

Does wash trading distort asset prices? Evidence from NFT markets^{*}

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Abstract

Wash trades inflate volumes, but do they distort prices? Using Non-fungible token (NFT) markets as a natural laboratory, where blockchain transparency enables direct observation of every wash trade, we analyze 42.9 million transactions on the Ethereum blockchain and provide the first direct evidence that they do. Although wash trades represent only 2% of transactions, they account for 40% of the \$89 billion in total traded value. A 10 ETH wash trading shock generates a 0.32% increase in returns, statistically indistinguishable from the 0.34% generated by a genuine trading shock. Market participants cannot distinguish wash trades from genuine order flow, which is the precise mechanism that makes manipulation effective. Wash trading also amplifies genuine volume, with a 10 ETH shock raising genuine volume by 3.2 ETH, while wash trading declines following price surges as manipulators exit profitably. Wash trading concentrates on platforms offering volume-based rewards and migrates to venues with lower transaction costs when incentives shift. These results have direct implications for market regulation: if wash trading distorts prices at this scale even where every transaction is publicly recorded, the problem in traditional markets, where trade origins are opaque and detection is rare, is likely far greater, and price-based surveillance alone is structurally inadequate to address it.

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JEL classification: G14, G18, G19

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1. Introduction

How effective are manipulation practices in distorting asset prices? This has been a longstanding question that is difficult to answer because very few cases of manipulation are detected and prosecuted. Aggarwal and Wu (2006) and Comerton-Forde and Putniņš (2014) are two exceptions, who report evidence of trade-based and closing-price manipulation in stock markets, respectively. Wash trading is a prevalent form of market manipulation, it involves generating fake trading activity to inflate volumes artificially, which misleads investors, generates illicit profits and has adverse effects on market quality. This practice is banned in most developed markets, yet its impact on prices remains poorly understood because direct observation at scale has been impossible in traditional markets (e.g., Cumming et al., 2011).¹

We address this gap by exploiting Non-fungible token (NFT) markets as a natural laboratory. The transparency and immutability of blockchain data allow us to directly identify wash traders by linking addresses and tracing fund flows across every transaction, enabling the study of wash trading at scale rather than relying on the isolated prosecuted cases that characterize the traditional markets literature. Furthermore, limited regulatory oversight means wash trading occurs openly in cryptocurrency markets, generating a far richer dataset of manipulative trades than is available in traditional markets.²

To answer whether manipulation distorts asset prices, we develop a theoretical framework that builds on Aggarwal and Wu (2006) and incorporates key features central to NFT markets: platform trading rewards and transaction costs including gas fees, creator fees, and marketplace commissions. Our main prediction is that wash trading inflates prices because wash traders mimic informed traders, making their price impact indistinguishable from genuine informed trading. Additional predictions include a feedback dynamic between genuine and wash volume where each amplifies the other, creating the illusion of increased market demand. We further predict that rising returns attract genuine traders but deter wash traders as manipulation becomes more expensive, while lower transaction costs and exchange reward programs increase wash trading activity.

¹ For example, the Securities Exchange Act of 1934 prohibits manipulative practices in securities markets, while the Commodity Exchange Act (CEA) of 1936 extends similar restrictions to commodity markets. The Commodity Futures Modernization Act (CFMA) of 2000 details regulatory oversight and reaffirms the enforceability of anti-manipulation provisions. Additionally, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 significantly strengthens the regulatory framework, further reinforcing the ban on deceptive practices, such as wash trading, across financial markets.

² There are several notable enforcement actions against wash trading in cryptocurrency markets. In March 2021, Coinbase was fined \$6.5 million by the CFTC for automated wash trading on its GDAX platform. In March 2023, Justin Sun and associated entities faced SEC charges involving over 600,000 wash trades in TRX generating \$31 million in illicit proceeds. In April 2023, Kane, Hampton and Wolvaardt were charged by the DOJ for using a trading bot to execute wash trades in the HYDRO token. In June 2023, Binance and its founder Changpeng Zhao faced 13 SEC charges including wash trading to inflate volumes while misleading investors. In October 2024, Operation Token Mirrors, a coordinated DOJ and SEC action against 18 individuals and entities across multiple platforms, resulted in the first criminal charges against financial services firms for crypto wash trading.

To test these theoretical predictions, we analyze a comprehensive dataset of 42,903,654 NFT transactions recorded on the Ethereum blockchain between January 1, 2021 and June 30, 2024. We find that the total wash trading volume amounts to approximately \$34.2 billion, compared to \$54.7 billion for genuine trading. Although wash trading constitutes only 2% of total transactions, it accounts for an estimated 40% of the total trading volume. This volume inflation creates misleading signals for genuine buyers, but whether it also distorts prices is the central question we address.

We find that it does. Using a vector autoregressive framework, we find that wash trading inflates asset prices: the price impact of a 10 ETH wash trading shock (0.32%) is statistically indistinguishable from that of a genuine trading shock (0.34%), indicating that wash traders deliberately mimic the trading patterns of genuine participants to manipulate prices effectively. This result reflects the inability of market participants to distinguish wash trades from genuine order flow.

The VAR also reveals two additional findings. First, return shocks affect genuine and wash trading very differently: rising prices attract genuine traders seeking profitable opportunities, while wash traders exit the market as manipulation becomes more expensive. Second, genuine and wash trading volumes exhibit a dynamic feedback relationship: increases in genuine trading activity prompt wash traders to amplify their manipulative efforts, while increases in wash trading volume significantly boost genuine trading as artificial activity generates market momentum, attracting genuine traders through perceived liquidity and fear of missing out.

Beyond price distortion, we document that wash trading concentrates strategically across venues. Wash trading volumes spike when exchanges offer trading rewards programs, as on LooksRare, X2Y2, and Blur, and migrate to Layer 2 platforms as lower transaction costs make manipulation more economically feasible, consistent with evidence that market structure changes have first-order effects on trading behavior (Hendershott and Moulton, 2011; Patel et al., 2020).

Our paper makes four contributions. First, we provide the first direct evidence that wash trading inflates asset prices, not merely trading volumes. The theoretical possibility that trade-based manipulation can distort prices has been established for decades. Allen and Gale (1992) show that manipulation is possible when investors cannot distinguish genuine from manipulative trades; Jarrow (1992) shows how large traders exploit price momentum to profit from manipulation; and Aggarwal and Wu (2006) provide theoretical and empirical evidence that manipulation occurs in illiquid markets where manipulators imitate genuine trading behavior. However, direct empirical evidence has remained elusive because so few cases are detected and prosecuted in traditional markets.

As a result, we turn to blockchain data to provide direct evidence. Prior studies have reported evidence of artificial volume inflation on centralized exchanges and bitcoin (e.g., Cong et al., 2023; Aloosh and Li, 2024), but they leave the price distortion mechanism unexamined. Wang et al. (2025) document a temporary pump-and-dump price reversal effect on OpenSea (a platform accounting for just 5% of wash trading by value). Using a VAR framework (Hasbrouck, 1991) across NFT collections capturing 95% of total traded value, we identify a distinct and more fundamental mechanism that makes

manipulation effective: wash trading generates persistent price impacts statistically indistinguishable from genuine informed trading, with no subsequent reversal. Our results are consistent with Chakraborty and Yilmaz (2004), who model manipulation in market order settings where informed and uninformed trading are indistinguishable, and with Baruch, Panayides and Venkataraman (2017), who show that aggressive informed order flow directly drives the price formation process, which is precisely the channel that wash traders exploit.

Second, this mechanism generalizes beyond NFTs to any market where trade origins are opaque. The NFT blockchain setting provides a rare opportunity to identify this mechanism directly because every transaction is publicly recorded and fund flows are fully traceable, a form of post-trade transparency that Goldstein, Hotchkiss and Sirri (2007) show dramatically improves market quality in opaque markets, enabling direct identification of manipulative activity. Our findings suggest that wash trading likely distorts prices in traditional markets through the same channel, where the absence of comparable transparency has prevented direct detection and where the scale of distortion remains unknown.

Third, we document the economic scale, platform concentration, and cross-platform dynamics of wash trading across a broad sample of NFT markets. Although wash trades represent only 2% of transactions, they account for 40% of the \$89 billion in total traded value. Earlier NFT-specific studies substantially underestimate this scale: von Wachter et al. (2022) identify \$149.5 million through November 2021, and La Morgia et al. (2023) detect \$3.4 billion through January 2022, both predating the rewards-program era that drove the vast majority of all recorded wash trading.³ Wang et al. (2025) document comparable overall wash trading volume through June 2023, but restrict their analysis to OpenSea to exclude token-incentivized trading, leaving unexamined both the rewards-driven concentration on LooksRare, X2Y2 and Blur and the subsequent migration of wash trading to lower-cost platforms.

Fourth, our results carry direct implications for regulators and market design. Our central price distortion finding that wash trading generates price impacts statistically indistinguishable from genuine informed trading implies that price-based surveillance is structurally blind to manipulation: no monitoring tool that watches prices, order book patterns or volume anomalies can detect wash trading that successfully mimics genuine informed order flow. Detection requires account-level monitoring of fund flow patterns, and our four detection criteria, specifically self-trades, back-and-forth trades, shared funding sources and shared exit wallets, provide a concrete blueprint for surveillance tools in any market where transaction-level data is available.

Our rewards program results demonstrate that platform design choices intended to attract genuine liquidity instead caused manipulation, consistent with Goldstein and Kavajecz (2004) who

³ For other studies examining NFT wash trading, see Pennec et al. (2021), Bonifazi et al. (2023), Liu et al. (2023), Wen et al. (2023), Sifat et al. (2024) and Tahmasbi et al. (2024).

show that market design rules can trigger perverse unintended consequences when participants exploit them in ways designers did not anticipate. Regulatory attention must therefore focus on incentive structures at the design stage rather than enforcement after manipulation has occurred. Because wash traders migrate across platforms when incentives shift, effective regulation requires coordinated simultaneous action across venues rather than single-platform interventions. Blockchain technology creates new possibilities for transparency-based market design: Malinova and Park (2017) detail that full transparency of distributed ledgers maximizes investor welfare by enabling direct identification of counterparties, and our findings demonstrate that regulators should exploit this inherent transparency for systematic wallet-level surveillance, a detection approach that price-based monitoring cannot replicate. We develop these implications in more detail in Section 5.

The paper proceeds as follows. Section 2 details our theoretical framework which generates testable hypotheses. Section 3 details our data and methodology. Section 4 presents our empirical results. Section 5 concludes and details the implications of our results.

2. Theoretical framework

We develop a theoretical framework that adapts Aggarwal and Wu (2006) to the NFT setting to generate testable predictions. Two features specific to NFT markets alter wash trading incentives relative to those in equity markets. The first feature is platform-level trading rewards. For example, NFT marketplaces such as LooksRare and X2Y2 offer a per-unit trading reward (R), which provides direct financial incentives for wash traders to generate high trading volumes and earn token-based rewards. The second feature is transaction costs (τ), such as gas fees, marketplace commissions, and creator fees, which represent a key constraint on wash trading behavior. Together, these two features determine when wash trading is economically viable and generate the core empirical predictions we test below.

In our three-period model ($t = 0, 1, 2, 3$), there are four types of traders: genuine informed traders (I) who know if the NFT price will be high (V_H) or low (V_L), wash traders (W) who trade to generate illicit profits, uninformed noise traders (U) who provide liquidity, and information seekers (S) who react to observed trades and seek out information about whether the price will be high or low (also referred to as arbitrageurs).

Each agent's possible actions across the three periods are as follows. At $t = 0$, all agents share a common prior belief about the value of a specific NFT asset and uninformed noise traders hold all NFTs (where they are available to sell at $t = 1$ and 2). At $t = 1$, informed and wash traders can enter the market. At $t = 2$, informed and wash traders can buy or sell, and information seekers can buy NFTs conditional on what they observe at $t = 1$. At $t = 3$, the NFT is known to be V_H or V_L .

At $t = 0$, uninformed noise traders are willing to sell according to a linear supply curve with the quantity Q at a price P given by:

$$P(Q) = a + b(Q), \quad (1)$$

where $b > 0$ captures the sensitivity of price to trade size. As there is uncertainty about which traders will enter the market at $t = 1$, let δ be the probability that the trader is informed and knows the asset has a high fundamental value V_H at $t = 3$. The price at $t = 0$ can then be expressed as the expected value of NFTs:

$$a = \delta V_H + (1 - \delta) V_L. \quad (2)$$

If informed traders anticipate that the value at $t = 3$ will be V_L , they will choose not to participate in the market.

At $t = 1$, both informed and wash traders can enter the NFT market and purchase quantity q_1 from uninformed traders, anticipating a higher price p_2 at $t = 2$. Each trader chooses q_1 to maximize their profit, taking into account the purchase price (p_1), future resale value (p_2), trading rewards (R), and transaction costs (τ). The total profit function for each trader can be expressed as:

$$\Pi(q_1) = [p_2 - p_1 + R - \tau] \cdot q_1. \quad (3)$$

Substituting the linear pricing function $p_1 = a + bq_1$:

$$\Pi(q_1) = [p_2 - (a + bq_1) + R - \tau] \cdot q_1. \quad (4)$$

Each trader's optimization problem is then:

$$\max_{q_1} [p_2 - (a + bq_1) + R - \tau] \cdot q_1. \quad (5)$$

Solving the first-order condition yields the optimal trade size:

$$q_1^* = \frac{p_2 - a + R - \tau}{2b}. \quad (6)$$

At $t = 2$, each information seeker observes trades at $t = 1$ but cannot distinguish whether it is executed by a genuine informed trader who believes the NFT price will be V_H or from a wash trader. Let γ represent the prior probability that the trader entering at $t = 1$ is a wash trader. Upon observing a trade at $t = 1$, the information seekers update their beliefs via Bayes' rule; the posterior probability of a wash-initiated trade is:

$$\beta = \gamma / (\gamma + \delta), \quad (7)$$

where $(1 - \beta)$ is the posterior probability that the trade originates from a genuine informed trader.

Each information seeker then decides how much to trade based on this uncertainty, their per-unit trading reward (R) and a per-unit transaction cost (τ). The expected profit maximization problem for information seeker i becomes:

$$\begin{aligned} \max_{q_2^{Si}} (1 - \beta) & \left\{ V_H q_2^{Si} + R q_2^{Si} - \tau q_2^{Si} - \left[a + b \left(\sum_{j \in N} q_2^{Sj} \right) \right] q_2^{Si} \right\} + \beta \left\{ V_L q_2^{Si} + R q_2^{Si} - \tau q_2^{Si} \right. \\ & \left. - \left[a + b \left(\sum_{j \in N} q_2^{Sj} \right) \right] q_2^{Si} \right\}. \end{aligned} \quad (8)$$

Under symmetry, where all N information seekers submit the same quantity q_2 , the problem simplifies to:

$$\max_{q_2} \{[(1 - \beta)V_H + \beta V_L + R - \tau]q_2 - (a + b(N + 1)q_2)q_2\}. \quad (9)$$

This is a standard equilibrium problem in which each agent accounts for their own price impact while taking the actions of others as given. The symmetric equilibrium yields individual demand for the information seeker:

$$q_2^* = \frac{(1 - \beta)V_H + \beta V_L + R - \tau - a}{(N + 1)b}. \quad (10)$$

Then the market-clearing price at $t = 2$ is:

$$p_2 = a + bNq_2^* = \frac{N[(1 - \beta)V_H + \beta V_L + R - \tau - a] + (N + 1)a}{N + 1}. \quad (11)$$

Substituting Eq. (11) into Eq. (6) gives the optimal trading volume for the informed and wash traders and clearing price at $t = 1$ as:

$$q_1^* = \frac{N[(1 - \beta)V_H + \beta V_L + R - \tau - a] + (N + 1)(R - \tau)}{2b(N + 1)}, \quad (12)$$

$$p_1 = a + \frac{N[(1 - \beta)V_H + \beta V_L + R - \tau - a] + (N + 1)(R - \tau)}{2(N + 1)}. \quad (13)$$

Informed traders will choose to sell at $t = 2$, rather than wait until $t = 3$. Let k represent the cost of holding the asset until $t = 3$, then the condition for the informed trader to pool with the wash trader is:

$$p_2 > V_H + k. \quad (14)$$

Substituting Eq. (11) into Eq. (14) and rearranging the terms simplifies the condition to:

$$\frac{k(N + 1) - (1 - \delta)(V_H - V_L)}{-k(N + 1) + (1 - \delta)(V_H - V_L) + N(V_H - V_L) + N(R - \tau)} \cdot \delta \geq \gamma. \quad (15)$$

Eq. (15) shows that the conditions for informed traders to pool with wash traders are more likely to be satisfied when the probability of wash trading (γ) decreases, the probability of genuine trading (δ) increases, the cost of holding until $t = 3$ (k) increases, the difference between expected values at $t = 3$ ($V_H - V_L$) decreases, the number of information seekers (N) increases, the incentive program (R) decreases, and the transaction cost (τ) increases.

However, if the condition fails, informed traders prefer to delay their sales and separate from wash traders. In this scenario, the market learns to identify wash trades and no longer interprets them as signals of fundamental value. As a result, wash traders can no longer mislead other participants and cannot profit from price manipulation. The wash trader's activity then depends solely on the trading incentives and transaction costs. Without sufficient rewards to cover transaction costs and the loss in

resale value, wash trading becomes unprofitable and unsustainable, and wash traders do not participate in the market.⁴

From our model, we derive the following testable propositions.

Proposition 1: A positive shock to wash trading volume or genuine informed trading volume increases returns, and the price impact of both types of trades is statistically indistinguishable. Genuine informed traders enter the market at $t = 1$ only when they know the asset's fundamental value will be high (V_H). They buy at $t = 1$ and sell at $t = 2$, generating a profit from a price increase from p_1 to p_2 . Wash traders, in contrast, lack fundamental information but imitate the trading behavior of informed traders to manipulate prices and attract other participants. Because information seekers cannot distinguish whether a trade originates from a wash trader or an informed trader, both types of trades produce similar upward price movements. Thus, a positive shock to either kind of trading activity yields an equivalent increase in observed returns.

Proposition 2: A positive shock in returns leads to an increase in genuine trading volume. When prices increase from p_1 to p_2 , information seekers interpret the price movement as a signal of informed trading. They then choose to enter the market which increases genuine trading volume.

Proposition 3: A positive shock in returns leads to a decrease in wash trading volume. When prices increase from p_1 to p_2 , wash traders have less incentive to continue wash trading. Once prices rise and provide an opportunity to exit profitably, wash traders liquidate their positions rather than continue to create inflated volume, leading to a decline in wash trading activity.

Proposition 4: A positive shock in genuine trading volume leads to an increase in wash trading volume. Since wash traders strategically imitate the behavior of informed traders, an increase in genuine trading activity serves as a signal that informed traders are present in the market. To maintain the illusion of legitimacy and to amplify their market impact (while also earning trading rewards), wash traders increase their trading volume alongside genuine traders.

Proposition 5: A positive shock in wash trading volume leads to an increase in genuine trading volume. Wash traders mimic informed traders by entering the market at $t = 1$ and executing trades that resemble informed buying. These actions cause prices to increase, misleading information seekers into believing that genuine information has entered the market. As a result, information seekers enter the market, thereby increasing genuine trading volume.

Proposition 6: Higher transaction costs result in a decrease in wash trading volume. Higher transaction costs directly reduce the profitability of wash trading, making repeated transactions increasingly expensive and deterring manipulative activity.

⁴ See Aggarwal and Wu (2006) for a detailed discussion of the conditions and other scenarios in which informed traders break the equilibrium and do not pool. We focus on the most likely scenario where wash trading occurs, and informed traders pool with wash traders. The conditions in Eq. (15) are sufficient rather than necessary for the pooling equilibrium. The negative dependence on $V_H - V_L$ is intuitive: when the spread between fundamental values is large, informed traders have stronger incentives to separate from wash traders, making pooling harder to sustain.

Proposition 7: Rewards programs that incentivize trading result in an increase in wash trading volume. Trading reward programs lower the effective cost of wash trading by subsidizing transaction activity, making manipulation more economically viable. Eq. (12) confirms both predictions formally. *Propositions 6 and 7* characterize wash trading incentives within a single platform. We extend this logic to a multi-platform setting by considering a wash trader who allocates volume q_j across two platforms $j \in \{1,2\}$, each offering reward R_j and transaction cost τ_j , to maximize total profit:

$$\max_{q_1, q_2} \sum_{j=1}^2 [(R_j - \tau_j) \cdot q_j - \frac{b}{2} q_j^2], \quad (16)$$

subject to $q_1 + q_2 = \dot{q}$. Solving the first-order conditions yields the optimal platform allocation:

$$q_j^* = \frac{\dot{q}}{2} + \frac{(R_j - \tau_j) - (R_{-j} - \tau_{-j})}{2b}. \quad (17)$$

*Proposition 8: A reduction in trading rewards or an increase in transaction costs on one platform causes wash trading volume to migrate to competing platforms.*⁵ Eq. (17) shows that wash traders concentrate activity on whichever platform offers the higher net incentive and migrate volume to competing platforms when rewards fall or costs rise on their current platform.

3. Data and methodology

We analyze wash trading using the entire universe of 42,903,654 NFT transactions recorded on the Ethereum blockchain between January 1, 2021 and June 30, 2024.

Prior studies find that wash trading typically involves self-trades, transactions between two linked accounts, accounts funded by the same wallet or where funds are transferred to the same wallet after the transaction (e.g., Victor and Weintraud, 2021; von Wachter et al., 2022; Serneels, 2023; La Morgia et al., 2023; Wang et al., 2025). Furthermore, as multiple hops of transactions between wallets increase transaction costs and regulatory oversight remains limited, prior studies find that wash trading typically occurs using simpler single-hop transactions.

< Figure 1 here >

As a result, using Dune and Flipside (web-based platforms that allow the querying of public blockchain data), we classify an NFT transaction as a wash trade based on any of the following four criteria: (i) *Self-trade*: the same individual (A) trades the NFT with themselves. (ii) *Back-and-forth trades*: A transfers the NFT to B, who subsequently resells it back to A; A sends Ethereum to B to facilitate the NFT's repurchase; or A and B repeatedly buy and sell the NFT between each other. (iii)

⁵ *Propositions 6, 7 and 8* are derived from a single-agent optimization problem in which a wash trader allocates volume across platforms taking platform conditions as given, rather than from a strategic equilibrium with competing wash traders.

Shared funding source: A trades with B where both are funded by the same originating wallet C. (iv) *Shared exit*: A and B transfer funds to the same wallet C after their transaction. These criteria are grounded in prior literature and are more comprehensive than closed-loop detection methods alone, which capture criteria (i) and (ii) but miss the shared funding source and shared exit patterns in criteria (iii) and (iv) that are central to more sophisticated wash trading strategies. Figure 1 illustrates these patterns for NFT wash trading. Transactions that do not meet any of these four criteria are classified as genuine trades.⁶

4. Main results

4.1. Prevalence of wash trading in NFTs

We report descriptive statistics for the full sample of wash and genuine trading in NFTs during our sample period in Table 2 Panel A. We find that the total wash trading volume is \$34.30 billion (ETH 14.25 million) relative to genuine trading volume of \$54.72 billion (ETH 21.86 million). The number of wash trades is 723,591 versus genuine trades of 42.90 million. Our findings reveal that while wash trading constitutes only a tiny fraction of total transactions (approximately 2%), it accounts for a substantial portion of the total trading volume (approximately 40%). These findings indicate that wash traders strategically use relatively few trades to generate a disproportionately large volume, inflating the apparent demand for NFTs and misleading genuine traders.

< Table 2 here >

Figure 2 illustrates trends in genuine and wash trading volumes over time (represented on a logarithmic scale). Total trading volume experienced steady growth starting in early 2021, reaching its peak in August 2021 with over \$3 billion in trading activity, with wash trading volume accounting for approximately \$1.1 billion (i.e., approximately 40%). Wash trading spiked to \$4.3 billion in January 2022. This surge in wash trading can be attributed to the introduction of volume-based trading rewards programs by the LooksRare and X2Y2 exchanges, which resulted in a substantial increase in artificial transactions as traders sought to maximize their rewards.⁷ From January 2022 to January 2023, wash trading and genuine trading volume were approximately the same in total value.

Since mid-2022, total NFT trading volume declined, driven by the broader cryptocurrency market entering a bearish phase and exchanges discontinuing incentive programs and implementing algorithms to combat wash trading. However, both genuine and wash trading value remain economically significant by the end of our sample period.

⁶ We do not include the following as wash trades: collateralized lending and repossessions, fractionalization/redemption, DAO, multisig wallet transfers, and liquidity pool operations. These transactions typically reflect ownership changes or operational flows rather than wash trading.

⁷ See Appendix A for further details of NFT trading rewards programs.

< Figure 2 here >

Table 2 Panel B reports the breakdown of wash trading volume by exchange. We find that wash trading is concentrated on the LooksRare exchange, accounting for approximately \$26.74 billion or 78% of total wash trading volume, followed by X2Y2 and Blur at 12.39% and 6.22%, respectively.

Figure 3 illustrates wash trading volume over time for four major NFT exchanges: LooksRare, X2Y2, Blur, and OpenSea. We observe a sharp increase in wash trading volume on LooksRare, X2Y2, and Blur, coinciding with the introduction of their respective trading rewards programs in January 2022, February 2022, and October 2022, respectively. These programs incentivized trading by rewarding users based on their trading volumes, inadvertently encouraging wash trading as users engaged in self-trading to maximize rewards. In contrast, OpenSea, which did not implement such incentive programs, exhibited relatively stable wash trading volumes throughout the period, highlighting the significant role rewards programs played in driving artificial trading activity.

< Figure 3 here >

In response to the unintended consequences of these rewards programs, some platforms have taken steps to mitigate wash trading. For example, LooksRare ended its trading rewards program in March 2023 after significant pushback from the community regarding wash trading activities. As a result, wash trading subsequently migrated to competing venues and to lower-cost Layer 2 platforms, as we document below.

We also find that wash trading is concentrated within a few high-profile collections (see Table 2 Panel C, which reports descriptive statistics of the top 10 NFT collections with the highest wash trading activity). The Terraforms collection leads with \$12.2 billion in wash trading volume, representing 36.35% of the market. Meebits follows with \$9.4 billion, accounting for 27.93%, while Dreadfulz ranks third with \$1.9 billion, contributing 5.72% of the total wash trading volume.

Having established the scale of wash trading and its concentration across specific platforms and collections, we now address the paper's central question: does wash trading distort asset prices?

4.2. Does wash trading distort asset prices and volume?

In this section, we investigate the causal relationships between wash trading volume, genuine trading volume, and returns using a vector-autoregressive framework (VAR) following Hasbrouck (1991), estimated for each of the top 300 NFT collections with the highest wash trading volume. We use the following system of equations:

$$Wash_t = a_0 + \sum_{l=1}^6 a_{1,l} Wash_{t-l} + \sum_{l=1}^6 a_{2,l} Genuine_{t-l} + \sum_{l=1}^6 a_{3,l} Return_{t-l} + \varepsilon_{W,t},$$

$$\begin{aligned}
Genuine_t &= b_0 + \sum_{l=0}^6 b_{1,l} Wash_{t-l} + \sum_{l=1}^6 b_{2,l} Genuine_{t-l} + \sum_{l=1}^6 b_{3,l} Return_{t-l} + \varepsilon_{N,t}, \\
Return_t &= c_0 + \sum_{l=0}^6 c_{1,l} Wash_{t-l} + \sum_{l=0}^6 c_{2,l} Genuine_{t-l} + \sum_{l=1}^6 c_{3,l} Return_{t-l} + \varepsilon_{R,t},
\end{aligned}
\tag{18}$$

where $Wash_t$ ($Genuine_t$) is the signed dollar volume of wash (genuine) trades in hour t (we can observe whether each trade is a buy or sell trade), and $Return_t$ is the return of the NFT collection calculated as the log change of NFT floor price in the t^{th} hour. We use the NFT floor price to calculate returns because individual prices are noisy, whereas floor prices capture the baseline minimum value of a collection, and they are used by market participants to gauge liquidity, demand, and market sentiment.⁸

We use the median floor price recorded in each hourly interval rather than a single floor price at the end of the period, as it offers two methodological advantages. First, this method is not affected by temporarily low quoted prices, such as unreasonably low prices set for short periods to suppress the floor price, because such quoted prices must persist for more than half an hourly period to affect the median. Second, this method eliminates individual data entry errors and extreme outliers.

The VAR is estimated using a Cholesky decomposition with the ordering: wash volume, genuine volume, returns. This ordering reflects the recursive causal structure embedded in our theoretical framework and the institutional features of NFT markets. Wash trading is ordered first because wash trading decisions are typically algorithmic and driven by platform incentive structures; they are predetermined relative to the within-period responses of other market participants. Genuine volume is ordered second, as genuine traders respond contemporaneously to the perceived liquidity created by wash activity but do not yet observe the resulting price impact within the same period. Returns are ordered last as the most endogenous variable, reflecting the price discovery process that results from the combined order flow of both trader types. This ordering is consistent with the recursive structure of the VAR system in Eq. (18).

We use impulse response functions to understand the causal relationships between returns, genuine, and wash volume. This approach follows the tradition of Hasbrouck (1991) and Rosu (2019), who characterize the price impacts of heterogeneous trader types in a dynamic setting. At $t = 0$, we separately use a 10% shock in returns, a 10 ETH shock in genuine volume, and a 10 ETH shock in wash volume, and subsequently measure the cumulative response of returns, genuine, and wash volume to these shocks over a 24-hour period.

< Table 3 here >

Table 3 reports the mean and standard deviation for the 24-hour cumulative response of returns (%), genuine volume (ETH), and wash trading volume (ETH) to shocks in each of these variables. Our

⁸ For a more detailed explanation of NFT floor prices, see the Chainlink Education Hub at <https://chain.link/education-hub/what-is-an-nft-floor-price>.

first main finding is that wash trading inflates asset prices: a 10 ETH wash trading shock generates a 0.32% increase in returns, statistically indistinguishable from the 0.34% generated by a genuine trading shock, consistent with *Proposition 1*. This indicates that wash traders deliberately mimic genuine order flow to manipulate prices effectively.

Our next main finding is that return shocks affect genuine and wash trading very differently, consistent with *Propositions 2* and *3*. A 10% return shock increases genuine trading volume by approximately 28 ETH, reflecting that higher returns signal greater profits, liquidity, and market confidence, and draw additional traders into the market through the fear of missing out (FOMO) effect. In contrast, the same 10% return shock leads to a decrease in wash trading volume by approximately 9 ETH. When prices rise, profitable exit opportunities emerge and wash traders liquidate their positions rather than continue inflating volume. Higher returns also make manipulation more expensive and attract genuine traders, further reducing the relative impact of wash trading.

We also find a dynamic feedback relationship between genuine and wash trading volumes, consistent with *Propositions 4* and *5*. A 10 ETH shock to genuine trading volume leads to a 1.3 ETH increase in wash trading volume: when genuine trading rises, wash traders boost their activity to maintain the illusion of legitimacy, exploit the momentum of genuine trades, and enhance their rewards from platform incentive programs. Conversely, a 10 ETH shock in wash trading volume results in a 3.2 ETH increase in genuine trading volume, as the artificial boost in perceived liquidity makes collections appear more active and desirable, prompting genuine traders to participate through FOMO or a perceived increase in value.

< Figure 4 here >

While Table 3 reports the descriptive statistics of these responses, Figure 4 illustrates the cumulative impulse responses along with 95% confidence intervals. The horizontal axis represents time in hours, starting from the initial shock at $t = 0$. The response of returns to a shock in genuine or wash volume stabilizes at approximately 0.35% for both genuine volume and wash volume shock after $t = 4$. While the cumulative response of genuine volume to a return shock stabilizes at approximately 28 ETH and wash volume declines to approximately -9 ETH after $t = 5$. The wash trading shock's impact on genuine volume stabilizes at approximately 3.2 ETH after $t = 5$, while the genuine trading shock's impact on wash volume continues to increase during the ten-hour window, reaching approximately 1.1 ETH, suggesting a persistent and growing wash trading response to genuine market activity.

< Figure 5 here >

For robustness, we substitute the NFT floor price with the volume-weighted average genuine transaction price, providing a manipulation-resistant estimate of the price at which genuine market

participants were willing to transact (Hu, 2007; Konishi, 2002; Białkowski et al., 2008). Our main finding that wash trading generates price impacts statistically indistinguishable from genuine trading remains qualitatively unchanged, as detailed in Figure 5.

Overall, wash trading distorts asset prices: wash trading shocks inflate genuine volume, while genuine trading increases when prices rise, wash trading declines as it becomes uneconomical. We discuss the regulatory implications of these findings in Section 5.

4.3. Key drivers of wash trading

Having documented that wash trading significantly distorts asset prices, we now examine the key drivers of wash trading volume, including the level of genuine trading activity, transaction costs, platform incentive programs, and market volatility.

One of the main drivers of wash trading is the level of genuine trading, since wash traders must increase their activity proportionally to genuine trading to maintain the illusion of market demand. Aggarwal and Wu (2006) find that wash traders strategically mimic informed traders and rely on information seekers as buyers to generate profits, a pattern consistent with Baruch, Panayides and Venkataraman (2017), who show that aggressive informed order flow directly drives price formation, the same channel wash traders exploit to amplify their impact as genuine transactions grow.

The other main drivers relate to transaction costs in the form of creator fees and exchange fees, where higher fees deter wash trading. Cong et al. (2023) demonstrate that lower wash trading costs significantly increase wash trading activity on cryptocurrency exchanges, consistent with *Proposition 6*.

We also include dummy variables capturing platform incentive program periods for the two largest exchanges, LooksRare and X2Y2, set equal to one if the observation falls between January 9, 2022 and December 29, 2023, and equal to zero otherwise. Jayant (2023) and Niu et al. (2024) provide evidence that incentive programs implemented by NFT exchanges lead to an increase in wash trading, consistent with *Proposition 7*. Finally, we control for the number of exchanges listing each NFT collection and market volatility, where higher volatility discourages wash trading by raising its potential costs (Cong et al., 2023).

Table 4 reports descriptive statistics for the key drivers of wash trading across the top 300 NFT collections with the highest wash trading volumes. The average daily wash trading volume is 435.83 ETH (or \$1.05 million), approximately four times the genuine trading volume of 109.01 ETH (\$0.26 million), with some collections experiencing extreme wash trading volumes of up to \$425 million in a single day.

We also find that wash traders face lower transaction costs than genuine traders, with an average exchange fee of 1.07% compared to 1.54% and an average creator fee of 2.19% versus 3.03%. These lower fees suggest that wash traders strategically minimize costs by targeting platforms or collections with lower fees, consistent with *Proposition 6*.

We also find that NFTs involved in wash trading are listed on fewer exchanges, with an average exchange count of 1.12 and a maximum of 5, compared to 1.83 and a maximum of 9 for NFTs traded by genuine users. This indicates that wash traders concentrate their activity on a limited number of platforms offering favorable conditions, such as incentive rewards or lower transaction costs, while genuine traders engage across multiple exchanges to benefit from better price discovery and greater liquidity.

< Table 4 here >

To examine the key drivers of wash trading volume in a multivariate setting, we estimate the following panel regression for NFT collection i at day t :

$$\begin{aligned} \text{Wash volume}_{it} = & \alpha + \beta_1 \text{Genuine volume}_{it} + \beta_2 \text{Platform fee}_{it} \\ & + \beta_3 \text{Creator fee}_{it} + \beta_4 D_t^{\text{Incentive}} + \delta_t + \gamma_i + \varepsilon_{it}, \end{aligned} \quad (19)$$

where Wash volume_{it} and $\text{Genuine volume}_{it}$ is wash and genuine trading volume expressed in logarithmic form, respectively, Platform fee_{it} is platform fees for wash trading, Creator fee_{it} is creator fees for wash trading, and $D_t^{\text{Incentive}}$ is the dummy variable for the incentive programs of exchanges. We use day and collection fixed effects.

< Table 5 here >

Table 5 reports our findings. The $\text{Genuine volume}_{it}$ coefficient estimate is 0.597 in the univariate specification (Model 1) and 0.330 in the fully specified model (Model 6), remaining positive and statistically significant throughout. A 1% increase in genuine trading volume is associated with an approximate 0.6% increase in wash trading volume in the univariate model, highlighting that wash traders must increase activity proportionally to genuine trading to maintain the illusion of market demand.

The platform fee (Platform fee_{it}) and creator fee (Creator fee_{it}) are negatively related to wash trading volume, indicating that higher transaction fees deter wash trading as the costs of repeated transactions increase with higher fees, consistent with *Proposition 6* and Cong et al. (2023). The $D_t^{\text{Incentive}}$ coefficient estimate indicates that wash trading volume increases significantly following the introduction of NFT exchange incentive programs, consistent with *Proposition 7* and the evidence in Jayant (2023) and Niu et al. (2024).

Finally, we find that the number of exchanges ($\text{Exchange count}_{it}$) trading an NFT collection has a positive and significant coefficient estimate, indicating that collections listed on more exchanges

provide more opportunities for wash trading, likely due to differences in oversight and enforcement across platforms. Rising volatility reduces wash trading, consistent with Cong et al. (2023), as higher volatility raises the potential costs of manipulation.

4.4. Do rewards programs and transaction costs drive wash trading?

The panel regressions in the previous section establish the cross-sectional determinants of wash trading volume. We now examine how these incentives play out dynamically, focusing on whether wash traders strategically migrate across platforms in response to reward differentials and transaction cost changes, as predicted by *Proposition 8*. Our theoretical framework predicts two key determinants: transaction costs (*Proposition 6*) and trading reward programs (*Proposition 7*).

4.4.1. Transaction costs

Figure 6 illustrates wash trading volume expressed on a logarithmic scale (in dollars) on the Ethereum blockchain and its Layer 2 platforms (Polygon, Arbitrum, Optimism, Celo, zkSync, Zora, Base, Scroll, and Blast) between January 2021 and June 2024. The figure reveals a striking pattern consistent with *Proposition 6*: wash trading is highly sensitive to transaction costs, and manipulators rapidly migrate to lower-cost environments as they become available.

< Figure 6 here >

Prior to 2023, wash trading was concentrated on the Ethereum blockchain, consistent with Layer 2 platforms being in early development stages with limited adoption. From March 2023 onwards, wash trading migrated rapidly to Layer 2 platforms, driven by anticipation of the Dencun upgrade implemented in March 2024, which introduced EIP-4844 and significantly reduced transaction costs for Layer 2 rollups. Simultaneously, the expansion of zero-knowledge rollups (zkRollups) such as zkSync, StarkNet, and Polygon zkEVM enhanced scalability, privacy, and cost efficiency, creating a favorable environment for wash traders. The subsequent launch of new platforms including Base, Scroll, and Blast, alongside the expansion of zero-knowledge rollups, provided additional low-cost venues attracting wash traders. The adoption of Uniswap v2 on multiple blockchains including Arbitrum, Polygon, Optimism, and Base further drove trading volumes, enabling wash traders to blend their manipulative activity within surges of genuine trading traffic. The rapid development and adoption of Layer 2 solutions have significantly increased wash trading activity, reaching levels similar to those observed on the Ethereum blockchain in its later stages. Overall, consistent with *Proposition 6*, lower transaction costs are a key driver of wash trading migration across platforms.

4.4.2. Incentive programs and cross-platform strategic migration

To examine how incentive programs influence wash trading behavior, we focus on the two exchanges with the largest wash trading volumes, LooksRare (ETH 9.9 million) and X2Y2 (ETH 2.7 million), both of which operated trading reward programs that provided per-unit incentives for trading volume during our sample period. This analysis directly tests *Proposition 7* (that rewards programs increase wash trading) and *Proposition 8* (that wash traders strategically migrate across platforms in response to reward differentials).

We use the following VAR system of equations to examine how a 10 ETH shock to wash trading on each exchange influences wash trading on the other:

$$\begin{aligned} Wash_Looksrare_t &= a_0 + \sum_{l=1}^6 a_{1,l} Wash_Looksrare_{t-l} + \sum_{l=1}^6 a_{2,l} Wash_X2Y2_{t-l} + \varepsilon_{1,t}, \\ Wash_X2Y2_t &= b_0 + \sum_{l=0}^6 b_{1,l} Wash_LooksRare_{t-l} + \sum_{l=1}^6 b_{2,l} Wash_X2Y2_{t-l} + \varepsilon_{2,t}, \end{aligned} \quad (20)$$

where $Wash_Looksrare_t$ ($Wash_X2Y2_t$) is the daily wash trading volume on LooksRare (X2Y2). The cross-platform VAR is estimated using daily data, reflecting that platform migration decisions occur over longer horizons.

< Figure 7 here >

Figure 7 illustrates the cumulative responses: a 10 ETH shock to wash trading volume on LooksRare reduces wash trading on X2Y2 by approximately 4,000 ETH, while a 10 ETH shock on X2Y2 reduces wash trading on LooksRare by approximately 250 ETH. Both responses are negative and statistically significant, consistent with *Proposition 8*. Wash traders treat the two platforms as strategic substitutes, reallocating activity toward whichever platform offers superior net incentives at a given point in time. The asymmetry in the magnitude of these responses is itself informative: LooksRare offered substantially stronger rewards and had more than three times the wash trading volume of X2Y2, so a shock on the dominant platform produces a larger reallocation effect than an equivalent shock on the smaller platform.

This cross-platform substitution pattern is consistent with Figures 3 and 6. When LooksRare terminated its rewards program in October 2023, wash trading did not simply disappear; it migrated first to X2Y2 and Blur, and subsequently to lower-cost Layer 2 platforms. This behavior underscores that wash traders are economically rational actors who continuously optimize across venues, and that platform interventions such as the termination of reward programs are necessary but not sufficient to eliminate manipulation. Effective regulation requires coordinated action across platforms and blockchains simultaneously, as we discuss below.

5. Conclusion and regulatory implications

We use NFT markets as a natural laboratory, exploiting the transparency and immutability of blockchain data to answer a question that has remained unanswered for decades: does wash trading distort asset prices, or merely inflate volumes? We build on the model of Aggarwal and Wu (2006) for the NFT setting and test our theoretical predictions using 42.9 million transactions on the Ethereum blockchain. We provide the first direct evidence that wash trading inflates both. Although wash trades represent only 2% of transactions, they account for 40% of the \$89 billion in total traded value. Crucially, a 10 ETH wash trading shock generates a 0.32% increase in returns, statistically indistinguishable from the 0.34% generated by a genuine trading shock. This is the precise mechanism that makes manipulation effective: market participants cannot distinguish wash trades from genuine informed order flow, so both generate equivalent and persistent price impacts.

Our empirical findings are consistent with the theoretical predictions of our model. Positive shocks to genuine trading volume attract wash traders, who amplify the illusion of market demand, while a 10 ETH wash trading shock raises genuine volume by 3.2 ETH through attention and liquidity externalities. Unlike genuine trading, which rises with prices as profitable opportunities attract participants, wash trading declines following price surges as manipulators exit profitably. Wash trading is concentrated on platforms offering volume-based rewards programs, with LooksRare alone accounting for 78% of all wash trading by value, and manipulators migrate strategically across platforms when incentives shift, first to X2Y2 and Blur when LooksRare terminated its program, and subsequently to lower-cost Layer 2 platforms as transaction costs fell.

Our finding that wash trading inflates 40% of \$89 billion in total traded value, even in a market where every transaction is publicly recorded, carries direct implications for traditional markets where trade origins are opaque and detection is rare. The mechanism we identify, the inability of market participants to distinguish wash trades from genuine informed order flow, is not specific to NFTs; it operates wherever manipulators can mimic informed trading behavior. If wash trading distorts prices at this scale even under full blockchain transparency, this suggests the scale of price distortion in traditional markets, where comparable transparency is absent, is likely larger. The complete transaction traceability of the NFT blockchain, which Goldstein, Hotchkiss and Sirri (2007) show dramatically improves market quality in opaque markets by enabling investors to negotiate better terms of trade, provides the rare empirical window through which manipulation can be directly identified at scale.

Our results carry three concrete regulatory implications. First, and most fundamentally, our finding that wash trading generates price impacts statistically indistinguishable from genuine informed trading implies that price-based surveillance is structurally blind to manipulation. No monitoring tool that watches prices, order book patterns or volume anomalies can detect wash trading that successfully mimics genuine informed order flow. Detection requires account-level monitoring of fund flow patterns. Our four detection criteria, specifically self-trades, back-and-forth trades, shared funding sources and shared exit wallets, provide a concrete blueprint for surveillance tools in any market where transaction-level data is available. Blockchain technology creates new possibilities for transparency-

based market design: Malinova and Park (2017) detail that full transparency of distributed ledgers maximizes investor welfare, and regulators in digital asset markets should exploit this inherent transparency for systematic wallet-level surveillance rather than relying on price-based monitoring that cannot detect this form of manipulation.

Second, our rewards program results show that platform design choices directly cause manipulation. LooksRare's trading rewards program immediately generated billions in wash trading volume; when the program ended, wash trading migrated rather than disappeared. Regulatory attention must therefore focus on incentive structures at the design stage, before manipulation takes hold, consistent with Goldstein and Kavajecz (2004) who show that market design rules intended to improve market functioning can instead generate perverse unintended consequences when participants exploit them in ways designers did not anticipate. Volume-based incentive programs in any market, whether exchange rebates, payment for order flow or token rewards, warrant regulatory scrutiny for their potential to incentivize artificial trading activity.

Third, our cross-platform migration results demonstrate that single-venue interventions are insufficient. Terminating rewards programs on one exchange relocates rather than eliminates manipulation, as wash traders migrate to competing venues and lower-cost platforms. Effective regulation requires coordinated simultaneous action across all venues. The Layer 2 platforms that attracted wash trading following the Dencun upgrade represent an emerging regulatory blind spot, as manipulation moved outside the oversight of regulators focused on the Ethereum mainnet. Cross-platform and cross-jurisdictional coordination is therefore a minimum requirement for effective enforcement, not an optional enhancement.

Table 1: Key variables and parameters in the model

This table defines the key variables and parameters in the model detailed in Section 2.

Symbol	Definition	Description
a	Price at time 0	The market's prior expectation of the NFT's value at time 0, before any trade occurs. Defined as $a = \delta V_H + (1 - \delta)V_L$
V_H	High fundamental value (realized at time 3)	The true high fundamental value of the NFT, revealed at time 3. Known to genuine informed traders at time 0.
V_L	Low fundamental value (realized at time 3)	The true low fundamental value of the NFT, revealed at time 3. Known to genuine informed traders at time 0.
b	Price impact parameter	Determines the sensitivity of prices to trade size. Higher b implies lower market depth.
q_1	Quantity traded at time 1 (by the informed or wash trader)	The number of NFTs purchased from noise traders at time 1 by either a genuine informed trader or a wash trader. This trade is publicly observed and influences the beliefs of information seekers.
p_1	Price at time 1	The price per NFT at time 1, determined by the linear pricing rule $p_1 = a + bq_1$
q_2	Quantity traded at time 2 (per information seeker)	The number of NFTs sold by the informed trader or wash trader and purchased by each information seeker at time 2.
p_2	Price at time 2	The market-clearing price at time 2, determined by the function $p_2 = a + bNq_2$, where N is the number of information seekers.
γ	Probability of wash trader	The prior probability at time 1 that the trader is a wash trader.
δ	Probability of informed trader	The prior probability at time 1 that the trader is a genuine informed trader.
β	Probability that an observed trade is from wash trading	The probability at time 2 that the observed trade came from a wash trader. Computed using Bayes' rule: $\beta = \gamma / (\gamma + \delta)$
R	Trading reward incentives	Per-unit reward awarded by platforms for trading activity.
τ	Transaction cost	Total per-unit cost of trading, including gas fees, creator royalties, and platform commissions.
k	Holding cost	The cost borne by the informed trader if they choose to delay selling until time 3 instead of selling at time 2. Appears in the incentive compatibility constraint.

Table 2. Descriptive statistics - Genuine and wash trading

This table reports descriptive statistics for genuine and wash trading in ETH and USD (\$) from 43 million+ NFT transactions on the Ethereum blockchain during our sample period between January 1, 2021 and June 30, 2024. Panel A reports descriptive statistics for the full sample. Panel B reports descriptive statistics by exchange with the highest wash trading volume. Panel C reports descriptive statistics by collection with the highest wash trading volume.

Panel A: Full sample

	ETH value	\$ value	# trades	ETH value (%)	\$ value (%)	# trades (%)
Genuine	21,857,813	54,721,628,569	42,903,654	60%	60%	98%
Wash	14,248,626	34,297,771,721	723,591	40%	40%	2%
Total	36,106,439	89,019,400,289	43,627,245	100%	100%	100%

Panel B: By exchange

Exchange	ETH wash volume	Percent (%)	\$ wash volume	Percent (%)
LooksRare	9,900,101	69.48	26,741,697,962	77.97
X2Y2	2,712,111	19.03	4,248,853,604	12.39
Blur	1,115,676	7.83	2,134,999,365	6.22
Opensea	412,416	2.89	910,319,145	2.65
Gem	28,728	0.20	81,267,855	0.24
Element	24,039	0.17	31,778,568	0.09
Magic eden	17,610	0.12	63,705,324	0.19
Larva labs	13,371	0.09	32,326,291	0.09
Rarible	11,461	0.08	25,440,056	0.07
NFTX	6,747	0.05	16,413,511	0.05
Sudoswap	5,677	0.04	9,143,771	0.03
Art blocks	624	0.01	1,732,504	0.01
Total	14,248,626	100.00	34,297,769,846	100.00

Panel C: By collection

Collection	ETH wash volume	Percent (%)	\$ wash volume	Percent (%)
Terraforms	4,502,095	32.17	12,211,391,722	36.35
Meebits	3,458,640	24.71	9,383,056,908	27.93
Dreadfulz	1,191,144	8.51	1,921,792,322	5.72
More Loot	970,112	6.93	1,512,063,229	4.50
dotdotdot	960,450	6.86	2,682,258,881	7.98
MineablePunks	378,442	2.70	615,053,355	1.83
Loot	208,828	1.49	663,698,808	1.98
Bored Ape Yacht Club	182,218	1.30	317,371,190	0.94
Catgirl Academia	150,003	1.07	339,375,317	1.01
Hashmasks	139,442	1.00	225,412,263	0.67
Others	2,107,252	13	4,426,295,851	11
Total	14,248,626	100.00	34,297,769,846	100.00

Table 3. Cumulative 24-hour impulse response of returns, genuine trading volume and wash trading volume

This table reports the mean and standard deviation of the cumulative 24-hour impulse response functions of the VAR model given by Eq. (18) which models the cumulative change in returns, signed genuine volume and signed wash volume as a result of a shock in returns of 10%, genuine volume of 10 ETH and wash volume of 10 ETH. The sample consists of the top 300 NFT collections by wash trading volume (approximately 16,488 hourly observations in time series for each NFT collection).

Effect	Mean	Std. dev
Genuine → Return	0.346	1.196
Wash → Return	0.322	0.812
Return → Genuine	28.064	57.971
Return → Wash	-9.309	25.737
Genuine → Wash	1.300	4.560
Wash → Genuine	3.222	4.627

Table 4. Descriptive statistics – Top NFT collections

This table reports descriptive statistics for the top 300 NFT collections on the Ethereum blockchain with the highest wash trading volume during our sample period between January 1, 2021 and June 30, 2024. *Trading volume* is daily wash (genuine) volume in ETH and USD millions. *Exchange fee (%)* is the transaction fee paid to the exchange by the wash traders. *Creator fee (%)* is the average transaction fee paid to the NFT creator by the wash traders. *Exchange count* is the number of exchanges on which an NFT collection can be traded.

Variable	N	Mean	Std. dev.
<i>Wash</i>			
<i>Trading volume (ETH)</i>	32,192	435.83	4,045.98
<i>Trading volume (\$m)</i>	32,192	1.05	11.30
<i>Exchange fee (%)</i>	32,192	1.07	1.55
<i>Creator fee (%)</i>	32,192	2.19	4.18
<i>Exchange count</i>	32,192	1.12	0.36
<i>Genuine</i>			
<i>Trading volume (ETH)</i>	122,366	109.01	793.82
<i>Trading volume (\$m)</i>	122,366	0.26	2.50
<i>Exchange fee (%)</i>	122,366	1.54	1.12
<i>Creator fee (%)</i>	122,366	3.03	3.64
<i>Exchange count</i>	122,366	1.83	0.99

Table 5. Key determinants of wash trading volume

This table presents panel regression results examining the key determinants of NFT wash trading volume (*Wash volume*). The key determinants include: *Genuine volume* is genuine volume. *Exchange fee* (%) is the transaction fee paid to the exchange by the wash traders. *Creator fee* (%) is the average transaction fee paid to the NFT creator by the wash traders. *Exchange count* is the number of exchanges on which an NFT collection can be traded. Daily volatility (*Volatility*) is measured by the standard deviation of hourly price returns. $D_t^{Incentive}$ is a dummy variable equal to one if the observation falls within the incentive program period of the two largest exchanges, LooksRare and X2Y2; otherwise equal to zero. Wash and genuine trading volume is expressed in ETH and in logarithmic form. The unit of observation is NFT collection (*i*) on day (*t*). We apply NFT collection and day fixed effects. Standard errors are clustered by NFT collection. The sample consists of the top 300 NFT collections by wash trading volume between January 1, 2021 and June 30, 2024. *t*-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

<i>Wash volume</i> _{it}	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
<i>Genuine volume</i> _{it}	0.597*** (10.552)					0.330*** (5.123)
<i>Platform fee</i> (%) _{it}		-0.244*** (-2.934)				-0.153** (-2.164)
<i>Creator fee</i> (%) _{it}		-0.096*** (-3.253)				-0.084** (-2.126)
<i>Volatility</i> _{it}			-0.000*** (-9.548)			-0.000*** (-3.848)
<i>Exchange count</i> _{it}				1.222*** (7.449)		0.500*** (4.955)
$D_t^{Incentive}$					0.502** (2.451)	0.189** (2.055)
<i>Wash volume</i> _{it-1}						0.460*** (9.407)
<i>Intercept</i>	-0.516*** (-2.839)	2.029*** (16.330)	1.954*** (3.8e+04)	0.174 (0.939)	1.276*** (11.401)	0.286* (1.763)
Collection FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
N	29,154	31,352	18,562	31,352	31,357	11,578
Adj. R-sq	0.641	0.592	0.650	0.595	0.5311	0.791

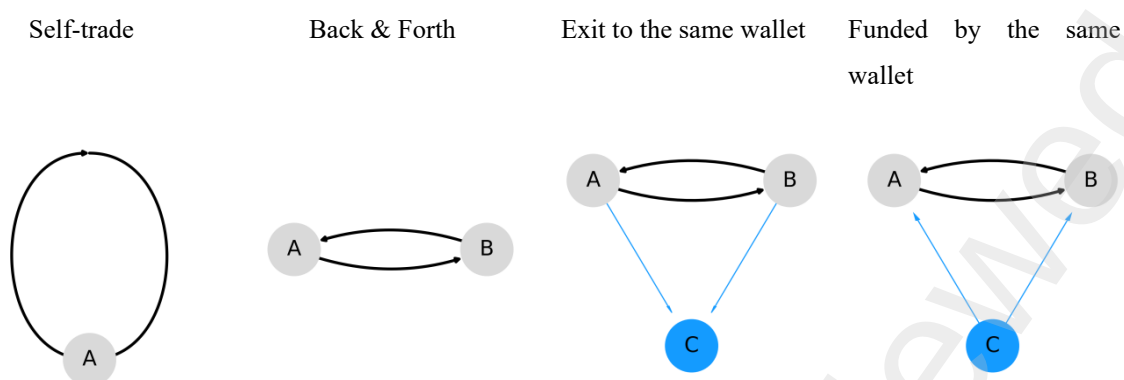


Figure 1. Commonly used patterns of NFT wash trading

This figure shows four of the most commonly used patterns for NFT wash trading. *Self-trade*: Individual A trades the NFT with themselves. *Back-and-Forth*: A transfers the NFT to B, who subsequently resells it back to A; A sends Ethereum to B to facilitate the NFT's repurchase; or A and B repeatedly buy and sell the NFT between each other. *Exit to the same wallet*: A and B transfer funds to the same wallet C after their transaction. *Funded by the same wallet*: A trades with B when both are funded by the same originating wallet C.

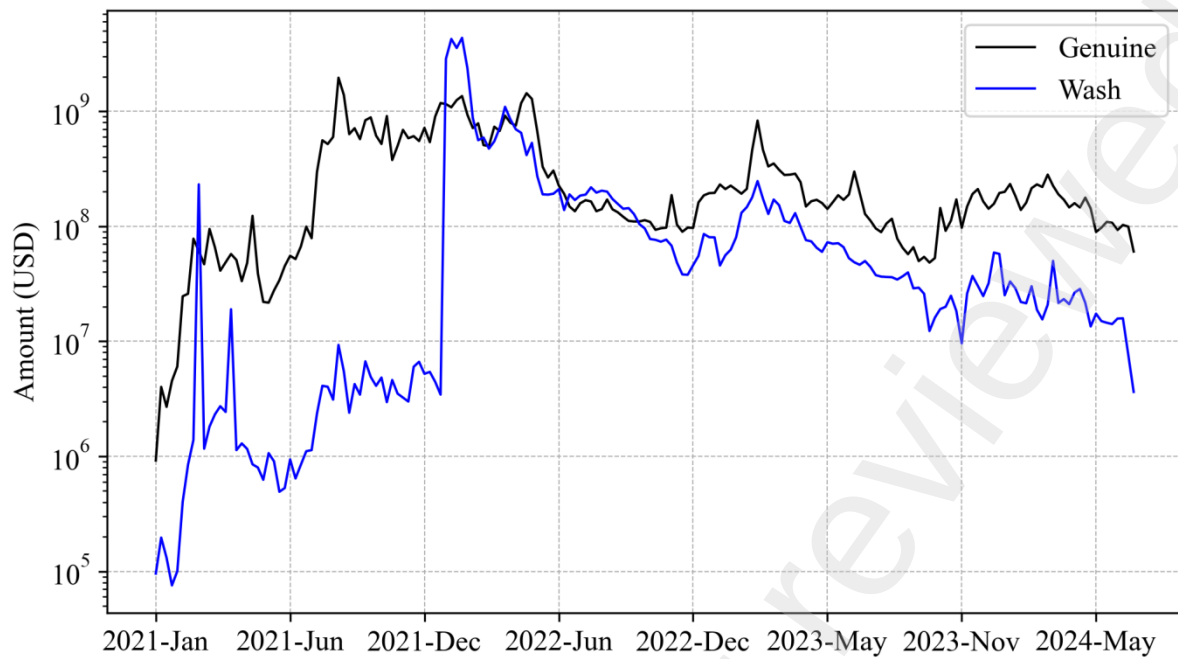


Figure 2. Genuine and wash trading volume over time

This figure illustrates the total genuine trading and wash trading volume between January 1, 2021 and June 30, 2024. The volumes are represented in ETH and USD on a logarithmic scale.

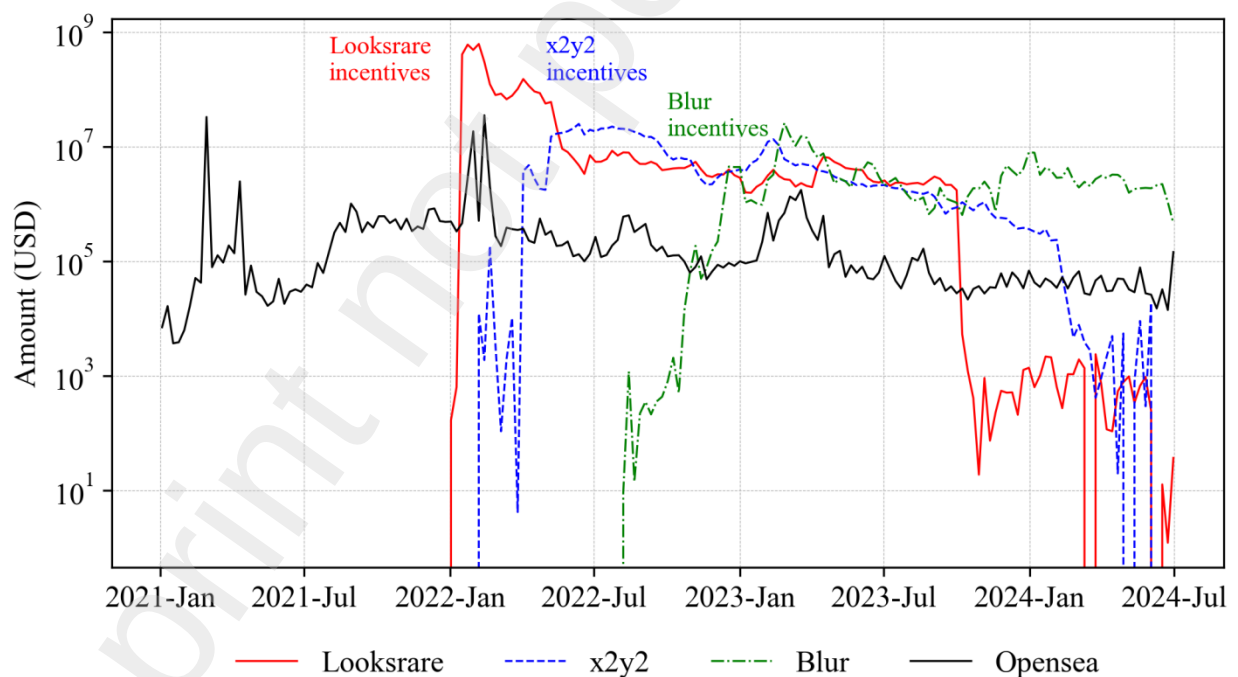


Figure 3. Wash trading volume by exchange over time

This figure illustrates the wash trading volume on four exchanges with the highest wash volume (LooksRare, X2Y2, Blur, and OpenSea) between January 1, 2021 to June 30, 2024. The volumes are represented in ETH and USD on a logarithmic scale.

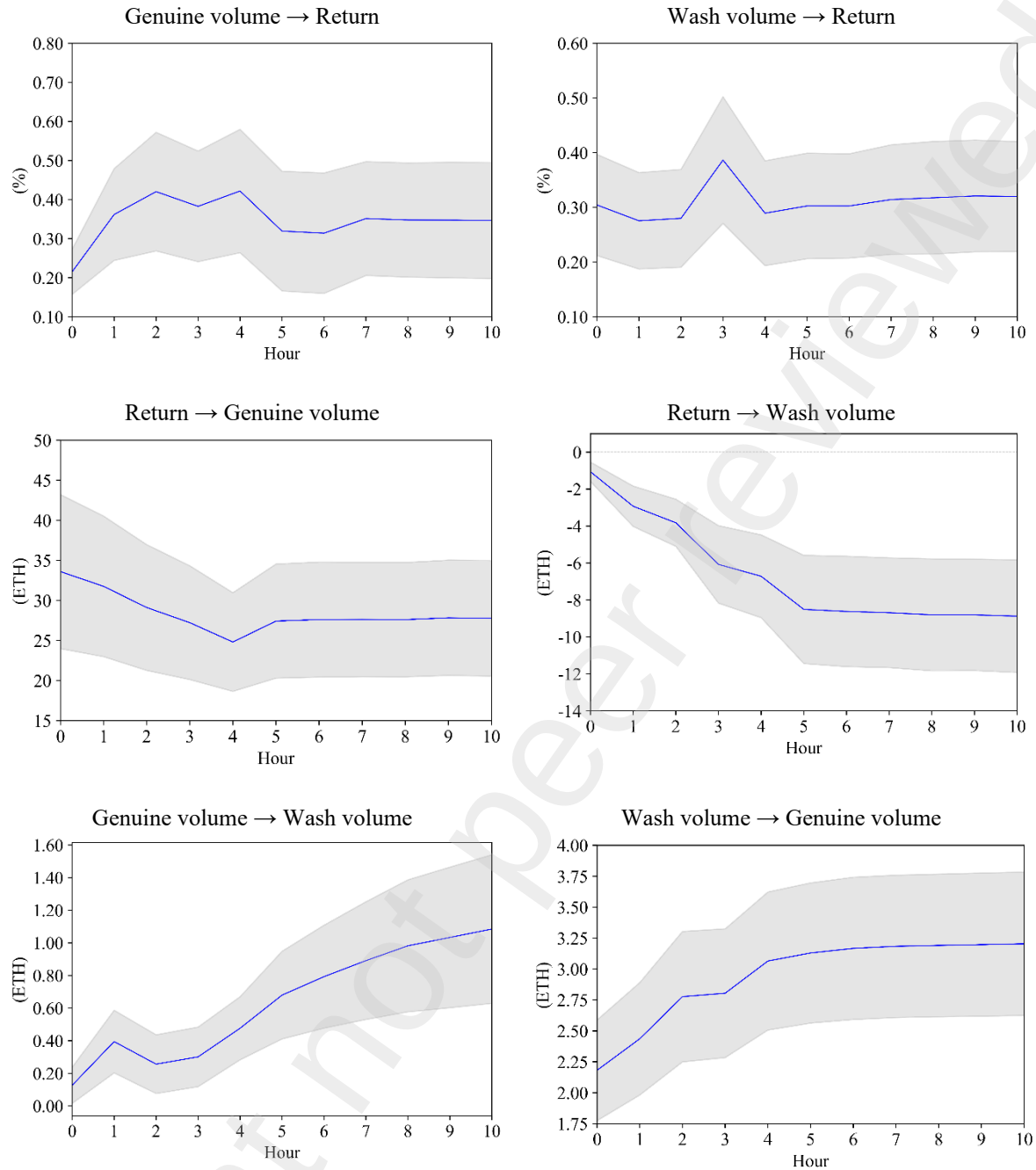


Figure 4. Cumulative impulse response of returns, genuine trading volume and wash trading volume

This figure illustrates the mean cumulative impulse response functions and 95% confidence intervals of the VAR model given by Eq. (18). The vertical axis measures the estimated cumulative change in NFT price floor returns, genuine volume and wash volume as a result of the shock in returns of 10%, genuine volume of 10 ETH and wash volume of 10 ETH. The horizontal axis represents the time (in hours) progressing from the initial shock at hour $t = 0$. The sample consists of the top 300 NFT collections by wash trading volume between January 1, 2021 and June 30, 2024.

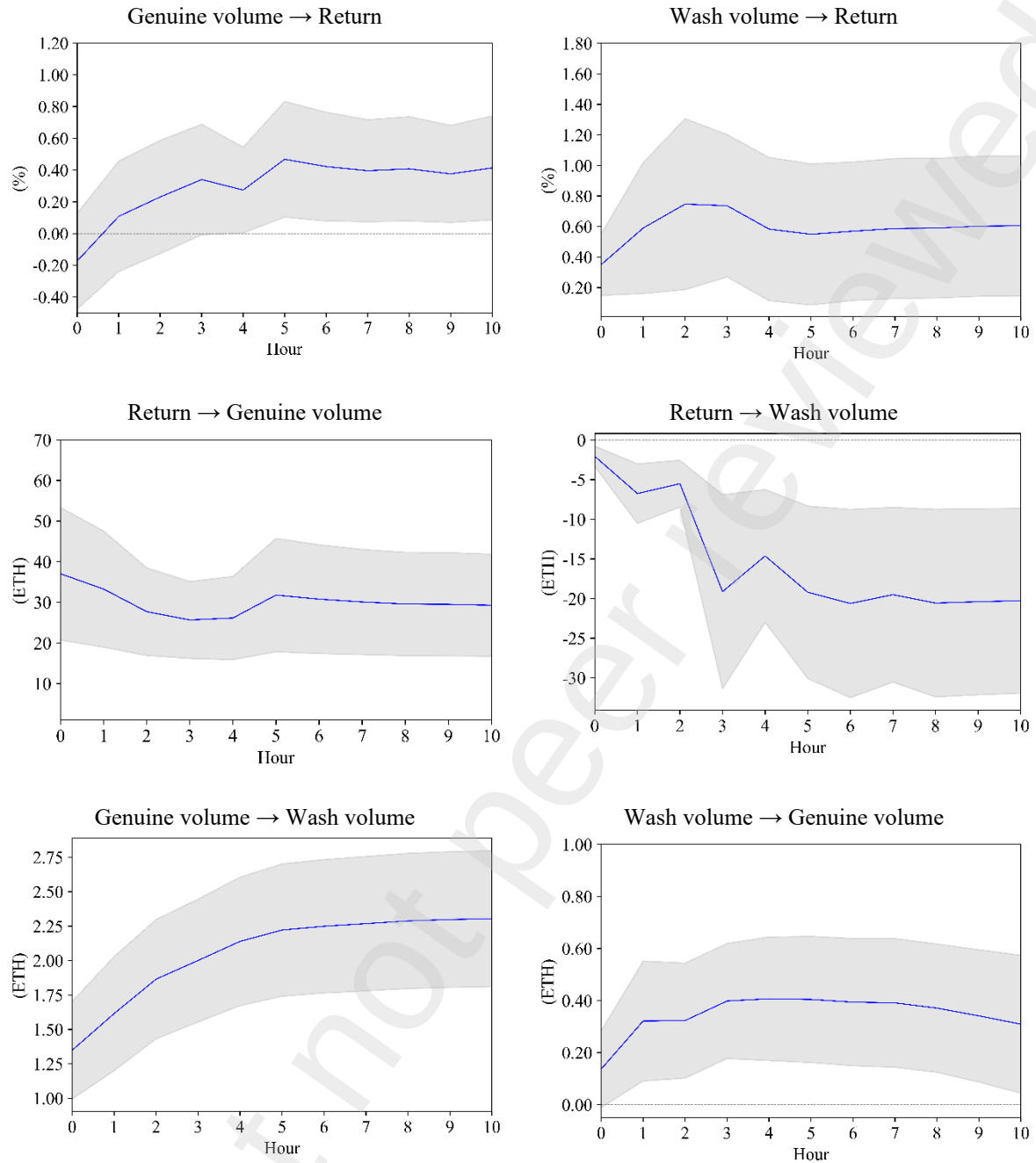


Figure 5. Cumulative impulse response of returns, genuine trading volume and wash trading volume

This figure illustrates the mean cumulative impulse response functions and 95% confidence intervals of the VAR model given by Eq. (18). The vertical axis measures the estimated cumulative change in returns of the volume-weighted average transaction price, genuine volume and wash volume as a result of the shock in returns of 10%, genuine volume of 10 ETH and wash volume of 10 ETH. The horizontal axis represents the time (in hours) progressing from the initial shock at hour $t = 0$. The sample consists of the top 300 NFT collections by wash trading volume between January 1, 2021 and June 30, 2024.

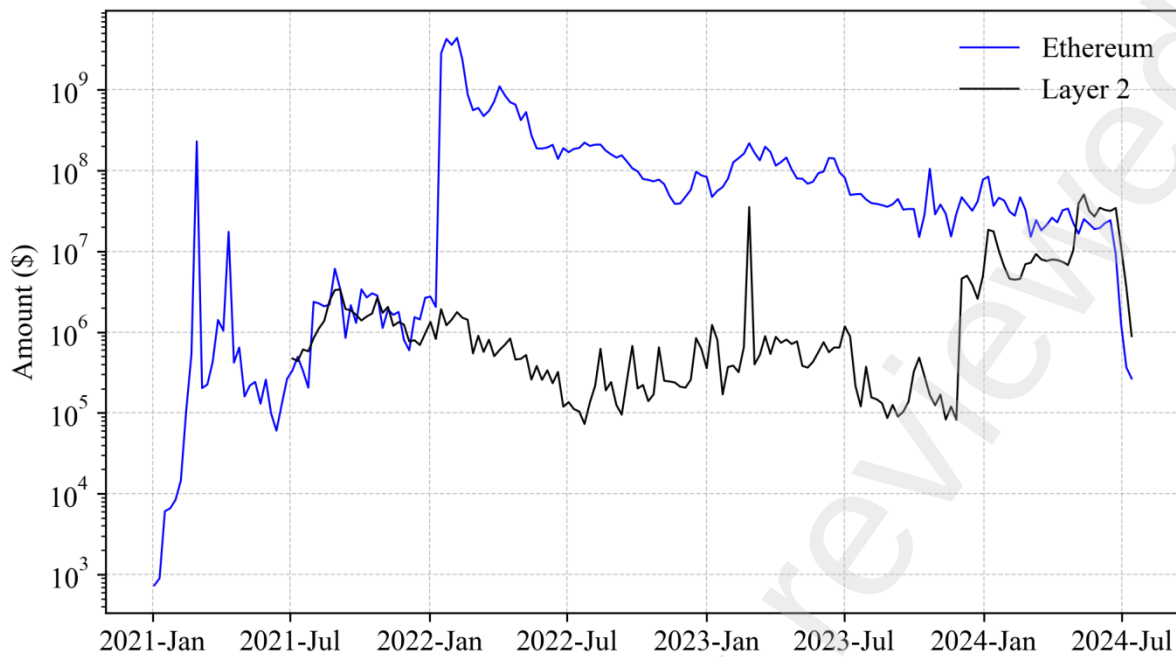


Figure 6. Wash trading volume on Ethereum and Layer 2.

This figure illustrates the wash trading volume on the Ethereum blockchain and its Layer-2 (Polygon, Arbitrum, Optimism, Celo, 'ZK-sync', Zora, Base, Scroll, Blast) between January 1, 2021 to June 30, 2024. The volumes are represented in ETH and USD on a logarithmic scale.

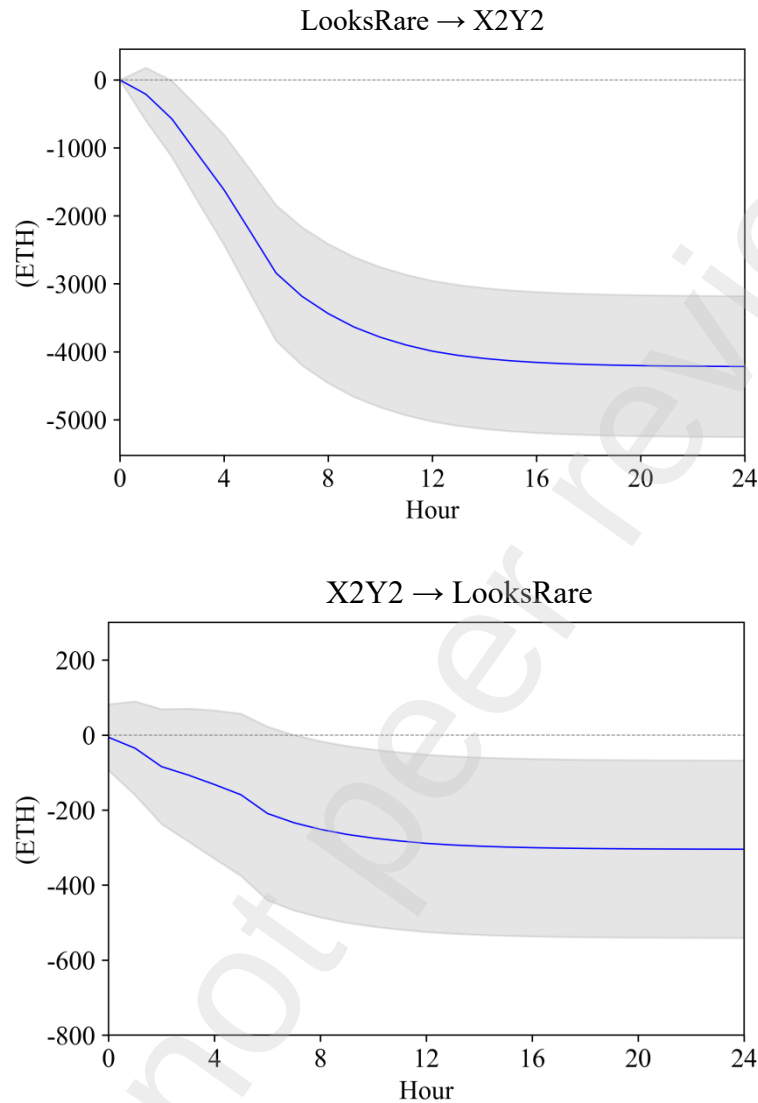


Figure 7. Cumulative impulse response of returns, genuine trading volume and wash trading volume

This figure illustrates the cumulative impulse response functions and 95% confidence intervals of the VAR model given by Eq. (20). The vertical axis measures the estimated cumulative change in wash volume on the LooksRare exchange as a result of the shock in wash volume of 10 ETH on the X2Y2 exchange (and vice versa). The horizontal axis represents the time (in hours) progressing from the initial shock at hour $t = 0$. The sample consists of the LooksRare and X2Y2 exchanges between January 1, 2021 and June 30, 2024.

Appendix A: NFT reward programs

This table summarizes reward programs for popular NFT marketplaces, including the starting and ending dates and program details. The program details include trends in user incentives, program discontinuation, and platform strategies to reduce wash trading and enhance long-term user engagement. Programs are subject to change, for the most current information refer to official announcements or platform documentation.

Marketplace	Program Name	Start Date	End Date	Program Details
LooksRare	Trading Rewards	Jan-2022	Oct-2023	- Offered LOOKS tokens to users based on trading volume and NFT rarity. - Aimed to reduce fees and boost liquidity. - Discontinued to focus on staking and other incentives.
X2Y2	Trading Rewards	Feb-2022	Aug-2023	- Distributed X2Y2 tokens to active traders. - Discontinued to minimize wash trading and encourage genuine engagement.
Blur	Airdrop Rewards	Oct-2022	Ongoing	- Distributed BLUR tokens through airdrops to reward organic trading activity. - Focus on professional traders with advanced tools.
Magic Eden	Rewards Program	Mar-2023	Ongoing	- Introduced "diamonds" as rewards for trading activities, redeemable for perks like lower fees and whitelist access. - Expanded to multiple blockchains.
EXA Market	Rewards Campaign	Sep-2024	Dec-2024	- Launched 12-week campaign offering EXA tokens to users engaging in trading and referrals. - Built on the Algorand blockchain.
Algorand NFT Marketplaces	NFT Rewards Program	Aug-2023	Ongoing	- Distributed ALGO tokens to boost the NFT ecosystem, rewarding collectors and creators. - Aims to increase user engagement and trading volume.
Binance NFT	Zero Trading Fee Promotion	Jan-2023	Jan-2023	- Offered zero trading fees for selected NFT collections and a reward pool of up to 40,000 BUSD for participants.

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