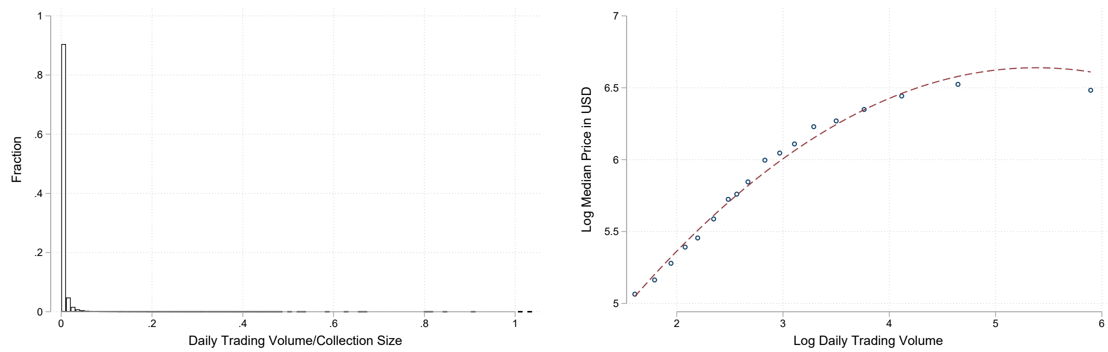

Figure 5. Trading volume and Median Price of NFT
Notes. The figure left shows the daily secondary market trading volume divided by each collection supply in collection-wise. The plot on the right depicts the square-root relationship between logged daily median price and logged daily secondary market trading volume.

Figure 5 displays the illiquidity of NFT markets in plots. The left figure shows the daily secondary market trading volume divided by each collection's minted items. It is evident that transactions are rare compared to the number of issued items. The right plot shows the positive square-root relation between daily median price and daily trading volume which is similar to the traditional price-volume relationship observed in finance. As a result, investors pay attention to a collection's trading volume since the market is illiquid on average. This implies that increased investor attention and the introduction of new information can significantly drive up the price (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-day 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, 2022). Wash trades can distort the representative market price and trading volume of NFTs; therefore, it is more appropriate to consider

Table 3. Variable Definitions
Notes. This table shows the definition of variables in this paper. Only at least 0.01 ETH secondary market trades are considered in the sample and variables with † is further winsorized at 1/99 percentile level. Daily transaction volume less than 5 is also 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	
Insider Buy Activity	Free minters' buying 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 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 × Trading Volume at day t)
Dummy category Art	1 if the purpose of an NFT collection is related to pure art (used as baseline)
Dummy category Gaming	1 if the purpose of an NFT collection is related to games
Dummy category Metaverse	1 if the purpose of an NFT collection is related to Metaverse
Dummy category Social	1 if the purpose of an NFT collection is related to social group
Dummy has twitter url	1 if an NFT collection has its own twitter account
Dummy has website url	1 if an NFT collection has its own website
Dummy has roadmap	1 if an NFT collection has roadmap for its project
Dummy artist name	1 if creators revealed their name (including nickname)

values that account for wash sales, which are prevalent in the experiences of most novice traders. While investors typically focus on the floor price, which is the minimum available list price at that time, median price is the best possible measure for the price index due to data constraints.

The independent variables are insider buy volume and wash trade volume at day t, both scaled by the total minted amount in each collection. Insiders' sell volume is not included, as it is challenging to distinguish routine trades from information-based trades of free minters. Instead, buying additional illiquid items when already holding items is more likely to represent an informational advantage and positive prospect of the collection's success as chat group members. 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, are daily median price in USD omitting wash sales are not winsorized in the table.

Table 4. Summary Statistics
Notes. This table shows the summary statistics of variables defined at Table 3. Only at least 0.01 ETH secondary market trades are considered in the sample and variables with † are further winsorized at 1/99 percentile level. Daily transaction volume less than 5 is 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.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	mean	sd	min	p50	max
†Price Return nowash	58,213	0.0330	0.261	-0.544	0.000473	1.275
†Price Return	58,206	0.0328	0.260	-0.544	0.000538	1.262
†Volume Change	58,220	0.245	1.097	-0.833	-0.0357	6.500
†Volume Change nowash	58,214	0.245	1.097	-0.833	-0.0357	6.500
InsiderBuy Activity	75,399	0.000105	0.000940	0	0	0.0775
Wash Activity	75,399	2.44e-05	0.00118	0	0	0.125
Wash Dummy	75,399	0.0172	0.130	0	0	1
Days between wash and first mint sales	75,399	175.0	143.2	0	138	711
†Past Day Returns	50,393	0.0271	0.248	-0.544	-0.00146	1.275
†Past Week Returns	46,591	0.0562	0.429	-0.620	-0.0264	2.232
Market Value of Collection	75,386	2.256e+07	1.748e+08	11,298	2.297e+06	5.675e+09
Dummy category Gaming	75,399	0.0706	0.256	0	0	1
Dummy category Art	75,399	0.0170	0.129	0	0	1
Dummy category Metaverse	75,399	0.0605	0.238	0	0	1
Dummy category Social	75,399	0.852	0.355	0	1	1
Dummy Has Twitter	75,399	0.989	0.105	0	1	1
Dummy Has Website	75,399	0.987	0.113	0	1	1
Dummy Has Roapmap	75,399	0.606	0.489	0	1	1
Dummy Artist Name	75,399	0.569	0.495	0	1	1
Secondary Market Trading Volume (Raw)	75,399	47.16	177.2	5	13	7,995
Daily median price in USD (Raw)	75,386	2,405	17,552	9.699	282.9	567,495
Daily median price in USD omitting wash sales (Raw)	75,378	2,359	16,949	9.699	282.7	540,458

4 The Impact of Manipulative Trades

In this section, I examine the impact of manipulative trades on both the rate of price index return and trading volume changes using predictive regressions. The regression structure is similar to Cohen, Malloy, and Pomorski (2012). I focus on analyzing the collection-day level, as simple values such as index price and trading volume are easily accessible but still vital market signals for investors. The dependent variables are the rate of index price change or trading volume change, and the main independent variables are insider buy or wash activity scaled by the amount of mints. As discussed in the previous section, it is inappropriate to include *InsiderSell* in the model due to the market structure. For a collection c and day t, the baseline regression model is as below:

$$DV_{c,t+1} = \beta_1 InsiderBuyActivity_{c,t} + \beta_2 WashActivity_{c,t} + \gamma X_{c,t} + FE_c + u_{c,t+1} \qquad (1)$$

where $DV_{c,t+1}$ is the median price return or volume change variable from day t to $t+1$ as defined in Table 3. The main independent variables are insider buy and wash volume of collection c at day t divided by the total minted amount of collection c. $X_{c,t}$ is a control variable matrix at day t, and FE_c is date fixed effects.

For the choice of control variables, I assume that investors focus on the past day return from day $t-2$ to $t-1$ and past week return from day $t-7$ to $t-2$ as momentum factor. Market value of collection which is median price times total minted volume is considered, and as a general classification of NFTs that are either arts, gaming, metaverse, or social is included. Dummy variable whether a collection is arts is used as a baseline. Lastly, quality-related information such as the existence of a collection Twitter account, collection website, roadmap, presence of artist for a collection is also considered. Regression tables with all control variables are in the appendix.

Note that the daily index price 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 that includes manipulative trades. The other is the true or real value, which excludes wash trades since wash trades distort the price and trading volume. I present both estimated results in Table 5 that uses nominal information and Table 6 that only considers real information.

The estimated result without omitting wash trades is shown at Table 5. Columns (1) and (2) show regression results with only insider buying term. Column (1) explains returns on day $t+1$ without date fixed effects while Column (2) regress with date fixed effects. Both have positive coefficients and p-values close to 0. One standard deviation increase in *InsiderBuy Activity* or $\frac{InsiderBuyVolume}{TotalMinted}$ lead to 4.6, or 4.2 percentage points increase in future

Table 5. Performance of Manipulative Trades: With Wash Trades

Notes. In this table, I report the results from estimates of specification (1) in which I regress future median price returns on a daily activity of insider and wash trade activity scaled by NFT collection-size for collection c as of day t. The dependent variable, $Return_{c,t+1}$, represents the rate of median price change in USD from day t to day $t+1$. Control variables are a day before price return, weekly price return, collection age, market value of collection, and other collection characteristics. Standard errors are clustered by collection. 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	24.60***	22.65***			24.61***	22.66***
	(5.604)	(5.274)			(5.605)	(5.275)
Wash Activity			-1.412***	-1.250***	-1.424***	-1.259***
			(-3.594)	(-3.674)	(-3.530)	(-3.642)
Observations	39,838	39,814	39,838	39,814	39,838	39,814
Collection Controls	YES	YES	YES	YES	YES	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.0154	0.0158	0.0134	0.0140	0.0154	0.0158
Adj R-squared	0.0154	0.0602	0.0134	0.0585	0.0154	0.0602

daily index returns, controlling for other factors. Columns (3) and (4) of Table 5 present results on wash trades. The coefficient of *Wash Activity* is negative and near 0 p-value, meaning that wash trades decrease the future nominal return. One standard deviation increase in *Wash Activity* induces 0.6 percentage point decrease in daily price return. Thus actual economic significance is negligible even if it is daily price return. These results are consistent in Columns (5) and (6) with two variables (*InsiderBuy, Wash Activity*) combined. As in Columns (2) and (4), insiders buy do meaningfully increase future returns but wash trades is economically insignificant. The economic impact is similar to that of (2).

Next I examine the impact of misconduct behavior on real market value that is without wash sales in index price calculation. The structure is exactly same as Table 5 and the estimated result is presented at Table 6. Surprisingly, the standardized coefficients are very similar to nominal outcomes, and again, *Wash Activity* slightly decreases the real price returns, but its impact on economic significance is small. One standard deviation increase in *InsiderBuy Activity* leads to a 4.6 or 4.2 percentage point increase in future daily index returns, and one standard deviation increase in *Wash Activity* leads to a 0.6 or 0.5 percentage point decrease in future daily index returns.

Table 6. Performance of Manipulative Trades: Without Wash Trades
Notes. In this table, I report the results from estimates of specification (1) in which I regress future median price returns on a daily activity of insider and wash trade activity scaled by NFT collection-size for collection c as of day t. The dependent variable is $Return_{c,t+1}$ which is the rate of median price change in USD from day t to day $t+1$ omitting all trades that are classified as wash trades. Control variables are a day before price return, weekly price return, collection age, market value of collection, and other collection characteristics. Standard errors are clustered by collection. 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	24.59***	22.62***			24.59***	22.62***
	(5.610)	(5.274)			(5.611)	(5.274)
Wash Activity			-1.336***	-1.169***	-1.348***	-1.178***
			(-3.808)	(-3.884)	(-3.749)	(-3.860)
Observations	39,838	39,814	39,838	39,814	39,838	39,814
Collection Controls	YES	YES	YES	YES	YES	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.0153	0.0157	0.0133	0.0139	0.0153	0.0157
Adj R-squared	0.0153	0.0602	0.0133	0.0585	0.0153	0.0602

However, these results are somewhat confusing, given that wash trades are typically conducted at high ETH prices and can distort the market price as in Table 1. It is unclear whether most investors realize the unusual market outcome while wash trading, even though they can check through free websites that provide detailed records. It is possible that wash trades have temporary effects on market outcomes that do not persist beyond a single day.

To investigate this possibility, I test a modified version of equation 1 in Table 7, in which I regress the rate of median price change in USD from day $t-1$ to day t (i.e., same-day return) on daily activity of Free Minters scaled and wash trade activity scaled by NFT collection-size for collection c as of date t, omitting all wash trades. The control variables are the same as in the previous estimations.

Table 7. Performance of Manipulative Trades: Same Day Without Wash Trades
Notes. In this table, I report the results from estimates of specification (1) in which I regress future median price returns on a daily activity of insider and wash trade activity scaled by NFT collection-size for collection c as of day t. The dependent variable is $Return_{c,t}$ which is the rate of median price change in USD from day $t-1$ to day t omitting all trades that are classified as wash trades. Control variables are a day before price return, weekly price return, collection age, market value of collection, and other collection characteristics. Standard errors are clustered by collection. 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	35.48***	32.18***			35.48***	32.18***
	(5.527)	(5.084)			(5.527)	(5.083)
Wash Activity			-0.521	-0.217	-0.538	-0.229
			(-0.577)	(-0.239)	(-0.607)	(-0.254)
Observations	42,946	42,922	42,946	42,922	42,946	42,922
Collection Controls	YES	YES	YES	YES	YES	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.0538	0.0649	0.0500	0.0616	0.0538	0.0648
Adj R-squared	0.0538	0.104	0.0500	0.101	0.0538	0.104

The estimated results in Table 7 continue to support the argument that wash trades have little effect on market outcomes. The coefficient of *Wash Activity* remains statistically insignificant, while *InsiderBuy Activity* remains statistically significant and economically meaningful (6.5 and 5.7 percentage points, respectively). This suggests that wash trades do not influence the returns of NFTs; otherwise, we would anticipate an effect on same-day returns.

Does it capture trivial mechanism? The demand for an illiquid item increases the price, which is nothing special. If insider buy and wash trades does not meaningfully change the trading volume, then it is not a simple price-demand relation. The other dimension of market outcome I haven't tested is trading volume. It can be examined using similar manner as in previous estimation with same control variables.

The result at Table 8 shows that the impact of manipulative behavior on the rate of change in future daily trading volume without wash sales. Columns (1) and (2) show

Table 8. Impact of Manipulative Trades on Trading Volume: Without Wash Trades
Notes. In this table, I report the results from estimates of specification (1) in which I regress the rate of change in daily trading volume on a daily activity of insider and wash trade activity scaled by NFT collection-size for collection c as of day t. The dependent variable is *Volume Change*$_{c,t+1}$ which is the rate of daily trading volume change from day t to day $t+1$ omitting all trades that are classified as wash trades. Control variables are a day before price return, weekly price return, collection age, market value of collection, and other collection characteristics. Standard errors are clustered by collection. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) Volume	(2) Volume	(3) Volume	(4) Volume	(5) Volume	(6) Volume
InsiderBuy Activity	-127.1***	-126.1***			-127.1***	-126.1***
	(-9.290)	(-9.200)			(-9.284)	(-9.196)
Wash Activity			-8.368***	-9.069***	-8.305***	-9.022***
			(-3.414)	(-3.770)	(-3.497)	(-3.822)
Observations	39,838	39,814	39,838	39,814	39,838	39,814
Collection Controls	YES	YES	YES	YES	YES	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.00597	0.00585	0.00354	0.00344	0.00601	0.00590
Adj R-squared	0.00597	0.0255	0.00354	0.0232	0.00601	0.0256

one standard deviation change in insider buying ratio decreases 5 percentage points future volume change. Columns (3) and (4) displays one standard deviation change in wash trades leads to 1 percentage points decrease in future trading volume. Note that the average daily trading volume is 47, so 5 percentage points decrease in trading volume is less than two transactions on average. These values indicate a relatively marginal change in trading volume that is not economically significant in an illiquid market, a result consistently shown in Columns (5) – (6) as well.

In summary, the results suggest that insider buying strongly predicts higher future price index returns, while wash trades do not have a significant impact on the returns. Therefore, investors are not lured into NFT collections by wash traders, but insiders still have an advantage due to their internal information.

5 More Evidence of Information Advantage

To provide further evidence of insiders' information advantage, this section explores the heterogeneity of insiders' behavior by examining both their purchase and sell activities. An insider's buying behavior can be classified into two types: buying while already holding other NFTs and buying without having any NFTs in their collection. Similarly, selling behavior can be categorized as selling remaining other NFTs and selling when there are no NFTs left in the same collection.

Insiders who already possess NFTs may have an additional advantage, as they can leverage the information obtained from the members-only chat rooms to make informed purchasing or selling decisions. Therefore, the variable *InsiderBuy Activity* × *Additional* captures insiders' additional purchase behavior when they already hold at least one different NFT within their collection. Similarly, *InsiderSell Activity* × *Additional* represents insiders' additional sell behavior when they already possess at least one different NFT.

On the other hand, insiders who do not have any NFTs may not have access to the members-only community and its associated advantages. The variables *InsiderBuy Activity* × *Not Additional* and *InsiderSell Activity* × *Not Additional* capture insiders' trading behavior when they do not have any NFTs in their collection, indicating a purchase without information advantage or an exit trade by insiders.

Table 9 shows results from regression analysis using similar specification. Column (1) – (2) is copied from column (1) – (2) of Table 6. Columns (3) and (4) show that *InsiderBuy Activity* × *Additional* is statistically significant while *InsiderBuy Activity* × *Not Additional* is insignificant when controlled. It means that not all insiders (free minters) may obtain information advantage, but only insiders with access to the community can gain advantage. The sizes of the standardized coefficients are 4.6 and 4.3, respectively. For selling behavior in Columns (5) and (6), both *InsiderSell Activity* terms are either statistically insignificant or weakly significant. Therefore, insiders selling behavior is less likely to be associated with future price returns.

In Table 10, where I use *InsiderSell Activity* terms for regression on the same day returns, both terms are still weakly significant. However, *InsiderSell Activity* terms are more

Table 9. Heterogeneity in Insider Behavior

Notes. In this table, I report the results from estimates of specification (1) in which I regress future median price returns on a daily trades of insider buy and sell activity scaled by NFT collection-size for collection c as of day t. The dependent variable is $Return_{c,t+1}$ which is the rate of median price change in USD from day t to day $t+1$ omitting all trades that are classified as wash trades. Control variables are a day before price return, weekly price return, collection age, market value of collection, and other collection characteristics. Standard errors are clustered by collection. 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	24.59***	22.62***				
	(5.610)	(5.274)				
InsiderBuy Activity x Additional			24.97***	23.03***		
			(5.617)	(5.277)		
InsiderBuy Activity x Not Additional			-25.48	-30.06		
			(-0.523)	(-0.685)		
InsiderSell Activity x Additional					2.850	1.399
					(0.605)	(0.350)
InsiderSell Activity x Not Additional					38.64*	42.21**
					(1.832)	(2.305)
Observations	39,838	39,814	39,838	39,814	39,838	39,814
Collection Controls	YES	YES	YES	YES	YES	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.0153	0.0157	0.0153	0.0156	0.0147	0.0152
Adj R-squared	0.0153	0.0602	0.0153	0.0602	0.0147	0.0598

consistently associated with same day price returns than Table 9. One standard deviation increase in *InsiderSell Activity*×*Additional* is associated with 6 or 5.2 percentage points increase in the same day price returns. One standard deviation increase in *InsiderSell Activity*×*Not Additional* is associated with 4.5 or 4.7 percentage points increase in the same day price returns. Equivalently, insiders sell behavior is positively associated with current price returns both when insiders keep holding at least one NFTs, or when insiders exit the NFT collection. Combining with findings that (1) only insiders who maintain the connection to creators strongly predict future returns in purchase, (2) insiders sell is statistically insignificant or weak in predicting future returns, and (3) insiders sell is still statistically not strong but better at explaining current returns, it is more clear that insiders who are in the community are exploiting information advantage.

Table 10. Heterogeneity in Insider Sell Behavior: Same day
Notes. In this table, I report the results from estimates of specification (1) in which I regress future median price returns on a daily trades of insider sell activity scaled by NFT collection-size for collection c as of day t. The dependent variable is $Return_{c,t}$ which is the rate of median price change in USD from day $t-1$ to day t omitting all trades that are classified as wash trades. Control variables are a day before price return, weekly price return, collection age, market value of collection, and other collection characteristics. Standard errors are clustered by collection. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1)	(2)
VARIABLES	Price	Price
InsiderSell Activity x Additional	16.28**	14.12**
	(2.541)	(2.574)
InsiderSell Activity x Not Additional	64.09**	66.61**
	(2.106)	(2.212)
Observations	42,946	42,922
Collection Controls	YES	YES
Date FE	NO	YES
Within Adj R-squared	0.0597	0.0705
Adj R-squared	0.0597	0.109

6 The Purpose of Wash Trade

In fact, the total traded amount of money identified as wash sales in the sample is 422 million USD. It is noteworthy that despite circulating vast amounts of money, wash traders fail to attract investors. This empirical result contradicts the theoretical predictions by Banerjee, Davis, and Gondhi (2018) that "improving information access about asset fundamentals can be counterproductive when speculative motives dominate". This raises questions about whether NFT investors actively check freely available transaction history data, identify wash trade information, examine Discord and Twitter accounts, and subsequently avoid purchasing such items during the NFT boom. Moreover, Aggarwal and Wu (2006) and Massoud, Ullah, and Scholnick (2016) discussed the potential involvement of insiders in manipulative trades.

Perhaps the purpose of wash trades is not related to market manipulation. For example, there have been discussions about cryptocurrency rewards in NFT marketplaces, such

Table 11. Wash Trades and NFT Marketplaces
Notes. In this table, I present the descriptive statistics related to NFT marketplaces and their potential wash trades. The numbers represent the observations out of secondary market trades in the 558 collection sample, and the figures in parentheses indicate the percentage of trades in that particular marketplace. The marketplace fee policy data is as of March 5th, 2023.

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)	

as the case of LooksRare, which reportedly generated 8 billion USD in NFT wash trading[10]. Thus it is important to check the distribution of wash trades in terms of exchanges. Table 11 presents a two-way frequency table of wash trades and NFT marketplaces, showing that OpenSea is the largest and leading NFT marketplace. Additionally, many marketplaces have policies in which market fees are rewarded as marketplace coin or near 0 percent fee compared to the leading marketplace. Thus, it is plausible to speculate that the purpose of wash trades in NFT marketplaces may be to generate a profit through artificially inflated cryptocurrency rewards, or to gain attention to marketplaces as followers.

Due to data constraints, instead of accumulating token rewards at each wash trader's wallet, I regress the likelihood of wash trading on various marketplaces using transaction-level data from the secondary market. Furthermore, assessing whether buyers and sellers are insiders enables us to explore the potential involvement of insiders in wash trades. The binary dependent variable, *WashTradeDummy*, is set to 1 if a trade qualifies as a wash

[10]See an article about LooksRare.

trade as defined in subsection 2.3, and 0 otherwise. The primary independent variable is a combination of the eight NFT marketplaces listed in Table 11, along with a combination of two dummy variables, *InsiderBuyDummy* and *InsiderSellDummy*, which are set to 1 if the buyer or seller is a free minter, respectively. The control variables include the logged holding period (expressed in fractional days), the log of the transaction price, the volume of the collection, and the characteristics of the collection.

Table 12. Determinants of Wash Trades
Notes. In this table, I present the estimates of linear probability model related to wash trades and their potential factors using secondary market transaction level data. The dependent variable is *WashTradeDummy* that is 1 if a trade is denoted as a wash trade. Dependent variables are marketplace dummy, and interaction of insider buy and seller dummy. Control variables are log holding period and log NFT transaction price. Standard errors are clustered by collection. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) Wash Trade Dummy	(2) Wash Trade Dummy	(3) Wash Trade Dummy
Marketplace = OpenSea		(baseline)	(baseline)
Marketplace = Blur		0.0360***	0.0360***
		(3.896)	(3.895)
Marketplace = Element		0.181	0.181
		(1.526)	(1.526)
Marketplace = Foundation		0.00700	0.00701
		(1.513)	(1.515)
Marketplace = LooksRare		0.0238**	0.0238**
		(2.026)	(2.026)
Marketplace = Sudoswap		0.0326***	0.0326***
		(4.827)	(4.822)
Marketplace = X2Y2		0.364***	0.364***
		(3.191)	(3.192)
Marketplace = Zora		0.0573*	0.0573*
		(1.663)	(1.664)
InsiderBuyer=0×InsiderSeller=0	(baseline)		(baseline)
InsiderBuyer=0×InsiderSeller=1	0.000838		0.000992
	(1.020)		(1.379)
InsiderBuyer=1×InsiderSeller=0	-0.00109		-0.000303
	(-0.840)		(-0.380)
InsiderBuyer=1×InsiderSeller=1	7.65e-05		0.00131*
	(0.0955)		(1.896)
Observations	3,303,324	3,303,324	3,303,324
Collection Controls	YES	YES	YES
Date FE	YES	YES	YES
Within Adj R-squared	0.0213	0.245	0.245
Adj R-squared	0.115	0.317	0.317

The estimated result of linear probability model is shown at Table 12. Column (1) shows controlling for holding period and NFT price, insiders do not increase the probability of an occurrence of wash sale. In other words, insiders do not participate in wash trades. Column (2) shows the impact of marketplace in the probability of wash trades. When a trade is in X2Y2 platform, the probability that a trade is wash is 36 percentage points higher compared to that in OpenSea, controlling for holding period, price, and collection volume. Sudoswap and Blur is 3 percentage points higher, LooksRare is 2 percentage higher than OpenSea. These results are consistent in Column (3). In conclusion, wash trades in NFT market is not to allure investors, but to generate artificial financial reward to wash traders, or make market attention and attract NFT investors to start-up marketplaces.

Lastly, whether investors still trade a wash traded item after wash trade is eventually finished can be investigated. If so, is there any difference in returns compared to non-wash traded NFTs? Investors may avoid and penalize buying such an item like plague. This can be discussed whether the realized return is substantially different when the previous trade of an item is flagged as a wash trade. As in Oh, Rosen, and Zhang (2022), the realized return for a collection c, item i, purchased at τ, sold at t is defined as $RealizedReturn_{c,i,\tau,t} = \frac{Price_{c,i,t}}{Price_{c,i,\tau}} - 1$, without considering gas, royalty, and marketplace fee. Further it is winsorized at 1/99 percentile level.

Table 13. Realized Returns After Wash Trades
Notes. In this table, I present the estimates that I regress realized return on the past wash trade history. The independent variable is 1 if a previous trade for the same collection c, item i is wash trade, current trade is not wash trade, and previous buyer is recorded as seller at current trade. Control variables are log holding period, log collection volume, and other collection quality characteristics. Standard errors are clustered by collection. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) Realized Return	(2) Realized Return	(3) Realized Return
Dummy Previous Is Wash	-0.293**	0.218	0.231
	(-2.094)	(1.078)	(1.096)
Observations	3,303,324	3,303,324	3,293,225
Collection Controls	NO	YES	YES
Date FE	YES	YES	YES
Within Adj R-squared	1.10e-06	0.00837	0.00830
Adj R-squared	0.0445	0.0525	0.0521

Simple regression estimation using realized return is shown at Table 13. The independent variable is *Dummy previous is wash*, which is 1 if a previous trade for the same collection c, item i is wash trade, current trade is not wash trade, and previous buyer is recorded as seller at current trade. Control variables are collection characteristic variables and holding period. Column (1) describes that wash traded NFTs has 29.3 percentage points lower realized returns than non-wash traded NFTs without control variables. The result at Column (2) indicates that there is no difference in returns depending on the history that previous trade is wash trade, controlling for holding period, collection volume, and other collection characteristics. This is consistent in Column (3) where all transactions marked as wash trades are eliminated for precise subsample analysis.

7 Conclusion

NFTs represent a new form of crowdfunding facilitated by blockchain technology. The unregulated yet data-transparent environment provides unique opportunities to analyze market misconduct that is limited in traditional financial research. It is available to detect possible unrevealed insider and manipulative trading in NFT markets using publicly available blockchain data. Insiders are investors who obtained free items in the primary market directly from creators, and wash trades are classified using 3 types of transactions similar to the definition of the United States Internal Revenue Service. Insiders constitute 4.9% of the total wallets that participated in the primary market, and wash trades account for 0.3% of the 3.6 million transactions in the secondary market.

I examine the effect of misconduct behaviors on market outcomes for NFT projects that successfully minted all items over March 2021 to January 2023. The results indicate that insiders' buying activities strongly predict future daily price index returns. However, wash trading is economically insignificant. Moreover, insider purchases and wash trades do not significantly affect future changes in trading volume. This suggests that unreported insiders take an advantage of information asymmetry in NFT markets but wash trade is actually ineffective to manipulate market outcomes. Lastly, I checked the purpose of wash trades. The empirical analysis shows that some investors perform wash trade to artificially gain platform reward, or make market attention to start-up marketplaces to catch up a dominant marketplace.

For further research, alternative measure can be considered. Investors care more about the floor price which is minimum available listed price in each NFT collection. Instead of median price that can be affected a lot by wash trading, new outcomes can be considered as an alternative independent variable. Another point to consider is the network of wash traders. These wash traders' identity and connection can be analyzed further.

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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 2.2 and subsection 2.3. 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					
Total Trading Volume	558	6,602	7,263	13	44,372
Collection Volume (# of Minted Items)	558	6,535	3,780	1,000	25,000
Insider Buying Volume	558	105.4	343.5	0	5,777
Insider Buy/Collection Volume	558	0.0323	0.0762	0	0.701
Wallets in Primary Market	558	1,528	1,113	61	7,724
Potential Insider Wallets (Free Minted)	558	61.61	164.8	0	1,964
Insider Wallets/Total Wallets in Primary Market	558	0.0464	0.105	0	0.725
Panel B: Wash Trade					
Average # of Type 1 Wash Sales	558	0.620	3.617	0	67
Average # of Type 2 Wash Sales	558	15.78	166.3	0	3,375
Average # of Type 3 Wash Sales	558	2.120	15.86	0	297
Average # of Wash Sales	558	18.22	168.9	0	3,385
Collection Volume (Total # of Minted Items)	558	6,535	3,780	1,000	25,000
Average Type 1 Wash Sales Volume/Collection Volume	558	6.94e-05	0.000373	0	0.00670
Average Type 2 Wash Sales Volume/Collection Volume	558	0.00305	0.0484	0	1.125
Average Type 3 Wash Sales Volume/Collection Volumes	558	0.000238	0.00164	0	0.0297
Average Wash Sales Volume/Collection Volume	558	0.00332	0.0486	0	1.128
Has Type 1 Wash Sales	558	0.115	0.319	0	1
Has Type 2 Wash Sales	558	0.398	0.490	0	1
Has Type 3 Wash Sales	558	0.142	0.349	0	1
Has Wash Sales	558	0.432	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 nowash, (2) Price Return, (3) Volume Change, (4) Volume Change nowash, (5) InsiderBuy Activity, (6) Wash Activity, (7) Wash Dummy, (8) Days between wash and first mint sales, (9) Past Day Returns, (10) Past Week Returns, (11) Market Value of Collection, (12) Dummy category Gaming, (13) Dummy category Metaverse, (14) Dummy category Social, (15) Dummy Has Twitter, (16) Dummy Has Website, (17) Dummy Has Roadmap, and (18) Dummy Artist Name. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(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)	-0.01	-0.01	-0.01	-0.01	-0.00	1.00												
(7)	0.01*	0.01*	0.01	0.01	-0.08***	0.01*	1.00											
(8)	-0.01*	-0.01*	-0.02***	-0.02***	0.00	-0.00	-0.00	1.00										
(9)	-0.00	-0.01	-0.01**	-0.01**	0.02***	-0.01	-0.03***	-0.14***	1.00									
(10)	-0.02***	-0.02***	-0.01*	-0.01**	-0.01**	0.02***	0.08***	-0.00	0.00	1.00								
(11)	0.00	0.00	0.01*	0.01*	-0.02***	-0.00	0.02***	0.00	0.01*	-0.02***	1.00							
(12)	0.01**	0.01**	-0.00	-0.00	0.01*	0.00	-0.05***	0.01	0.03***	0.01*	-0.04***	1.00						
(13)	-0.00	-0.00	0.00	0.00	0.04***	-0.00	0.07***	-0.00	-0.01*	-0.01**	-0.07***	-0.03***	1.00					
(14)	-0.00	-0.00	-0.01*	-0.01	-0.02***	0.00	-0.05***	-0.00	-0.01*	0.02***	-0.66***	-0.32***	-0.61***	1.00				
(15)	0.00	0.00	0.00	0.00	-0.01**	0.00	0.00	0.00	-0.00	0.01**	-0.17***	0.01***	0.03***	0.10***	1.00			
(16)	-0.00	-0.00	0.00	0.00	-0.01	0.00	0.02***	0.00	0.01	0.01**	-0.16***	-0.03***	0.03***	0.10***	0.53***	1.00		
(17)	-0.00	-0.00	-0.00	-0.00	-0.01*	-0.02***	0.02***	-0.00	-0.02***	0.04***	-0.06***	-0.10***	0.17***	-0.03***	0.07***	0.13***	1.00	
(18)	-0.01	-0.00	-0.00	-0.00	-0.01*	-0.02***	0.04***	-0.01	0.01	0.06***	0.00	-0.06***	-0.07***	0.06***	0.07***	0.12***	0.25***	1.00

Table A.3. Performance of Manipulative Trades: With Wash Trades
Notes. In this table, I report the results from estimates of specification (1) in which I regress future median price returns on a daily activity of insider and wash trade volume scaled by NFT collection-size for collection c as of day t. The dependent variable, $Return_{c,t+1}$, represents the rate of median price change in USD from day t to day $t+1$. Control variables are a day before price return, weekly price return, collection age, market value of collection, and other collection characteristics. Standard errors are clustered by collection. 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	24.60***	22.65***			24.61***	22.66***
	(5.604)	(5.274)			(5.605)	(5.275)
Wash Activity			-1.412***	-1.250***	-1.424***	-1.259***
			(-3.594)	(-3.674)	(-3.530)	(-3.642)
Log(1+Days after mints)	0.00483***	0.0223***	0.00344***	0.0202***	0.00486***	0.0223***
	(3.771)	(8.077)	(2.716)	(7.369)	(3.792)	(8.082)
Past Day Returns	-0.0169**	-0.0222***	-0.0161**	-0.0216***	-0.0169**	-0.0222***
	(-2.175)	(-2.864)	(-2.071)	(-2.792)	(-2.175)	(-2.863)
Past Week Returns	-0.00193	-0.00609*	-0.00145	-0.00591*	-0.00195	-0.00610*
	(-0.643)	(-1.934)	(-0.484)	(-1.877)	(-0.651)	(-1.938)
Log Market Value of Collection	-0.0167***	-0.0170***	-0.0169***	-0.0171***	-0.0167***	-0.0170***
	(-6.075)	(-6.678)	(-6.091)	(-6.658)	(-6.074)	(-6.674)
Dummy category Gaming	0.00864	0.00379	0.00905	0.00441	0.00862	0.00380
	(0.740)	(0.366)	(0.786)	(0.432)	(0.738)	(0.367)
Dummy category Metaverse	0.000728	-0.00497	0.00463	-0.00139	0.000698	-0.00496
	(0.0595)	(-0.459)	(0.368)	(-0.125)	(0.0570)	(-0.459)
Dummy category Social	-0.00592	-0.00813	-0.00504	-0.00730	-0.00591	-0.00809
	(-0.604)	(-0.906)	(-0.527)	(-0.832)	(-0.604)	(-0.904)
Dummy Has Twitter	-0.00470	-0.0235	-0.0103	-0.0280**	-0.00468	-0.0235
	(-0.328)	(-1.461)	(-0.871)	(-2.093)	(-0.327)	(-1.459)
Dummy Has Website	0.000525	0.00764	0.00482	0.0116	0.000565	0.00768
	(0.0391)	(0.496)	(0.399)	(0.841)	(0.0421)	(0.498)
Dummy Has Roadmap	-0.00703*	-0.00757**	-0.00731**	-0.00770**	-0.00706*	-0.00760**
	(-1.939)	(-2.185)	(-2.018)	(-2.229)	(-1.948)	(-2.193)
Dummy Artist Name	0.00543*	0.00259	0.00582**	0.00298	0.00538*	0.00255
	(1.850)	(0.898)	(1.966)	(1.026)	(1.835)	(0.884)
Observations	39,838	39,814	39,838	39,814	39,838	39,814
Collection Controls	YES	YES	YES	YES	YES	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.0154	0.0158	0.0134	0.0140	0.0154	0.0158
Adj R-squared	0.0154	0.0602	0.0134	0.0585	0.0154	0.0602

Table A.4. Performance of Manipulative Trades: Without Wash Trades
Notes. In this table, I report the results from estimates of specification (1) in which I regress future median price returns on a daily activity of insider and wash trade activity scaled by NFT collection-size for collection c as of day t. The dependent variable is $Return_{c,t+1}$ which is the rate of median price change in USD from day t to day $t+1$ omitting all trades that are classified as wash trades. Control variables are a day before price return, weekly price return, collection age, market value of collection, and other collection characteristics. Standard errors are clustered by collection. 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	24.59***	22.62***			24.59***	22.62***
	(5.610)	(5.274)			(5.611)	(5.274)
Wash Activity			-1.336***	-1.169***	-1.348***	-1.178***
			(-3.808)	(-3.884)	(-3.749)	(-3.860)
Log(1+Days after mints)	0.00478***	0.0221***	0.00339***	0.0200***	0.00481***	0.0221***
	(3.744)	(8.023)	(2.684)	(7.315)	(3.764)	(8.028)
Past Day Returns	-0.0168**	-0.0222***	-0.0160**	-0.0216***	-0.0168**	-0.0222***
	(-2.175)	(-2.868)	(-2.071)	(-2.795)	(-2.175)	(-2.867)
Past Week Returns	-0.00222	-0.00644**	-0.00174	-0.00626**	-0.00224	-0.00645**
	(-0.736)	(-2.033)	(-0.578)	(-1.976)	(-0.743)	(-2.037)
Log Market Value of Collection	-0.0166***	-0.0169***	-0.0168***	-0.0170***	-0.0166***	-0.0169***
	(-6.073)	(-6.676)	(-6.089)	(-6.657)	(-6.072)	(-6.672)
Dummy category Gaming	0.0103	0.00543	0.0107	0.00605	0.0103	0.00544
	(0.894)	(0.527)	(0.940)	(0.593)	(0.893)	(0.529)
Dummy category Metaverse	0.00235	-0.00339	0.00625	0.000183	0.00232	-0.00338
	(0.195)	(-0.315)	(0.502)	(0.0166)	(0.192)	(-0.314)
Dummy category Social	-0.00422	-0.00646	-0.00334	-0.00564	-0.00422	-0.00643
	(-0.439)	(-0.723)	(-0.354)	(-0.641)	(-0.439)	(-0.721)
Dummy Has Twitter	-0.00408	-0.0226	-0.00968	-0.0271**	-0.00406	-0.0226
	(-0.286)	(-1.415)	(-0.820)	(-2.038)	(-0.284)	(-1.413)
Dummy Has Website	0.000481	0.00754	0.00477	0.0115	0.000518	0.00757
	(0.0359)	(0.491)	(0.395)	(0.836)	(0.0386)	(0.493)
Dummy Has Roadmap	-0.00689*	-0.00742**	-0.00716**	-0.00754**	-0.00692*	-0.00744**
	(-1.909)	(-2.151)	(-1.987)	(-2.194)	(-1.917)	(-2.158)
Dummy Artist Name	0.00546*	0.00264	0.00585**	0.00303	0.00542*	0.00260
	(1.871)	(0.919)	(1.987)	(1.048)	(1.857)	(0.905)
Observations	39,838	39,814	39,838	39,814	39,838	39,814
Collection Controls	YES	YES	YES	YES	YES	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.0153	0.0157	0.0133	0.0139	0.0153	0.0157
Adj R-squared	0.0153	0.0602	0.0133	0.0585	0.0153	0.0602

Table A.5. Performance of Manipulative Trades: Same Day Without Wash Trades
Notes. In this table, I report the results from estimates of specification (1) in which I regress future median price returns on a daily activity of insider and wash trade activity scaled by NFT collection-size for collection c as of day t. The dependent variable is $Return_{c,t}$ which is the rate of median price change in USD from day $t-1$ to day t omitting all trades that are classified as wash trades. Control variables are a day before price return, weekly price return, collection age, market value of collection, and other collection characteristics. Standard errors are clustered by collection. 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	35.48***	32.18***			35.48***	32.18***
	(5.527)	(5.084)			(5.527)	(5.083)
Wash Activity			-0.521	-0.217	-0.538	-0.229
			(-0.577)	(-0.239)	(-0.607)	(-0.254)
Log(1+Days after mints)	-0.00361**	0.00476*	-0.00563***	0.00180	-0.00360**	0.00476*
	(-2.457)	(1.656)	(-4.005)	(0.625)	(-2.448)	(1.657)
Past Day Returns	-0.221***	-0.246***	-0.220***	-0.245***	-0.221***	-0.246***
	(-18.86)	(-22.13)	(-18.61)	(-21.94)	(-18.86)	(-22.13)
Past Week Returns	-0.0247***	-0.0362***	-0.0240***	-0.0360***	-0.0247***	-0.0362***
	(-6.291)	(-9.029)	(-6.113)	(-8.950)	(-6.292)	(-9.029)
Log Market Value of Collection	0.00469***	0.00513***	0.00437***	0.00499***	0.00469***	0.00513***
	(3.437)	(2.988)	(3.336)	(2.985)	(3.437)	(2.988)
Dummy category Gaming	-0.0178*	-0.0179*	-0.0169	-0.0169*	-0.0178*	-0.0180*
	(-1.710)	(-1.814)	(-1.641)	(-1.700)	(-1.713)	(-1.815)
Dummy category Metaverse	-0.0310**	-0.0361***	-0.0252**	-0.0309***	-0.0310**	-0.0361***
	(-2.537)	(-3.039)	(-2.216)	(-2.798)	(-2.540)	(-3.041)
Dummy category Social	-0.0286***	-0.0294***	-0.0272***	-0.0281***	-0.0286***	-0.0294***
	(-3.240)	(-3.372)	(-3.136)	(-3.248)	(-3.244)	(-3.375)
Dummy Has Twitter	0.0179	0.00523	0.0108	-0.000238	0.0179	0.00524
	(1.166)	(0.428)	(0.613)	(-0.0156)	(1.167)	(0.429)
Dummy Has Website	-0.00842	0.00136	-0.00337	0.00593	-0.00841	0.00137
	(-0.507)	(0.111)	(-0.193)	(0.437)	(-0.506)	(0.111)
Dummy Has Roadmap	-0.00213	-0.000710	-0.00243	-0.000809	-0.00214	-0.000716
	(-0.661)	(-0.209)	(-0.755)	(-0.237)	(-0.665)	(-0.211)
Dummy Artist Name	-0.00210	-0.00398	-0.00154	-0.00342	-0.00212	-0.00399
	(-0.662)	(-1.255)	(-0.491)	(-1.085)	(-0.667)	(-1.257)
Observations	42,946	42,922	42,946	42,922	42,946	42,922
Collection Controls	YES	YES	YES	YES	YES	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.0538	0.0649	0.0500	0.0616	0.0538	0.0648
Adj R-squared	0.0538	0.104	0.0500	0.101	0.0538	0.104

Table A.6. Impact of Manipulative Trades on Trading Volume: Without Wash Trades
Notes. In this table, I report the results from estimates of specification (1) in which I regress the rate of change in daily trading volume on a daily activity of insider and wash trade activity scaled by NFT collection-size for collection c as of day t. The dependent variable is *Volume Change*$_{c,t+1}$ which is the rate of daily trading volume change from day t to day $t+1$ omitting all trades that are classified as wash trades. Control variables are a day before price return, weekly price return, collection age, market value of collection, and other collection characteristics. Standard errors are clustered by collection. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) Volume	(2) Volume	(3) Volume	(4) Volume	(5) Volume	(6) Volume
InsiderBuy Activity	-127.1***	-126.1***			-127.1***	-126.1***
	(-9.290)	(-9.200)			(-9.284)	(-9.196)
Wash Activity			-8.368***	-9.069***	-8.305***	-9.022***
			(-3.414)	(-3.770)	(-3.497)	(-3.822)
Log(1+Days after mints)	0.0364***	0.0595***	0.0440***	0.0712***	0.0366***	0.0596***
	(7.912)	(6.388)	(9.818)	(7.844)	(7.940)	(6.398)
Past Day Returns	-0.112***	-0.131***	-0.116***	-0.134***	-0.112***	-0.131***
	(-4.495)	(-4.812)	(-4.672)	(-4.931)	(-4.494)	(-4.809)
Past Week Returns	-0.0284***	-0.0357***	-0.0311***	-0.0368***	-0.0285***	-0.0358***
	(-2.822)	(-3.378)	(-3.144)	(-3.537)	(-2.837)	(-3.388)
Log Market Value of Collection	-0.0300***	-0.0318***	-0.0288***	-0.0313***	-0.0301***	-0.0319***
	(-7.697)	(-7.482)	(-7.772)	(-7.638)	(-7.696)	(-7.474)
Dummy category Gaming	0.0377	0.0365	0.0354	0.0332	0.0376	0.0366
	(0.709)	(0.707)	(0.653)	(0.631)	(0.707)	(0.711)
Dummy category Metaverse	0.0398	0.0421	0.0193	0.0223	0.0396	0.0422
	(0.711)	(0.745)	(0.350)	(0.400)	(0.708)	(0.748)
Dummy category Social	-0.00878	-0.00266	-0.0133	-0.00686	-0.00876	-0.00243
	(-0.178)	(-0.0560)	(-0.265)	(-0.142)	(-0.178)	(-0.0511)
Dummy Has Twitter	-0.0548	-0.0782	-0.0256	-0.0528	-0.0546	-0.0780
	(-0.771)	(-1.022)	(-0.301)	(-0.571)	(-0.769)	(-1.019)
Dummy Has Website	0.100	0.0920	0.0783	0.0703	0.100	0.0922
	(1.404)	(1.223)	(0.993)	(0.830)	(1.406)	(1.226)
Dummy Has Roadmap	-0.0253**	-0.0268**	-0.0243**	-0.0265**	-0.0255**	-0.0270**
	(-2.388)	(-2.421)	(-2.363)	(-2.450)	(-2.403)	(-2.439)
Dummy Artist Name	0.0145	0.0130	0.0120	0.0103	0.0142	0.0127
	(1.393)	(1.147)	(1.200)	(0.942)	(1.367)	(1.120)
Observations	39,838	39,814	39,838	39,814	39,838	39,814
Collection Controls	YES	YES	YES	YES	YES	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.00597	0.00585	0.00354	0.00344	0.00601	0.00590
Adj R-squared	0.00597	0.0255	0.00354	0.0232	0.00601	0.0256

Table A.7. Heterogeneity in Insider Behavior

Notes. In this table, I report the results from estimates of specification (1) in which I regress future median price returns on a daily trades of insider buy and sell activity scaled by NFT collection-size for collection c as of day t. The dependent variable is $Return_{c,t+1}$ which is the rate of median price change in USD from day t to day $t+1$ omitting all trades that are classified as wash trades. Control variables are a day before price return, weekly price return, collection age, market value of collection, and other collection characteristics. Standard errors are clustered by collection. 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	24.59***	22.62***				
	(5.610)	(5.274)				
InsiderBuy Activity x Additional			24.97***	23.03***		
			(5.617)	(5.277)		
InsiderBuy Activity x Not Additional			-25.48	-30.06		
			(-0.523)	(-0.685)		
InsiderSell Activity x Additional					2.850	1.399
					(0.605)	(0.350)
InsiderSell Activity x Not Additional					38.64*	42.21**
					(1.832)	(2.305)
Log(1+Days after mints)	0.00478***	0.0221***	0.00477***	0.0221***	0.00402***	0.0210***
	(3.744)	(8.023)	(3.739)	(8.022)	(3.174)	(7.762)
Past Day Returns	-0.0168**	-0.0222***	-0.0168**	-0.0222***	-0.0177**	-0.0229***
	(-2.175)	(-2.867)	(-2.175)	(-2.867)	(-2.286)	(-2.969)
Past Week Returns	-0.00222	-0.00644**	-0.00221	-0.00642**	-0.00259	-0.00676**
	(-0.736)	(-2.033)	(-0.734)	(-2.029)	(-0.858)	(-2.139)
Log Market Value of Collection	-0.0166***	-0.0169***	-0.0166***	-0.0169***	-0.0168***	-0.0170***
	(-6.073)	(-6.675)	(-6.071)	(-6.674)	(-6.094)	(-6.673)
Dummy category Gaming	0.0103	0.00543	0.0103	0.00543	0.00923	0.00446
	(0.894)	(0.527)	(0.893)	(0.526)	(0.809)	(0.437)
Dummy category Metaverse	0.00235	-0.00339	0.00241	-0.00332	0.00346	-0.00238
	(0.195)	(-0.315)	(0.200)	(-0.308)	(0.285)	(-0.219)
Dummy category Social	-0.00422	-0.00646	-0.00421	-0.00645	-0.00439	-0.00665
	(-0.439)	(-0.723)	(-0.437)	(-0.721)	(-0.464)	(-0.754)
Dummy Has Twitter	-0.00408	-0.0227	-0.00412	-0.0227	-0.00953	-0.0277*
	(-0.286)	(-1.416)	(-0.289)	(-1.420)	(-0.747)	(-1.939)
Dummy Has Website	0.000481	0.00754	0.000507	0.00757	0.00413	0.0112
	(0.0359)	(0.491)	(0.0379)	(0.493)	(0.327)	(0.786)
Dummy Has Roadmap	-0.00689*	-0.00742**	-0.00689*	-0.00742**	-0.00695*	-0.00742**
	(-1.909)	(-2.151)	(-1.909)	(-2.151)	(-1.927)	(-2.160)
Dummy Artist Name	0.00546*	0.00264	0.00546*	0.00264	0.00605**	0.00320
	(1.871)	(0.919)	(1.872)	(0.921)	(2.061)	(1.112)
Observations	39,838	39,814	39,838	39,814	39,838	39,814
Collection Controls	YES	YES	YES	YES	YES	YES
Date FE	NO	YES	NO	YES	NO	YES
Within Adj R-squared	0.0153	0.0157	0.0153	0.0156	0.0147	0.0152
Adj R-squared	0.0153	0.0602	0.0153	0.0602	0.0147	0.0598

Table A.8. Heterogeneity in Insider Sell Behavior: Same Day
Notes. In this table, I report the results from estimates of specification (1) in which I regress future median price returns on a daily trades of insider sell activity scaled by NFT collection-size for collection c as of day t. The dependent variable is $Return_{c,t}$ which is the rate of median price change in USD from day $t-1$ to day t omitting all trades that are classified as wash trades. Control variables are a day before price return, weekly price return, collection age, market value of collection, and other collection characteristics. Standard errors are clustered by collection. t-statistics are in parentheses. $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$.

	(1)	(2)
VARIABLES	Price	Price
InsiderSell Activity x Additional	16.28**	14.12**
	(2.541)	(2.574)
InsiderSell Activity x Not Additional	64.09**	66.61**
	(2.106)	(2.212)
Log(1+Days after mints)	-0.00394***	0.00419
	(-2.703)	(1.431)
Past Day Returns	-0.225***	-0.249***
	(-19.17)	(-22.41)
Past Week Returns	-0.0266***	-0.0376***
	(-6.780)	(-9.403)
Log Market Value of Collection	0.00440***	0.00490***
	(3.317)	(2.916)
Dummy category Gaming	-0.0204*	-0.0205**
	(-1.959)	(-2.074)
Dummy category Metaverse	-0.0328***	-0.0378***
	(-2.693)	(-3.186)
Dummy category Social	-0.0300***	-0.0307***
	(-3.361)	(-3.507)
Dummy Has Twitter	0.0124	0.000333
	(0.771)	(0.0255)
Dummy Has Website	-0.00581	0.00385
	(-0.336)	(0.296)
Dummy Has Roadmap	-0.00204	-0.000668
	(-0.635)	(-0.197)
Dummy Artist Name	-0.00114	-0.00300
	(-0.362)	(-0.949)
Observations	42,946	42,922
Collection Controls	YES	YES
Date FE	NO	YES
Within Adj R-squared	0.0597	0.0705
Adj R-squared	0.0597	0.109

Table A.9. Determinants of Wash Trades
Notes. In this table, I present the estimates of linear probability model related to wash trades and their potential factors using secondary market transaction level data. The dependent variable is *WashTradeDummy* that is 1 if a trade is denoted as a wash trade. Dependent variables are marketplace dummy, and interaction of insider buy and seller dummy. Control variables are log holding period and log NFT transaction price. Standard errors are clustered by collection. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) Wash Sales Dummy	(2) Wash Sales Dummy	(3) Wash Sales Dummy
Marketplace = OpenSea		(baseline)	(baseline)
Marketplace = Blur		0.0360***	0.0360***
		(3.896)	(3.895)
Marketplace = Element		0.181	0.181
		(1.526)	(1.526)
Marketplace = Foundation		0.00700	0.00701
		(1.513)	(1.515)
Marketplace = LooksRare		0.0238**	0.0238**
		(2.026)	(2.026)
Marketplace = Sudoswap		0.0326***	0.0326***
		(4.827)	(4.822)
Marketplace = X2Y2		0.364***	0.364***
		(3.191)	(3.192)
Marketplace = Zora		0.0573*	0.0573*
		(1.663)	(1.664)
InsiderBuyer=0×InsiderSeller=0	(baseline)		(baseline)
InsiderBuyer=0×InsiderSeller=1	0.000838		0.000992
	(1.020)		(1.379)
InsiderBuyer=1×InsiderSeller=0	-0.00109		-0.000303
	(-0.840)		(-0.380)
InsiderBuyer=1×InsiderSeller=1	7.65e-05		0.00131*
	(0.0955)		(1.896)
Log(1+Holding Period)	-0.00462***	-0.00301***	-0.00301***
	(-2.840)	(-4.409)	(-4.410)
Log(NFT Price)	0.00202**	0.00143*	0.00143*
	(2.440)	(1.751)	(1.747)
Log(Mint Volume)	-0.00320	-0.00206	-0.00206
	(-0.723)	(-0.798)	(-0.797)
Dummy category Gaming	-0.00938	-0.00820	-0.00820
	(-0.764)	(-0.664)	(-0.664)
Dummy category Metaverse	-0.00869	-0.00834	-0.00835
	(-0.681)	(-0.659)	(-0.659)
Dummy category Social	-0.00775	-0.00698	-0.00698
	(-0.625)	(-0.566)	(-0.566)
Dummy Has Twitter	0.00686**	0.00582*	0.00584*
	(2.016)	(1.686)	(1.703)
Dummy Has Website	0.000590	-0.000557	-0.000570
	(0.216)	(-0.188)	(-0.192)
Dummy Has Roadmap	9.87e-05	0.000424	0.000422
	(0.0581)	(0.399)	(0.397)
Dummy Artist Name	-0.00173	-0.00119	-0.00119
	(-1.010)	(-1.130)	(-1.128)
Observations	3,303,324	3,303,324	3,303,324
Collection Controls	YES	YES	YES
Date FE	YES	YES	YES
Within Adj R-squared	0.0213	0.245	0.245
Adj R-squared	0.115	0.317	0.317

Table A.10. Realized Returns After Wash Trades

Notes. In this table, I present the estimates that I regress realized return on the past wash trade history. The independent variable is 1 if a previous trade for the same collection c, item i is wash trade, current trade is not wash trade, and previous buyer is recorded as seller at current trade. Control variables are log holding period, log collection volume, and other collection quality characteristics. Standard errors are clustered by collection. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

VARIABLES	(1) Realized Return	(2) Realized Return	(3) Realized Return
Dummy Previous Is Wash	-0.293**	0.218	0.231
	(-2.094)	(1.078)	(1.096)
Log(1+Holding Period)		0.267***	0.268***
		(3.031)	(2.987)
Log(Mint Volume)		0.174	0.173
		(1.001)	(0.993)
Dummy category Gaming		0.877	0.880
		(1.515)	(1.507)
Dummy category Metaverse		0.178	0.179
		(0.292)	(0.292)
Dummy category Social		0.567	0.569
		(1.164)	(1.154)
Dummy Has Twitter		-0.132	-0.135
		(-0.186)	(-0.189)
Dummy Has Website		0.946**	0.949**
		(2.279)	(2.278)
Dummy Has Roadmap		-0.552*	-0.553*
		(-1.831)	(-1.832)
Dummy Artist Name		0.139	0.139
		(0.564)	(0.563)
Observations	3,303,324	3,303,324	3,293,225
Collection Controls	NO	YES	YES
Date FE	YES	YES	YES
Within Adj R-squared	1.10e-06	0.00837	0.00830
Adj R-squared	0.0445	0.0525	0.0521