Does wash trading distort asset prices?

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Abstract

Wash trading inflates volumes, but how effective is it as a market manipulation technique to influence prices? Using the Non-Fungible Token (NFT) market as a natural laboratory, we find that wash trading significantly inflates prices. It accounts for 2% of trades but 40% of traded value. It also lures more real trading activity through a volume multiplier effect that is consistent with attention and liquidity externalities. Unlike genuine trades, which typically increase with rising prices, wash trading activity significantly declines following sharp price surges. These findings have implications for wash trading prohibitions in financial markets, by quantifying the link between volume manipulation and artificial prices.

Keywords: market manipulation, wash trading, cryptocurrencies

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1. Introduction

As misconduct transitions from traditional financial markets to the blockchain space, its consequences could become even more severe due to the unique features of distributed ledger technology (DLT), tokenized ecosystems, and the anticipated future scale of these markets. By 2030, the DLT market is projected to surpass $140 billion,[1] while the tokenization market could reach a staggering $30 trillion,[2] reflecting the transformative potential of these innovations. However, blockchain's decentralized, pseudonymous, and borderless nature makes it a fertile ground for manipulative practices such as wash trading (Cong et al., 2023), pump-and-dump schemes (Dhawan and Putniņš, 2023), and insider trading (Félez-Viñas, Johnson, and Putniņš, 2022). These activities can proliferate rapidly and evade detection far more quickly than in traditional financial markets. The global accessibility of blockchain platforms further amplifies the scale and impact of such misconduct, placing a more significant number of unsuspecting participants at risk.

Wash trading, a long-standing and prevalent manipulative practice in traditional financial markets (e.g., Aggarwal and Wu, 2006; Cumming, Johan, and Li, 2011), has migrated to the blockchain space, where it is becoming increasingly widespread (e.g., Victor and Weintraud, 2021; Le Pennec et al., 2021; Wachter et al., 2022; Chen et al., 2022; Cong et al., 2023; La Morgia et al., 2024; Aloosh and Li, 2024). This manipulation involves generating fake trading activity to inflate volumes artificially, misleading investors, manipulating market prices, and undermining market integrity for illicit profit. As the cryptocurrency market expands, the scale and impact of wash trading have grown, prompting heightened scrutiny and enforcement actions by regulatory bodies. For example, Coinbase Inc. was fined $6.5 million in March 2021 for misleading reporting and wash trading on its GDAX platform. In January 2023, Avraham Eisenberg was charged with fraud for manipulating Mango Markets, misappropriating over $110 million. In March 2023, Justin Sun and his companies faced charges for extensive wash trading and unregistered sales, illicitly gaining

[1] Statista projects the DLT market will exceed $140 billion by 2030, highlighting its adoption in enhancing transparency and efficiency.

[2] Standard Chartered forecasts the market for tokenized real-world assets to reach approximately $30 trillion, while Chainlink predicts a $10 trillion market, marking a substantial increase from the current value of $118.57 billion. McKinsey & Company offers a more conservative outlook, estimating that tokenized assets will constitute between $1 trillion and $4 trillion. The World Economic Forum predicts a significant shift toward asset "tokenization," estimating that approximately 10% of the global GDP will be represented on blockchains in cryptographically secured forms by 2027.

$31 million. In April 2023, Michael Kane and others were charged with HYDRO token manipulation, generating $2 million in profits. In June 2023, Binance and its founder, Changpeng Zhao, faced 13 charges for unregistered operations and wash trading. In July 2023, Adam Todd and his companies were fined $15 million for manipulating the Digitex Futures token. In October 2024, Operation Token Mirrors charged 18 individuals and entities for market manipulation, while a joint SEC, FBI, and DOJ takedown targeted fraudulent crypto wash trading schemes, highlighting coordinated efforts to ensure market integrity.[3]

Our research aims to investigate how wash trading distorts asset prices by leveraging the NFT market as a natural laboratory. We address key questions: What is the scale and economic impact of wash trading on genuine trading behavior, price returns, and market perceptions? How do wash traders exploit information asymmetry, taking advantage of uninformed participants who struggle to distinguish between legitimate and manipulative activities? To what extent do wash traders mimic genuine trading patterns to create an illusion of liquidity and market demand, thereby inflating prices and misleading investors? By examining the interplay between wash trading and genuine trading activities, we provide insights into the mechanisms of market distortion and the broader implications of misconduct transitioning into blockchain-based financial ecosystems.

We analyze a dataset of 42,903,654 Non-Fungible Token (NFT) transactions recorded on the Ethereum blockchain from January 2021 to June 2024 and find that the total wash trading volume amounts to approximately $34.2 billion, compared to $54.2 billion for genuine trading. Although wash trading constitutes only about 2% of total transactions, it accounts for an estimated 40% of the total trading volume, revealing its disproportionately high impact on inflating apparent market demand and value. This inflation creates misleading signals for genuine buyers, distorting the perception of market activity.

Our analysis also shows that traders gravitate toward environments conducive to wash trading. Specifically, wash trading volumes spike when exchanges (e.g., Looksrare, X2Y2, and Blur) offer trading rewards programs or newer blockchains (e.g., Layer 2) mature with cheaper

[3] See our appendix for details on these prosecutions.

transaction costs than Ethereum. These conditions make wash trading more economically feasible and attractive to manipulators.

To explore the relationship between wash trading, genuine trading, and returns, we employ a Vector Autoregressive (VAR) model to estimate how each variable responds to shocks in the others. We find that the impact of wash trading and genuine trading volumes on returns is strikingly similar, suggesting that wash traders deliberately mimic the trading patterns of genuine participants to manipulate prices effectively. Consistent with Aggarwal and Wu (2006), our findings highlight the critical role of information asymmetry, as manipulators exploit the inability of uninformed traders to distinguish between genuine market signals and manipulative activity.

Our results also show that positive return shocks naturally attract genuine traders due to profit opportunities, liquidity, and market confidence. Meanwhile, wash traders, who aim to simulate market activity to attract genuine participants, retreat during favorable conditions as their role becomes redundant and manipulation becomes more costly. This divergence reflects the robustness of genuine trading in response to market signals and the diminishing role of wash trading in high-return environments.

Besides, we reveal a dynamic relationship between genuine and wash trading volumes. Increased genuine trading activity prompts wash traders to escalate their manipulative efforts to influence the market effectively. This behavior suggests that wash traders are opportunistic, leveraging periods of high genuine trading to create the illusion of even greater market demand by inflating volumes and riding the momentum of organic trades. Conversely, increased wash trading volume significantly boosts genuine trading, as the artificial activity generates market momentum, attracting real traders through perceived liquidity and fear of missing out (FOMO). These dynamic underscores the interplay between genuine and manipulative trading in shaping market perceptions.

We are the first to leverage NFT data as a natural laboratory to investigate the impact of wash trading on prices and genuine transactions. By utilizing the transparency and immutability of blockchain technology, we can closely examine wallet behavior and identify patterns of manipulation, offering a unique perspective on how misconduct influences market dynamics. As financial misconduct increasingly migrates to the blockchain space, blockchain's decentralized and pseudonymous nature makes it both a fertile ground for manipulation and an invaluable resource for uncovering such behavior. Our study provides critical insights into the strategies and activities of wash traders, which can serve as a foundation for regulators, exchanges, and policymakers to develop more effective measures for mitigating manipulation, enhancing market transparency, and protecting investors.

Our findings contribute to the literature that shows the manipulation thrives in environments with asymmetric information, low liquidity, and limited regulatory oversight, resulting in market inefficiencies and the exploitation of uninformed traders. For example, Allen and Gale (1992) demonstrate that trade-based manipulation is possible when investors cannot distinguish whether large trades indicate genuine undervaluation or manipulative intent, underscoring the pivotal role of information asymmetry in enabling profits without altering the intrinsic firm value. Jarrow (1992) explores how large traders generate risk-free profits by exploiting temporary price momentum and sensitivity to historical trades, creating avenues for manipulation. Aggarwal and Wu (2006) provide theoretical and empirical evidence, revealing that manipulation concentrates on illiquid and low-transparency markets, where manipulators imitate informed trading behavior to mislead participants, inflate prices, and extract profits.

We also contribute to the growing literature on misconduct in cryptocurrency asset markets,[4] particularly wash trading. For example, Victor and Weintraud (2021) explore wash trading on decentralized exchanges (DEXs) such as IDEX and EtherDelta, analyzing 8 million transactions from 2017 to 2020 and uncovering $159 million in manipulated trading volumes predominantly through self-trades and two-account structures. Chen et al. (2022) use a data-mining approach that integrates on-chain and off-chain data to examine wash trading across five major exchanges, uncovering distinct manipulation strategies and underscoring the prevalence of fraudulent activity on less-regulated platforms. Amiram et al. (2022) investigate the role of competition among centralized exchanges in driving volume inflation, revealing that static and dynamic competition incentivizes manipulative practices, which provide short-term benefits but lead to long-term reputational damage. Cong et al. (2023) systematically analyze 29 centralized exchanges, showing that unregulated platforms inflate trading volumes by an average of 70%, distorting market prices and improving exchange rankings, particularly on newer exchanges with

[4] For a comprehensive taxonomy of misconduct in cryptocurrency markets, refer to Eigelshoven et al. (2021), Clapham et al. (2023), and Putniņš (2024).

smaller user bases. Aloosh and Li (2024) offer direct evidence of wash trading by analyzing leaked transaction data from Mt. Gox, identifying over 115,000 manipulative trades and validating the effectiveness of indirect detection methods like Benford's Law. Collectively, these studies emphasize the widespread impact of wash trading, its economic incentives, and the need for enhanced regulation to maintain market integrity.

Our research is highly relevant to the literature on wash trading in NFTs by providing new insights into its patterns, scale, and consequences. Wachter et al. (2022) analyze 21.3 million transactions across 52 Ethereum-based NFT collections from 2018 to 2021, identifying $149.5 million in suspicious trading activity. Their findings reveal that wash trading peaks early in a collection's lifecycle but have limited long-term effects on pricing, which is influenced more significantly by broader market factors. Building on these insights, La Morgia et al. (2024) conduct a comprehensive blockchain-wide study using data on 34 million assets traded on Ethereum up to January 2022, detecting $3.4 billion in inflated trading volumes within NFT marketplaces. They attribute the majority of wash trading to platforms with token reward systems, such as LooksRare, where exploiting rewards proves significantly more profitable than attempts to inflate resale values, which often incur losses. Expanding on this literature, we analyze more recent data of more than 42.9 million transactions across 300 NFT collections from January 2021 to June 2024, when NFTs are more prevalent, and the market features more NFT exchanges. We demonstrate that wash trading has increased significantly in scale in recent years compared to earlier periods and provide compelling evidence of its impact on genuine trading volumes and price returns. [5]

2. Model

Consider a market composed of two types of traders: N_W wash traders, indexed by $i \in [1, N_W]$ and N_G genuine traders, indexed by $j \in [1, N_G]$. Table 1 summarizes the parameters and variables utilized in the model. Each wash trader i determines their wash trading volume $v_{W,i}$ to maximize their profit while accounting for the aggregate behavior of other wash traders and genuine traders. On the other hand, genuine traders observe the total trading wash volume $V_W =$

[5] For further research on the detection methods and impact of wash trading, see Tariq and Sifat (2022); Serneels (2023); Jayant (2023); Bonifazi et al. (2023); Liu et al. (2023); Wen et al. (2023); Tahmasbi et al. (2024); and Kong et al. (2024).

$\sum_{i=1}^{N_W} v_{W,i}$ and the returns R to select their trading volume $v_{G,i}$. Total genuine trading volume is $V_G = \sum_{j=1}^{N_G} v_{G,j}$. So the total genuine trading volume is:

$$V_G = \delta R + \kappa V_W \tag{1}$$

where $\delta > 0$ is the genuine traders' sensitivity to returns driven by fundamentals R. Higher δ indicates stronger genuine trader responsiveness to fundamental price signals. $\kappa > 0$ is genuine traders' response to aggregate wash trading volume V_W. A larger κ implies that genuine traders are more influenced by wash traders' artificial activity which inflates trading volume or returns independently of underlying market fundamentals. When genuine traders are better informed, or when the market consists predominantly of informed genuine traders, genuine trading volume is primarily driven by fundamental price signals (R) rather than the artificial volumes generated by wash traders (V_W). Equation (1) indicates that genuine trading volumes (V_G) rise with an increase in returns (R) and wash trading volumes (V_W).[6]

[Table 1]

Wash traders seek to maximize their profit by strategically balancing three key objectives: attracting genuine traders through inflated trading volumes, minimizing the costs associated with wash trading, and capturing rewards offered by exchanges for high trading activity. The profit function for each wash trader i is expressed as:

$$\pi_{W,i} = \beta v_{W,i} - C\left(v_{W,i}\right) + f(V_G) \tag{2}$$

where:

- $\beta v_{W,i}$ is the reward from the exchange for wash trading. β is the exchange reward per unit of trading volume.
- $C\left(v_{W,i}\right) = c v_{W,i}^2$ reflects the cost incurred by wash traders for artificially inflating trading volume. It increases quadratically with $v_{W,i}$, reflecting higher marginal costs at greater volumes. c is the cost sensitivity parameter of wash trading which determines

[6] Allen and Gale (1992) demonstrate that investors face uncertainty about whether a large trader purchases a stock due to the undervaluation or as part of an intentional price manipulation strategy. This ambiguity enables profitable manipulation, as it obscures the trader’s true intentions.

the degree to which the cost of wash trading rises with $v_{W,i}$. A larger c means higher costs for wash trading.

- $f(V_G)$ represents the profit from luring normal traders into the market, which depends on V_G.

Substitute V_G from Equation (1) into Equation (2) and let ρ represent the sensitivity of wash traders' profits from genuine trading volumes, reflecting the extent to which wash traders benefit from higher prices achieved by selling to genuine traders. Equation (2) becomes:

$$\pi_{W,i} = \beta v_{W,i} - \gamma v_{W,i}^2 + \rho(\delta R + \kappa V_W)$$

To determine the optimal wash trading volume , we derive the first-order condition (FOC) for the trader as follows:

$$\frac{\partial \pi_{W,i}}{\partial v_{W,i}} = \frac{\partial}{\partial v_{W,i}} (\beta v_{W,i} - c v_{W,i}^2 + \rho(\delta R + \kappa N_W v_{W,i}))$$

Set this equal to zero then rearranging to find the optimal $v_{W,i}$ gives:

$$\frac{\partial \pi_{W,i}}{\partial v_{W,i}} = \beta - 2c v_{W,i} + \rho\kappa N_W = 0$$

Rearranging:

$$v_{W,i}^* = \frac{\beta + \rho\kappa N_W}{2c}$$

The aggregate wash trading volume is the sum of the wash trading volumes of all N_W wash traders $V_{W,i}^* = N_W v_{W,i}^*$. Substitute $v_{W,i}^*$ into this expression to get the total wash trading volume:

$$V_W^* = \frac{N_W(\beta + \rho\kappa N_W)}{2c} \tag{3}$$

Equation (3) reveals the factors influencing the equilibrium wash trading volume V_W^*. First, as transaction costs (c) increase, the costs of wash trading rise, making it less profitable for traders to inflate trading volume, thereby reducing V_W^*. Conversely, increased exchange rewards (β) directly incentivize wash traders to engage in more activity to capture more significant benefits, leading to a proportional rise in V_W^*.

Furthermore, the number of wash traders (N_W) has a quadratic effect on the equilibrium wash trading volume V_W^*, as more wash traders collectively amplify the total wash trading volume and the feedback effects on genuine trading. Lastly, the interaction term ($\rho\kappa$) plays a critical role in strengthening the feedback loop between wash and genuine trading volumes. Here, ρ reflects the sensitivity of wash traders' profits from genuine trading volumes, while κ measures genuine traders' response to wash trading. A higher $\rho\kappa$ significantly magnifies this loop, further boosting V_W^* and compounding the overall market impact of wash trading.

To interpret the impact of returns (R) on wash trading, we deduce from Equation (1) as

$$V_W = \frac{V_G - \delta R}{\kappa} \tag{4}$$

Equation (4) highlights that as R increases, driven by changes in market fundamentals, the total volume of wash trading (V_W) decreases. This inverse relationship arises because higher returns signal a stronger market driven by organic activity, diminishing the perceived need or effectiveness of wash trading in generating artificial signals of market liquidity. Besides, the heightened market activity associated with high R can lead to increased transaction fees and liquidity competition, raising the operational costs of maintaining wash trading volumes.

The equation also demonstrates that if V_G is naturally high, such as during periods of heightened market activity that are not driven by returns (R), wash traders will require a higher V_W to maintain their influence and effectively compete with genuine trading activity. A larger V_G reduces the relative impact of artificial trading volumes on the total observed trading volume. To counteract this, wash traders must increase V_W, which raises their costs due to higher transaction fees and the quadratic nature of their cost function.

Conversely, when genuine traders are more sensitive to wash trading signals (i.e., when κ large), wash traders can achieve their objectives with smaller V_W. A higher κ means that genuine traders are more responsive to artificial trading volumes, amplifying the perceived market activity and making it easier for wash traders to influence market perceptions.

3. How severe and prevalent is wash trading?

To illustrate the interaction between wash trading volume, genuine trading volume, and returns as proposed in the model, we analyze the dataset of 42,903,654 NFT transactions recorded on the Ethereum blockchain from January 2021 to June 2024. Victor and Weintraud (2021) find that wash trading typically involves self-trades or transactions between two linked accounts. La Morgia et al. (2024) show that wash trading often occurs back and forth between two accounts or between two accounts that are either funded by the same wallet or transfer funds to the same wallet after the transaction. Based on these findings, we classify a transaction as wash trading according to the following criteria: (1) Self-trade: The same individual (A) trades the NFT with themselves. (2) 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. (3) Shared Funding Source: A trades with B when both are funded by the same originating wallet C. (4) Shared Exit: A and B transfer funds to the same wallet C after their transaction. Figure 1 illustrates these patterns for NFT wash trading.[7] Transactions that do not meet any of these criteria are classified as genuine.[8]

[Figure 1]

Table 2, Panel A, presents summary statistics for trading volume in ETH, trading volume in USD, and the number of transactions for both wash and genuine trades. In our sample, the total wash trading volume is approximately $34.2 billion, compared to $54.2 billion for genuine trading. The 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—around 40%. The disproportionately high wash volume inflates the apparent demand and market value, potentially misleading genuine buyers.

[Table 2]

[7] While wash trading can involve multiple hops of transactions among wallets before completing a trade, previous studies indicate that most wash trading follows these simpler patterns. Moreover, since multiple hops increase transaction costs and regulatory oversight in the blockchain space remains limited, it is reasonable to expect wash traders to minimize the number of hops to reduce costs.

[8] We use Dune and Flipside, web-based platforms that enable the querying of public blockchain data to identify and classify transactions based on the criteria above.

[Figure 2]

Figure 2 illustrates the trends in genuine and wash trading volumes over time, displayed 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. Of this, genuine trading volume accounted for approximately $1.9 billion. However, since mid-2022, total NFT trading volume has declined, driven by the broader cryptocurrency market entering a bearish phase and exchanges discontinuing incentive programs or implementing algorithms to combat wash trading.

For most of the observed period, wash trading volume constituted a small fraction of the total NFT trading volume. An exception occurred between January and February 2022, when wash trading spiked dramatically, reaching around $4.3 billion, significantly surpassing the genuine trading volume of approximately $1.3 billion. This surge was primarily driven by the introduction of volume-based trading rewards programs by the LooksRare exchange in January 2022 and X2Y2 in February 2022. These programs incentivized trading activity, leading to a substantial increase in artificial transactions as traders sought to maximize their rewards.[9]

Table 2, Panel B, reveals the significant concentration of wash trading among NFT exchanges, with LooksRare accounting for $26 billion (77.97%) of total wash trading volume, followed by X2Y2 and Blur at 12.39% and 6.22%, respectively. Figure 3 illustrates the wash trading volume over time for four major NFT exchanges: LooksRare, X2Y2, Blur, and OpenSea. The data reveals 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. 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, underscoring rewards programs' significant role in driving artificial trading activity. While these programs initially drove platform activity, they also distorted market metrics and raised concerns about market manipulation.

[Figure 3]

[9] See the Appendix for details on the trading rewards programs for NFT exchanges.

In response to the unintended consequences of these incentive structures, some platforms have taken steps to mitigate wash trading. LooksRare, for example, ended its trading rewards program in March 2023 after significant pushback from the community regarding wash trading activities. Similarly, X2Y2 faced challenges with inflated trading volumes due to its rewards program and has since implemented measures to reduce such activities. Blur, launched in October 2022 with a zero-fee structure and professional trading features, has also been scrutinized for potential wash trading, leading to discussions about the effectiveness and consequences of incentive programs in the NFT marketplace ecosystem.

These developments highlight the complexities and challenges of using incentive programs to boost platform activity. While such programs can attract users and increase trading volumes in the short term, they may also lead to market manipulation and undermine the integrity of the marketplace. As a result, NFT exchanges are re-evaluating their strategies to balance user engagement with the need to maintain authentic trading environments.

Panel C in Table 2 highlights the trading volumes of the top 10 NFT collections with the highest wash trading activity, revealing a significant concentration of wash trading in a few collections. The Terraforms collection leads with a staggering $12.2 billion wash trading volume, representing 36.35% of the market. Meebits follows with $9.3 billion, accounting for 27.93%, while Dreadfulz ranks third with $1.9 billion, contributing 5.72% of the total wash trading volume. These results indicate that wash trading is heavily concentrated in a few high-profile collections, likely due to their perceived value and liquidity, which make them attractive for manipulation.

[Table 3]

Table 3 provides descriptive statistics for the top 300 NFT collections with the highest wash trading volumes from January 2021 to June 2024, revealing key insights into the dynamics of wash versus genuine trading. The average daily wash trading volume is 435.83 ETH (or $1.05 million), significantly higher than the genuine trading volume of 109.01 ETH ($0.26 million). This stark contrast highlights the dominance of artificial trading in collections targeted for manipulation, with some collections experiencing extreme wash trading volumes of up to $424.75 million in a single day. The average exchange transaction fee is approximately 1.07%, while the creator fee averages 2.19%. These collections are traded on at least one exchange and a maximum of five exchanges.

We run a panel regression model to estimate the factors influencing wash trading for NFT collections. The analysis incorporates key variables such as genuine trading volume (VG_{it}) in logarithmic form, platform fees (PF_{it}), creator fees (CF_{it}), and the number of exchanges (NE_{it}) trading each NFT collection i at day t. Fixed effects for year (δ_t) and collection (γ_i) are included to control for time-invariant and collection-specific characteristics. The dependent variable (Vw_{it}) is the wash trading volume of collection i at day t, presented in logarithmic form, with results reported in panels A (volumes in ETH) and B (volumes in USD). The general specification of our linear panel regression model is:

$$Vw_{it} = \alpha + \beta_1 VG_{it} + \beta_2 PF_{it} + \beta_3 CF_{it} + \beta_4 NE_{it} + \delta_t + \gamma_i + \varepsilon_{it}$$

Table 4 shows that the coefficient for genuine trading volume is positive and statistically significant, with values of 0.608 in Panel A and 0.635 in Panel B. The result indicates that a 1% increase in genuine trading volume is associated with an approximate 0.6% increase in wash trading volume. This strong relationship highlights that in markets with higher genuine trading volumes, wash traders must increase their activity to effectively influence market dynamics and sustain their manipulative strategies. Besides, the platform fee and creator fee variable also negatively affect wash trading volume, indicating that higher transaction fees deter wash trading, as the costs of repeated transactions increase with higher fees, consistent with the predictions outlined in equation (3). Also, the number of exchanges trading an NFT collection shows a positive and significant relationship. The result highlights that collections on more exchanges provide more opportunities for wash trading, likely due to differences in oversight and enforcement across platforms.

[Table 4]

4. How wash trading distorts asset prices and volume?

To assess the impact of wash trading volume on the price and trading volume of an NFT collection, we adopt the Hasbrouck (1991) vector auto-regression (VAR) framework. This model includes the signed dollar volume of wash trades ($Wash_t$) and genuine trades ($Genuine_t$) in every one-hour interval, *t*, along with the returns of the collection ($Return_t$). The VAR equation system is as follows:

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

$$Genuine_t = b_0 + \sum_{l=0}^{6} b_{1,l} Wash_{t-l} + \sum_{l=1}^{6} b_{2,l} Genuine_{t-l} + \sum_{l=1}^{6} b_{3,l} Return_{t-l} + \varepsilon_{N,t}$$

$$Return_t = c_0 + \sum_{l=0}^{6} c_{1,l} Wash_{t-l} + \sum_{l=0}^{6} c_{2,l} Genuine_{t-l} + \sum_{l=1}^{6} c_{3,l} Return_{t-l} + \varepsilon_{R,t}$$

We calculate returns ($Return_t$) using the log change of NFT floor price in the t^{th} hour. NFT floor price is a pivotal metric for collectors and investors in evaluating an NFT collection's perceived and intrinsic value. The NFT floor price represents the lowest price at which an NFT from a given collection is listed for sale on a marketplace. It is a proxy for the minimum entry cost to own an item in the collection. Market participants use the floor price to gauge the collection's liquidity, demand, and overall market sentiment. Individual prices for each NFT can be noisy due to rarity or traits, but the floor price captures the baseline behavior of the collection, making it a cleaner metric for trend analysis.[10]

Wash trading, which involves artificially inflating trading volumes through coordinated buying and selling of NFTs within the same wallet or group of wallets, is expected to influence the floor price. By creating an illusion of heightened demand or desirability, wash trading can drive up the floor price, potentially enticing genuine buyers to enter the market under pretenses. This manipulation can cascade effects on the collection's perceived value and trading dynamics.

After estimating the VAR equations, we assess the impact of wash trading volume and genuine trading volume on returns and the reverse effects. To facilitate interpretation, we simulate a shock of 10 Ethereum for both genuine and wash trading volumes and a 10% shock for returns at $t = 0$. We then evaluate the cumulative response magnitudes over a 24-hour period ($t = 0$ to $t = 24$). Table 5 summarizes the statistics—mean, standard deviation, median, and quartile points—of the 24-hour cumulative responses for price returns (%), genuine volume (ETH), and wash trading volume (ETH) to shocks in these variables. Our analysis is based on the top 300 Non-Fungible Token (NFT) collections with the highest wash trading volumes, covering 18 April 2022 to 5 March 2024, comprising 16,488 hourly observations for each collection. We compute the cumulative response values for each NFT collection and then average them across all 300 collections. Figure 4 visualizes the cumulative response trajectories over time, along with 95%

[10] For a more detailed explanation of NFT floor prices, please visit the Chainlink Education Hub at https://chain.link/education-hub/what-is-an-nft-floor-price

confidence intervals, for the variables in the VAR model subjected to shocks from other variables. The horizontal axis represents time in hours, starting from the initial shock at $t = 0$.

[Table 5]

[Figure 4]

The results indicate that the impact of genuine and wash trading volumes on returns is remarkably similar. A shock of 10 ETH in genuine trading volume leads to an approximate 0.34% increase in returns, while the same shock in wash trading volume results in a 0.32% increase. This similarity suggests that wash traders deliberately mimic the patterns of genuine trading volume to manipulate prices effectively. By inflating trading volumes to resemble organic market activity, wash traders create the illusion of heightened demand, which can mislead other market participants and artificially influence asset prices. This strategic mirroring highlights the sophistication of wash trading practices and the challenges in distinguishing genuine trading from manipulative behavior.

Our findings closely align with Aggarwal and Wu (2006), who demonstrate that manipulators mimic the trading behaviors of informed traders to create the illusion of information-driven activity, misleading uninformed participants and artificially inflating prices. Similarly, our results show that wash traders replicate the patterns of genuine trading volumes to effectively manipulate asset prices, particularly in markets characterized by low transparency and liquidity, such as NFT marketplaces. These findings underscore the critical role of information asymmetry, as manipulators exploit the inability of uninformed traders to discern genuine market signals from deceptive, manipulative activity.

Interestingly, the results reveal a nuanced relationship between return shocks and trading behavior in the NFT market. A positive 10% shock to returns raises the genuine trading volume by approximately 28 ETH, indicating that higher returns encourage more legitimate market activity. This finding aligns with the expectation that higher returns signal improved profitability, liquidity, and market confidence, motivating genuine buyers and sellers to engage in trading activities. Besides, rising returns may trigger psychological factors like FOMO (Fear of Missing Out), driving more traders into the market to avoid missing potential gains.

On the other hand, the same 10% return shock leads to a decrease in wash trading volume by about 9 ETH, as high returns make market manipulation costlier and less necessary. Wash trading involves expenses such as transaction and platform fees, which become more expensive to justify when organic market growth already attracts genuine traders. High returns draw actual participants who trade based on demand and intrinsic value, increasing liquidity and reducing the relative impact of wash trades. Additionally, since the primary goal of wash traders is to inflate perceived returns and lure genuine traders, naturally high returns eliminate the need for such manipulative tactics, making wash trading both uneconomical and less effective in favorable market conditions.

The results also reveal an asymmetry in the relationship between genuine and wash trading volumes. A shock of 10 ETH to genuine trading volume leads to an increase of approximately 1.3 ETH in wash trading volume. The result indicates that increased genuine trading activity causes wash traders to escalate their wash trading volumes to manipulate the market effectively. It also suggests that wash traders are opportunistic and respond to higher genuine trading activity by amplifying their manipulative efforts. By inflating trading volume during periods of high genuine activity, wash traders aim to create the illusion of even greater market demand, leveraging the momentum generated by organic trades. Conversely, a shock of 10 ETH to wash trading volume results in a significantly more significant increase—about 3.2 ETH—in genuine trading volume. The result indicates that wash trading effectively achieves its goal of simulating market activity to attract real traders. The artificial boost in trading volume and perceived liquidity created by wash trading can make a collection appear more active or desirable, prompting genuine traders to participate due to FOMO or a perceived increase in the collection's value.

We next investigate whether wash traders seek opportunities for wash trading, such as lower transaction fees or exchanges offering attractive incentives to reward trading volume. To examine this, we analyze wash trading activity on the two exchanges with the largest wash trading volumes: LooksRare, with $9.9 billion in total wash trading, and X2Y2, with $2.7 billion. Using a Vector Autoregressive (VAR) model, we include two variables: daily wash trading volumes on LooksRare ($Wash_Looksrare_t$) and X2Y2 ($Wash_X2Y2_t$). By introducing shocks to the wash trading volume of 10 ETH on one exchange, we assess how it influences wash trading activity on the other. The VAR equation system is as follows:

$$Wash\_Looksrare_t = a_0 + \sum_{l=1}^{6} a_{1,l} Wash\_Looksrare_{t-l} + \sum_{l=1}^{6} a_{2,l} Wash\_X2Y2_{t-l} + \varepsilon_{1,t}$$

$$Wash\_X2Y2_t = b_0 + \sum_{l=0}^{6} b_{1,l} Wash\_Looksrare_{t-l} + \sum_{l=1}^{6} b_{2,l} Wash\_X2Y2_{t-l} + \varepsilon_{2,t}$$

Figure 5 reveals an interesting interaction between the two platforms. A shock that increases wash trading volume by 10 ETH on LooksRare reduces wash trading on X2Y2 by approximately 4,000 ETH. Conversely, a shock that increases wash trading volume by 10 ETH on X2Y2 reduces wash trading on LooksRare by about 250 ETH. These findings suggest that wash traders strategically shift their activity between exchanges, optimizing for better incentives and lower fees. The significant difference in wash trading responses reflects the dominance of LooksRare, which accounts for over three times the wash trading volume of X2Y2. This disparity indicates that LooksRare likely provides stronger incentives or more favorable conditions for wash trading, making it the primary platform of choice for manipulators. The findings underscore the competitive nature of wash trading, with traders opportunistically moving between platforms to maximize rewards.

[Figure 5]

We further assess the potential migration of wash trading activity from Ethereum to its Layer 2 solutions (such as Polygon, Arbitrum, Optimism, Celo, zkSync, Zora, Base, Scroll, and Blast), where transaction fees are significantly lower. Figure 5 illustrates the wash trading volumes on the Ethereum blockchain and its Layer 2 solutions from January 2021 to June 2024, plotted in USD on a logarithmic scale.

Figure 6 shows that Layer 2 platforms experienced relatively low adoption and activity before 2023 due to their early development stages and limited integration with major applications. However, wash trading spiked from March 2023 onwards, driven by anticipation of the Dencun upgrade, implemented in March 2024. This upgrade introduced EIP-4844 (Proto-Danksharding), significantly reducing data storage costs for L2 rollups and lowering transaction fees, making Layer 2 platforms more cost-effective and appealing for manipulative activities like wash trading. 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. In late 2023 and early 2024, the launch of new Layer 2 platforms like Base, Scroll, and Blast provided additional opportunities for wash trading, as these platforms offered competitive transaction costs and were less developed in monitoring manipulative activities. Furthermore, the adoption of Uniswap v2 on multiple blockchains, including Arbitrum, Polygon, Optimism, and Base, drove higher overall trading volumes, enabling wash traders to blend their activities within the surge of legitimate trading traffic. The rapid development and adoption of Layer 2 solutions have significantly increased wash trading activity, bringing it to levels nearly equal to that of Ethereum in its later stages. This trend highlights the strong relationship between transaction costs and wash trading volumes.

[Figure 6]

5. Conclusion

As blockchain technology transforms financial markets, it introduces unique challenges, including the proliferation of manipulative practices like wash trading. Leveraging the transparency and immutability of blockchain data, our research investigates the patterns, scale, and economic impact of wash trading in the NFT ecosystem, highlighting how these manipulations distort asset prices, genuine trading volumes, and market perceptions. By analyzing over 42.9 million NFT transactions from January 2021 to June 2024, we demonstrate that wash trading, comprising only 2% of total transactions, accounts for 40% of trading volume, significantly inflating perceived demand and misleading market participants.

Our findings reveal that wash trading thrives in environments offering incentives or reduced transaction costs, such as platforms with trading reward programs like LooksRare, X2Y2, and Blur. These conditions make manipulation more feasible and attractive, allowing opportunistic actors to exploit information asymmetry and mimic genuine trading patterns to distort prices effectively. Furthermore, we uncover a dynamic relationship between wash and genuine trading. While higher fundamental price returns cause genuine trading volumes to rise and wash trade to decline, heightened genuine trading activity often triggers increased manipulative efforts for the wash traders.

This study contributes to the growing body of literature on misconduct in blockchain markets by providing critical insights into the mechanisms of wash trading and its implications for market integrity. Our findings emphasize the urgent need for regulatory measures and enhanced detection tools to address this pervasive issue, ensuring transparency and fairness in blockchain-based financial ecosystems as they expand.

Table 1: Key variables and parameters in the model

Symbol	Description	Detailed Explanation
V_W	Wash trading volume (set by wash traders).	Represents the volume of artificial trades executed by wash traders to create the illusion of higher market activity. Wash traders use V_W to manipulate genuine traders and increase perceived liquidity.
V_G	Genuine trading volume (determined by genuine traders).	Reflects the actual trading volume generated by real market participants. It is influenced by returns (R) and observed trading activity (including V_W).
$C(V_W)$	Cost of wash trading	The cost incurred by wash traders for artificially inflating trading volume. It increases quadratically with V_W, reflecting higher marginal costs at greater volumes $C(V_W) = cV_W^2$:
R	Price return	The return or price change of the asset, driven by market fundamentals. Higher returns often attract genuine traders to the market, increasing V_G .
β	Exchange reward per unit of trading volume	Represents the reward or rebate wash traders receive from exchanges for their trading volume. This incentivizes wash traders to inflate V_W.
ρ	Sensitivity of wash traders' profits from genuine trading volumes	Reflects the extent to which wash traders benefit from higher prices achieved by selling to genuine traders
c	Cost sensitivity parameter of wash trading	Determines the degree to which the cost of wash trading rises with V_W. A larger c means higher costs for wash trading.
δ	Sensitivity of genuine traders to returns	Reflects the extent to which genuine traders increase their trading activity (V_G) in response to returns (R). Higher δ indicates stronger genuine trader responsiveness to price signals.
κ	Influence of wash trading volume on genuine trading volume	Measures the impact of wash trading volume (V_W) on genuine trading volume (V_G). A larger κ implies that genuine traders are more influenced by wash traders' artificial activity.

Table 2. Genuine and wash trading statistics

This table summarizes the statistical values for genuine and wash trading from 1 January 2021 to 30 June 2024 from over 43 million NFT transactions on the Ethereum blockchain. Panel A displays the transaction counts and volumes (in ETH and USD) for genuine and wash transactions. Panel B highlights the wash trading volumes (in ETH and USD) for the top exchanges by wash volume, while Panel C showcases the collections with the highest wash volumes (in ETH and USD).

Panel A.

	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

Exchange	Washed volume (ETH)	Percent (%)	Washed 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

Collection	Washed volume (ETH)	Percent (%)	Washed 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. Descriptive statistics for top washing NFT collections

This table presents the statistical values for the top 300 collections with the highest wash volumes from 1 January 2021 to 30 June 2024 on the Ethereum blockchain. The metrics include daily transaction volumes (in ETH and million USD for genuine and wash transactions. The creator fee (%) is the average transaction fee paid to the NFT creator, and the exchange fee (%) is the transaction fee paid to the exchange. The exchange count indicates the number of exchanges on which an NFT collection can be traded.

Variable	Obs	Mean	Std. dev.	Min	Max
Wash volume (ETH)	32,192	435.83	4,045.98	0	139,003.12
Wash volume (mil $)	32,192	1.05	11.30	0	424.75
Genuine volume (ETH)	122,366	109.01	793.82	0	136,039
Genuine volume (mil $)	122,366	0.26	2.50	0	540.31
Exchange fee (%)	32,192	1.07	1.55	0	13.95
Creator fee (%)	32,192	2.19	4.18	0	99.50
Exchange count	32,192	1.12	0.36	1	5.00

Table 4. Factors affecting wash trading volume.

This table presents a panel regression analysis of the total wash trading volume of an NFT collection based on its characteristics, including genuine volume, creator fees (%), platform fees (%), the number of exchanges, and fixed effect for year and NFT collection. The standard errors are clustered by NFT collection and year to ensure robust inference. Our analysis uses 300 collections with the largest wash trading volume on the Ethereum blockchain from 1 January 2021 to 30 June 2024. The genuine and wash volumes are presented in logarithmic form. Panel A analyzes the volumes in ETH, while Panel B shows the volume in USD. The table reports the estimated coefficients and t-statistics. The 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

Panel A

$Wash\ volume\ (ETH)_{it}$	(1)	(2)	(3)	(4)	(5)	(6)
$Genuine\ volume\ (ETH)_{it}$	0.627***				0.620***	0.608***
	(15.566)				(15.900)	(14.142)
$Platform\ fee\ (\%)_{it}$		-0.088			-0.163	-0.195**
		(-0.785)			(-1.579)	(-2.152)
$Creator\ fee\ (\%)_{it}$			-0.067**		-0.084***	-0.090***
			(-2.341)		(-3.224)	(-3.215)
$Number\ of\ exchanges_{it}$				1.375***	0.814***	0.802***
				(7.713)	(6.579)	(6.283)
$Intercept$	-0.609***	1.648***	1.702***	0.003	1.131***	0.991***
	(-4.710)	(13.547)	(26.727)	(0.015)	(4.148)	(3.556)
Collection FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	Yes
Observation	29173	31371	31371	31371	29173	29173
adj. R^2	0.245	0.001	0.010	0.043	0.282	0.285

Panel B

$Wash\ volume\ (\$)_{it}$	(1)	(2)	(3)	(4)	(5)	(6)
$Genuine\ volume\ (\$)_{it}$	0.647***				0.644***	0.635***
	(17.007)				(17.507)	(16.585)
$Platform\ fee\ (\%)_{it}$		-0.068			-0.162	-0.194**
		(-0.585)			(-1.546)	(-2.115)
$Creator\ fee\ (\%)_{it}$			-0.067**		-0.086***	-0.090***
			(-2.279)		(-3.277)	(-3.227)
$Number\ of\ exchanges_{it}$				1.321***	0.770***	0.767***
				(7.326)	(6.253)	(6.083)
$Intercept$	2.027***	9.266***	9.341***	7.708***	1.559***	1.831***
	(4.904)	(74.667)	(144.179)	(38.014)	(3.128)	(3.518)
Collection FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	Yes
Observation	29918	32128	32128	32128	29918	29918
adj. R^2	0.267	0.001	0.010	0.037	0.301	0.303

Table 5. The cumulative 24-hour responses of genuine, wash, and return

The table presents the statistics—mean, standard deviation, median, and quartile points—of the cumulative 24-hour responses of price return (%), genuine volume (ETH), and wash volume (ETH) to shocks from these variables. The shock to return is 10%, and the shocks to genuine and wash volumes are 10 ETH. Our statistics are from the top 300 Non-Fungible Token (NFT) collections with the highest wash volume from 18 April 2022 to 5 March 2024 (approximately 16,488 hourly observations in time series for each NFT collection). We calculate the cumulative response values for each NFT collection and then determine the average across all 300 NFT collections. $Return_t$ is calculated as the logarithm change of the NFT price floor of each collection at hour t. $Wash_t$ and $Genuine_t$ are the signed trading volumes (ETH) of the given collection (positive values for net buying and negative values for net selling) at hour t.

$$Wash_t = a_0 + \sum_{l=1}^{6} a_{1,l} Wash_{t-l} + \sum_{l=1}^{6} a_{2,l} Genuine_{t-l} + \sum_{l=1}^{6} a_{3,l} Return_{t-l} + \varepsilon_{W,t}$$
$$Genuine_t = b_0 + \sum_{l=1}^{6} b_{1,l} Wash_{t-l} + \sum_{l=1}^{6} b_{2,l} Genuine_{t-l} + \sum_{l=1}^{6} b_{3,l} Return_{t-l} + \varepsilon_{N,t}$$
$$Return_t = c_0 + \sum_{l=0}^{6} c_{1,l} Wash_{t-l} + \sum_{l=0}^{6} c_{2,l} Genuine_{t-l} + \sum_{l=1}^{6} c_{3,l} Return_{t-l} + \varepsilon_{R,t}$$

Effect	Mean	Std. dev	P25	Median	P75
Genuine → Return	0.346	1.196	0.005	0.050	0.338
Wash → Return	0.322	0.812	0.001	0.020	0.217
Return → Genuine	28.064	57.971	0.023	0.833	21.431
Return → Wash	-9.309	25.737	-2.286	-0.027	0.040
Genuine→ Wash	1.300	4.560	-0.047	0.076	0.621
Wash → Genuine	3.222	4.627	0.146	1.284	4.336

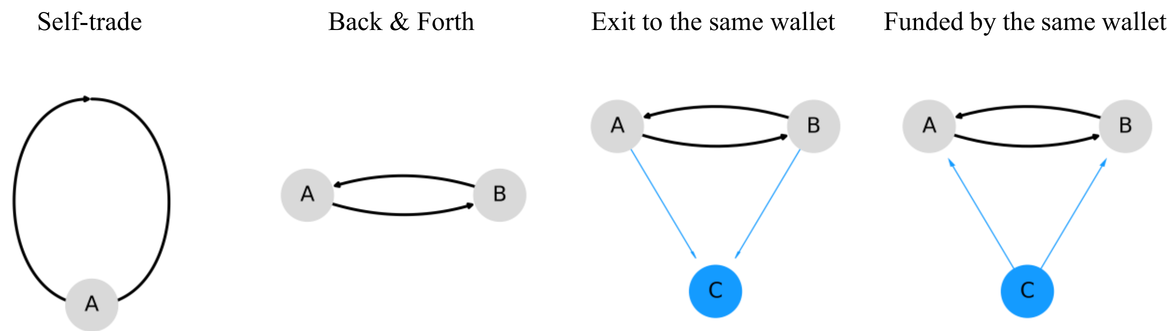

Figure 1. Most used patterns of NFT wash trading

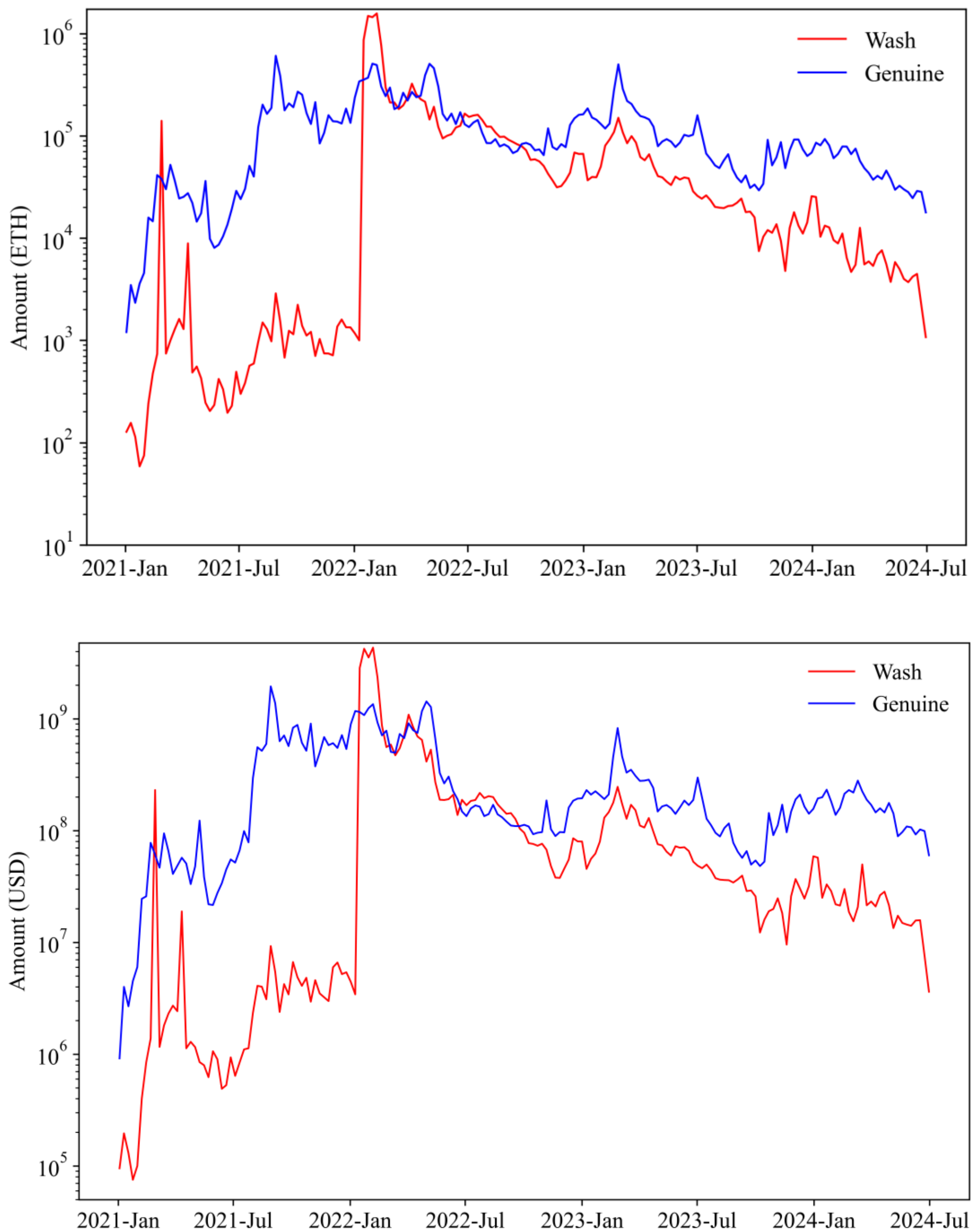

Figure 2. The genuine and wash trading volume over time
This chart displays the volumes of genuine and wash trading from 1 January 2021 to 30 June 2024. The volumes are represented in ETH and USD and plotted on a logarithmic scale.

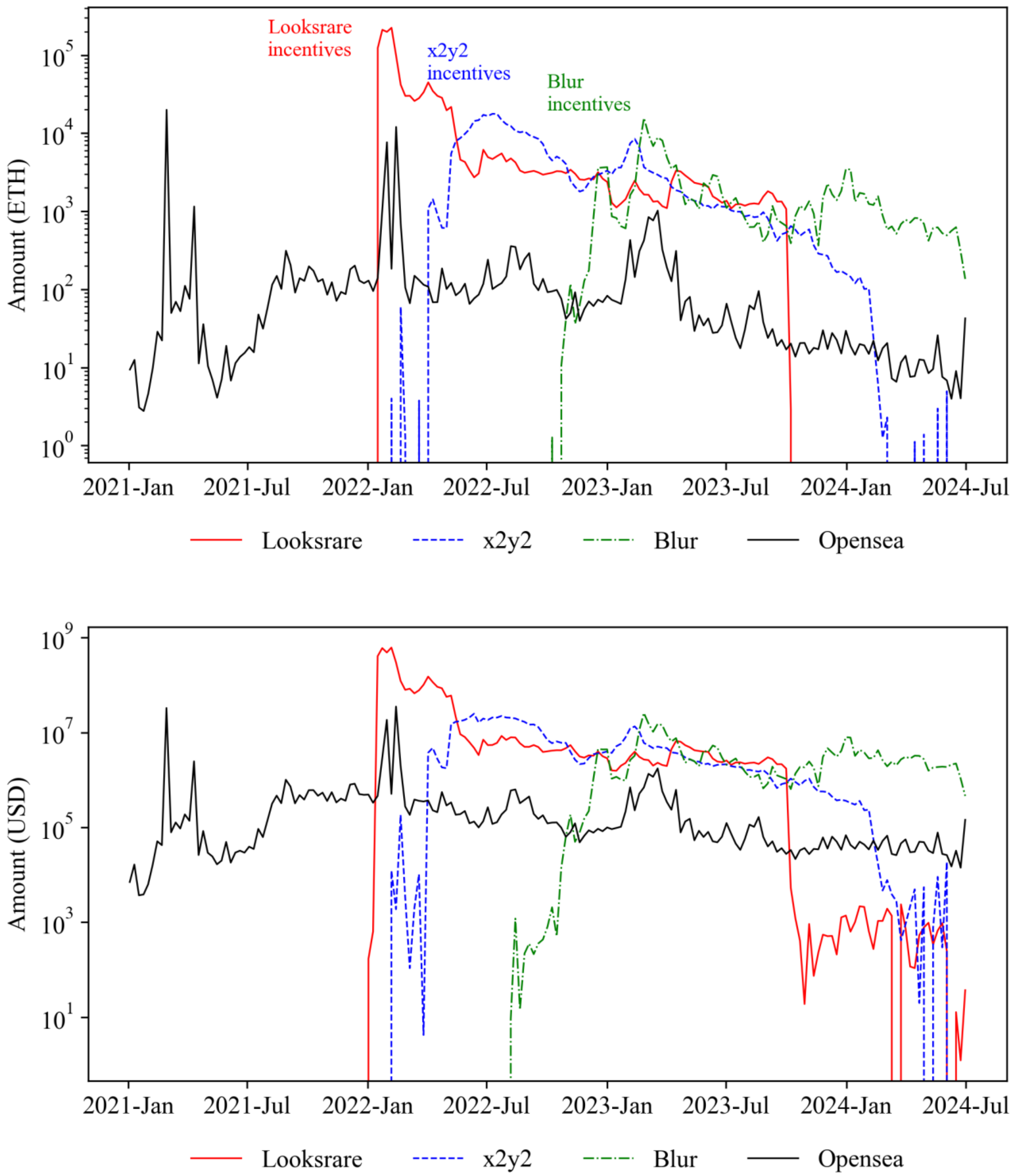

Figure 3. The wash trading volume by exchanges over time
This chart illustrates the wash trading volumes of the four exchanges (Looksrare, x2y2, Blur, and Opensea) with the highest wash volumes from 1 January 2021 to 30 June 2024. The data is presented in ETH and USD and plotted on a logarithmic scale.

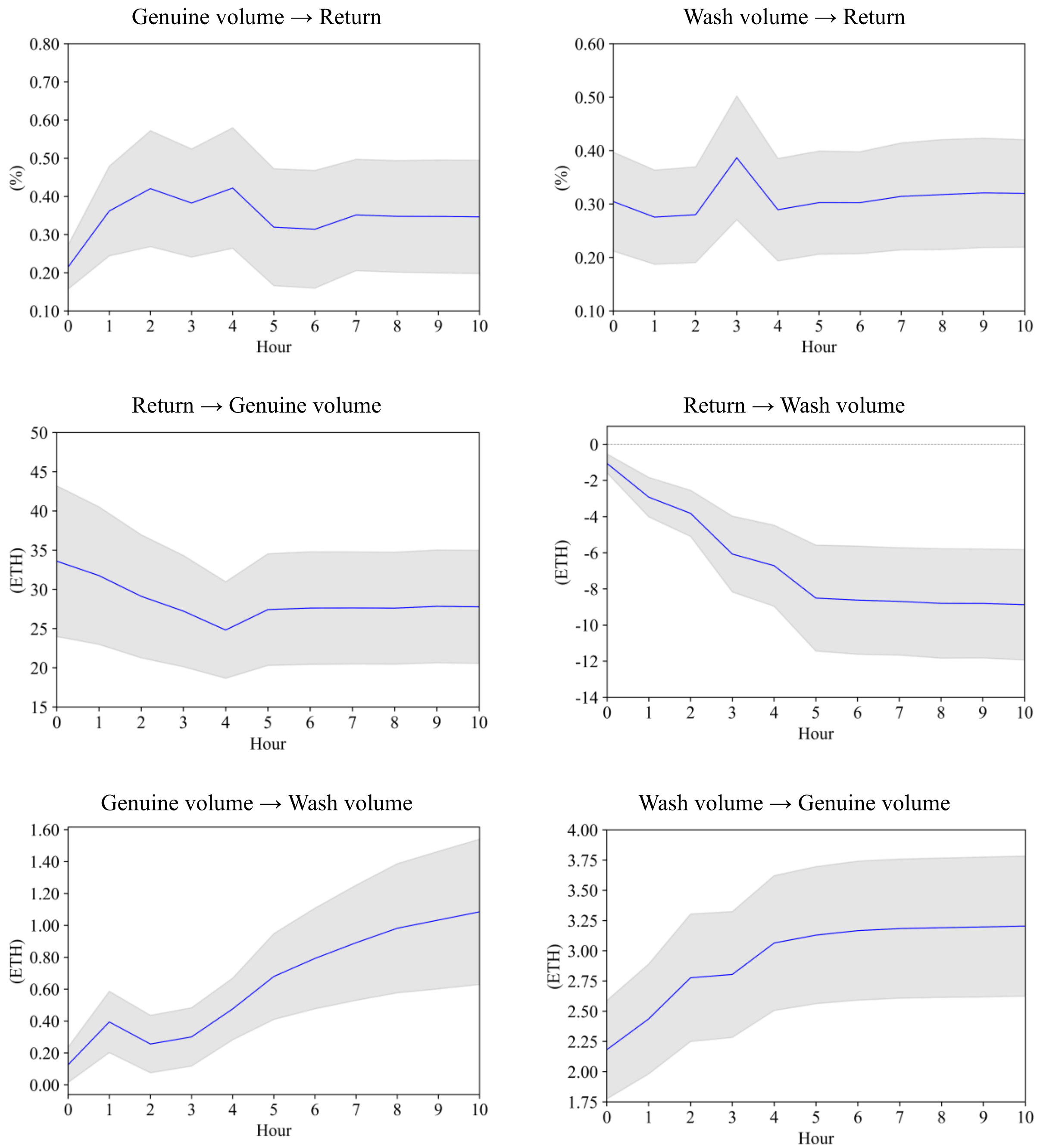

Figure 4. Cumulative response of return, genuine trading volume, and wash trading volume
This graph illustrates the cumulative response and 95% confidence interval over time of the variables in the VAR model to shocks from other variables. The horizontal axis represents the time (in hours) progressing from the initial shock at hour $t = 0$. The shock's magnitude for price return is 10%, while it is 10 ETH for both genuine and wash trading volumes. The above average cumulative responses and confidence intervals are computed across the 300 NFT collections with the highest wash trading volume in the market.

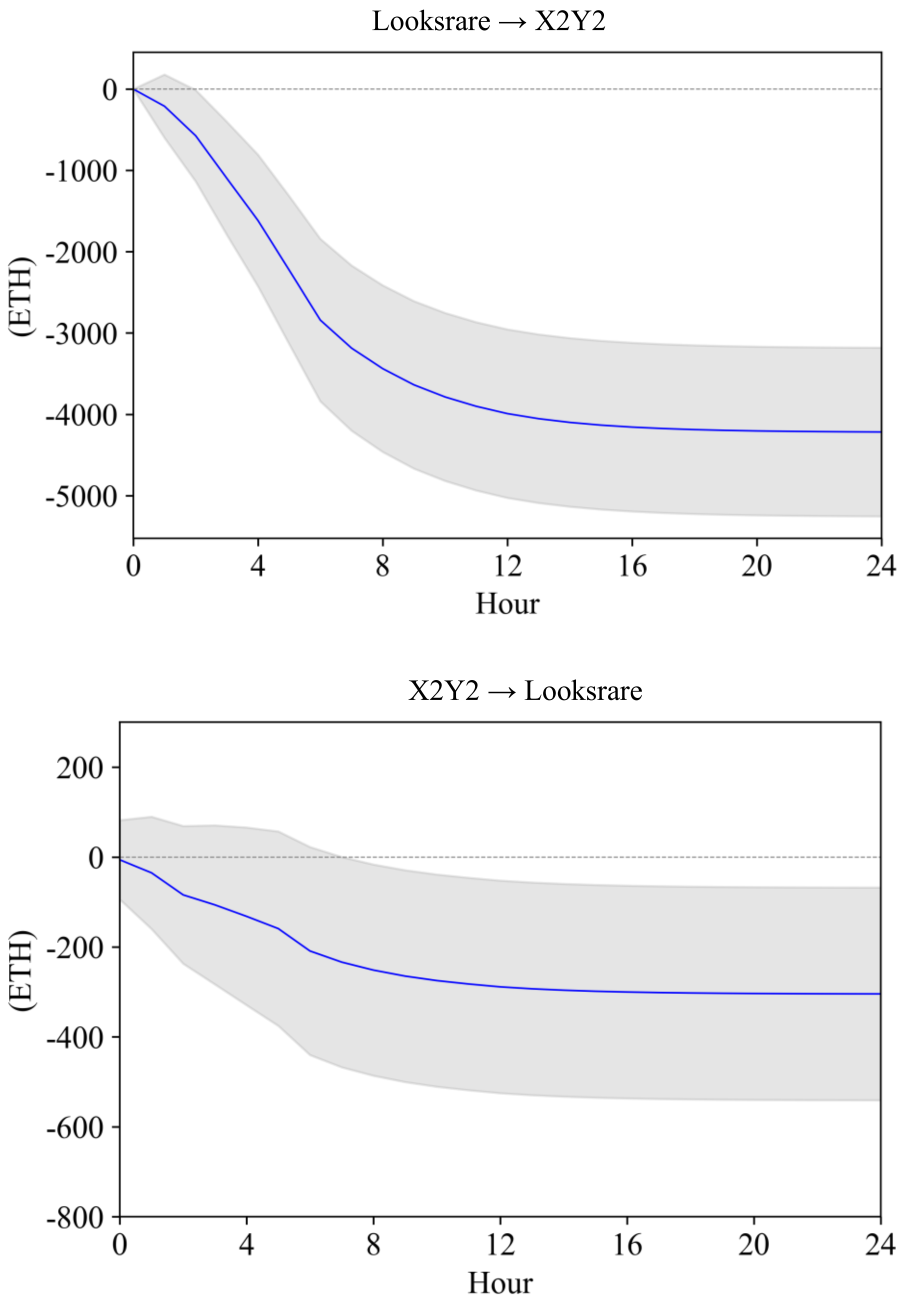

Figure 5. The cumulative response of wash trading volume to a shock from the other exchange
This graph depicts the cumulative response and 95% confidence interval of wash trading volume over time between two leading wash trade exchanges, Looksrare and X2Y2. It illustrates how Looksrare's wash trading volume responds to a positive shock in the wash trading volume of X2Y2 and vice versa. The shock magnitude of wash trading volume for each exchange is 10 ETH, with time progressing on the horizontal axis in hours starting from the initial shock at hour t = 0. The VAR model incorporates two endogenous variables: wash trading volume of Looksrare and X2Y2 exchange; our analysis is from 1 January 2024 to 30 June 2024.

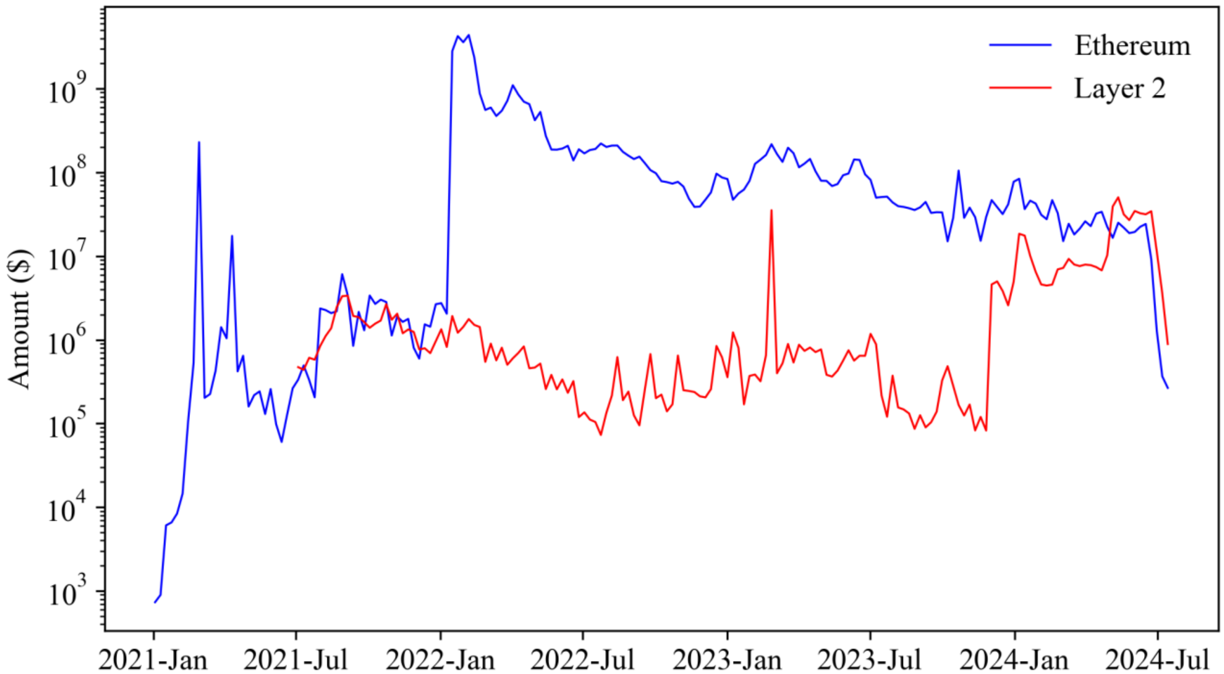

Figure 6. The wash trading volume of Ethereum and Layer 2.

This chart illustrates the wash trading volumes on the blockchain Ethereum and its Layer-2 (Polygon, Arbitrum, Optimism, Celo', 'ZK-sync', Zora, Base, Scroll, Blast) from 1 January 2021 to 30 June 2024. The data is presented in USD and plotted on a logarithmic scale.

Appendix A: Notable Cases of Cryptocurrency Wash Trading and Market Manipulation

Coinbase

On March 19, 2021, the CFTC settled charges against Coinbase Inc. for reckless false, misleading, or inaccurate reporting and wash trading by a former employee on its GDAX platform. From January 2015 to September 2018, Coinbase's trading programs Hedger and Replicator matched orders with one another, creating a false appearance of liquidity. A former Coinbase employee also engaged in wash trading in the Litecoin/Bitcoin trading pair on GDAX. Coinbase was ordered to pay a $6.5 million penalty and cease any further Commodity Exchange Act violations.

Avraham Eisenberg

On January 9, 2023, the CFTC charged Avraham Eisenberg with a fraudulent scheme to misappropriate over $110 million from Mango Markets, a decentralized digital asset exchange. Eisenberg manipulated the market by creating two anonymous accounts and engaging in wash trading to inflate the value of his positions. By artificially increasing the price of Mango's native token, MNGO, Eisenberg leveraged these inflated positions to withdraw substantial digital assets from the platform, causing significant financial harm to other users.

Justin Sun

On March 22, 2023, the SEC charged crypto entrepreneur Justin Sun and his companies—Tron Foundation Limited, BitTorrent Foundation Ltd., and Rainberry Inc.—with the unregistered offer and sale of crypto asset securities Tronix (TRX) and BitTorrent (BTT). Sun and his companies were also accused of manipulating the secondary market for TRX through extensive wash trading, conducting over 600,000 wash trades between April 2018 and February 2019 to inflate TRX's trading volume artificially. Additionally, they orchestrated a scheme to pay celebrities to promote TRX and BTT without disclosing their compensation, resulting in $31 million in illegal proceeds from unregistered sales.

Michael Kane, Shane Hampton, and George Wolvaardt

On April 24, 2023, the DOJ charged Michael Kane, Shane Hampton, and George Wolvaardt with conspiracy to manipulate the market for HYDRO, a token created by Hydrogen Technology

Corporation. They used a trading bot to place thousands of spoof orders and wash trades, creating a false appearance of supply and demand for HYDRO. This manipulation allowed them to sell the token artificially inflated prices, generating $2 million in profits. The charges include conspiracy to commit securities price manipulation and wire fraud.

Binance

On June 5, 2023, the SEC filed 13 charges against Binance Holdings Ltd., its U.S. affiliate BAM Trading Services Inc., and their founder, Changpeng Zhao. The charges included operating unregistered exchanges, broker-dealers, and clearing agencies and engaging in wash trading to inflate trading volumes on Binance.US. It was also accused of misleading investors about trading controls and oversight while secretly allowing high-value U.S. customers to trade on Binance.com, thus evading U.S. securities laws.

Adam Todd

On July 12, 2023, the CFTC announced a default judgment against Adam Todd and his companies—Digitex LLC, Digitex Limited, Digitex Software Limited, and Blockster Holdings Limited Corporation. Todd attempted to manipulate the price of Digitex Futures' native token, DGTX, using a computerized bot to inflate its value artificially. Additionally, Todd and his companies facilitated unlawful futures transactions, failed to register with the CFTC, and did not implement necessary anti-money laundering procedures. The court ordered Todd to pay over $15 million in penalties and banned him from trading in CFTC-regulated markets.

Operation Token Mirrors

In October 2024, the U.S. Department of Justice (DOJ) and the Securities and Exchange Commission (SEC) launched Operation Token Mirrors, targeting market manipulation and wash trading in cryptocurrency. This landmark enforcement action resulted in charges against 18 individuals and entities, marking the first criminal charges against financial services firms for engaging in such activities. The operation uncovered schemes where manipulators artificially inflated trading volumes to mislead investors, distort market prices, and undermine market integrity. The case highlighted the DOJ and SEC’s commitment to addressing fraudulent practices in the rapidly evolving cryptocurrency ecosystem and set a precedent for prosecuting wash trading in digital asset markets.

SEC and FBI Joint Takedown

In October 2024, the SEC, in collaboration with the Federal Bureau of Investigation (FBI) and the DOJ, executed a coordinated enforcement action targeting fraudulent crypto wash trading schemes. This operation focused on manipulators who used deceptive practices to inflate market activity and attract unsuspecting investors. The joint effort underscored the importance of inter-agency collaboration in combating manipulative practices that exploit blockchain technology's pseudonymous and decentralized nature. By targeting individuals and entities responsible for these schemes, the SEC and FBI demonstrated their resolve to protect market integrity and ensure accountability within the cryptocurrency space.

Appendix B: Overview of Trading Rewards Programs for NFT

This table summarizes trading rewards programs across popular NFT marketplaces, including their start and end dates (if applicable) and details about how these programs operate. The information highlights trends in user incentives, program discontinuation, and platform strategies to reduce wash trading and enhance long-term user engagement. Programs are subject to change, and 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-22	Oct-23	- 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-22	Aug-23	- Distributed X2Y2 tokens to active traders. - Ended to minimize wash trading and encourage genuine engagement.
Blur	Airdrop Rewards	Oct-22	Ongoing	- Provides BLUR tokens through airdrops to reward organic trading activity. - Focuses on professional traders with advanced tools.
Magic Eden	Rewards Program	Mar-23	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	9-Sep-24	9-Dec-24	- Launched a 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-23	Ongoing	- Allocated 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	3-Jan-23	31-Jan-23	- Offered zero trading fees for selected NFT collections and a reward pool of up to 40,000 BUSD for participants.

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