How Wash Traders Exploit Market Conditions in Cryptocurrency Markets

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Ants Exhaust Themselves To Death

Ant Death Spiral ⚖️

1. **Currently:** Many crypto trades are/were fake. Inflate volume to look busy.
2. **Unknown:** When do wash traders strike? Is it random or strategic?

⚠️ Most studies detect fake volume, not explain its behavior.

✅ Let me convince you it's strategic, and show when and why it happens.

How to catch a wash trader — Oct 2024

TL;DR: FBI Busts Wash Trading Ring ⚖️

- **8 charged:** crypto execs + market makers (Gotbit, ZM Quant, etc.)
- **$25M seized**, bots shut down, arrests in US, UK, Portugal
- **Tactics:** wash trades, fake tweets, pump-and-dump
- **FBI sting:** fake token + firm ("NexFundAI") exposed scheme 🕵️
- **Saitama:** $7.5B token allegedly boosted with fake trades

How to catch another wash trader — Apr 2025

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PRESS RELEASE

Cryptocurrency Financial Services Firm Sentenced for Cryptocurrency "Wash Trading"

Wednesday, April 2, 2025

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For Immediate Release

U.S. Attorney's Office, District of Massachusetts

TL;DR: CLS Global Sentenced for Wash Trading ⚖️

- **Firm:** CLS Global FZC LLC (UAE-based crypto market maker)
- **Charges:** Conspiracy to commit market manipulation and wire fraud
- **Penalty:** $428K fine and forfeiture; 3-year probation
- **Scheme:** Used algorithmic wash trades to inflate volume for FBI's fake token 🕵️
- **Tactics:** Self-trades via multiple wallets to mimic organic activity

Takeaway: Wash trading is not easy to detect nor catch

What's Wash Trading ⚠️

- Wash trading = buying and selling the same asset to yourself.
- Why? To fake volume, attract real traders, and pump prices.
- **Illegal in traditional markets**, but rampant in crypto.

Let’s Try to Catch a Wash-trader

Mt Gox Data

- **Mt. Gox collapsed** in 2014, claiming 850,000 BTC were lost to hackers.
- Anonymous sources leaked internal files:
  - Trade history with 18M+ transactions
  - User IDs, timestamps, prices, volumes
  - Back-office logs showing system-level actions

Bottom Line: The leak opened a rare forensic window into crypto manipulation.

Past Work on Crypto Wash Trading

- Glosten and Milgrom (1985), Kyle (1985), Allen and Gale (1992): Show how manipulators mimic informed traders to influence prices.
- Fox et al. (2018), Kyle and Viswanathan (2008): Legal frameworks struggle to prove manipulation without direct evidence of intent.
- Gandal et al. (2018): Identify Mt. Gox bots ("Willy" and "Markus") that faked volume
- Aloosh and Li (2024): Statistical Ways to detect wash trading using Mt. Gox data
- Cong et al. (2023): Proprietary data of 300+ cryptocurrency exchanges in 2019, large-scale forensic analysis showing that wash trading is pervasive on unregulated crypto exchanges, inflating reported volumes by over 70% on average


Let’s Try to Catch a Wash-trader

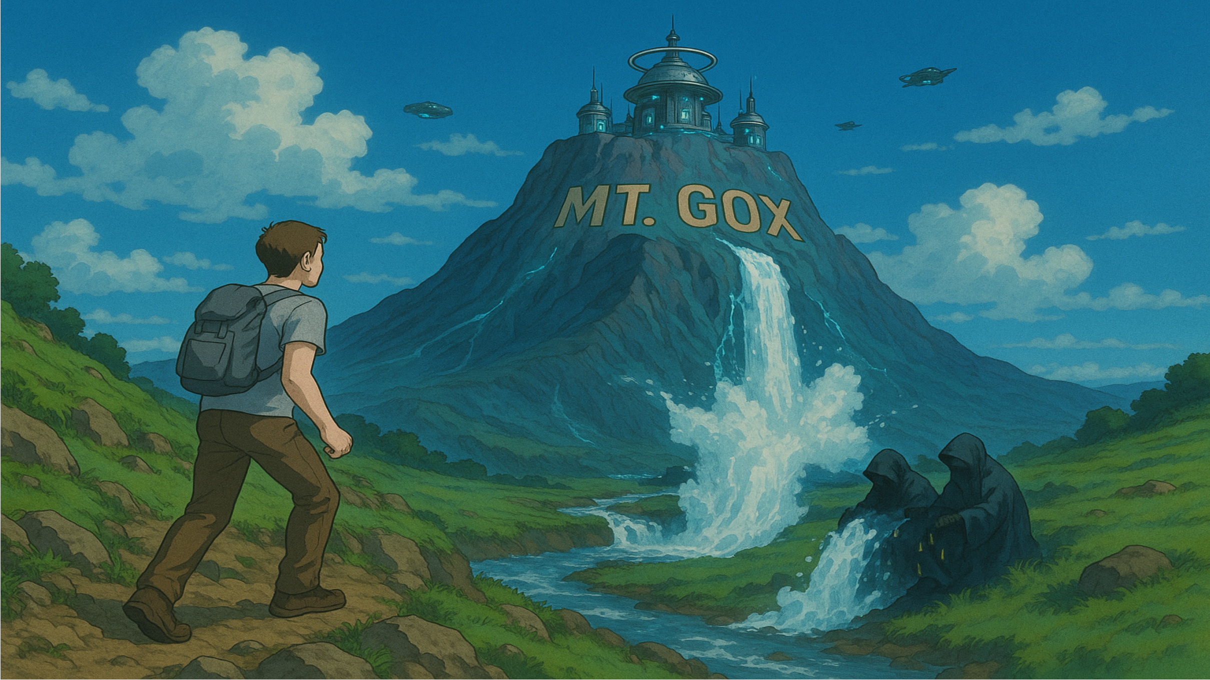
Research Question and Key Findings

Research Question:

Are wash trades in Bitcoin strategically timed to exploit market conditions?

Main Findings:

- Wash trading spikes during *low organic volume*, *high media attention*, and *inactive rival assets* (e.g., gold).
- Trades are timed to induce *crowd-in effects*, not just simulate volume.
- Machine learning and VAR models reveal *predictable patterns* of manipulation.
- Suggests need for *context-aware surveillance* beyond static thresholds.


MT. GOX

Do Wash Trades Follow Low Organic Volume?

Do Wash Trades Predict BTC Dynamics?

Do Wash Trades Spill Across Platforms?

Do Other Asset Markets Deter It?

Does Media Attention Amplify It?

Do Traders Exploit Exogenous Demand Shocks?

Do Wash Trades Follow Low Organic Volume?

Method: CART and deep learning (GRU, LSTM) using high-frequency Mt. Gox data.

Findings:

- Wash trades are predicted by non-wash trade volume at $t-2$ and $t-3$.
- Deep learning confirms pattern: wash traders act when organic activity is low.
- Supports strategic timing hypothesis.

Table 3. How do wash traders decide when to wash-trade? This panel presents coefficients from VAR examining lagged variables of liq_t, vol_t, $nonwash_t$, $total_t$ and their impact on $wash_t$. I use an arbitrary lag of up to $t-4$ The coefficients here do not refer directly to the variables in Table 1 but the weighted feature importance of each of them in the model. The higher the value, the more important the variable is. A placebo has been placed and as a guideline, any variable with importance lower than the placebo is not important as it shows that a randomly generated placebo has higher importance than it. Time period is from 26th June 2011 to 20th May 2013. The ranking of each variable in the corresponding model are shown in parentheses. Variable definitions are detailed in Table 1.

Feature Importance	(1) CART	(2) Random Forest	(3) AdaBoost	(4) XGBoost	(5) GRU	(6) LTSM
liq_{t-1}	6.28e+07	0	0.0147	0.0165	2.95e-06	1.81e-08
	(7)	(11.5)	(16)	(14)	(8)	(9)
liq_{t-2}	8.46e+07	0	0.0271	0.0113	−1.11e-05	1.31e-08
	(4)	(11.5)	(9)	(16)	(14)	(10)
liq_{t-3}	7.57e+07	0	0.0207	0.0267	2.91e-06	4.46e-09

Do Wash Trades Predict Market Dynamics?

Method: Johansen cointegration + Granger Causality + VAR using 30-min data.

Findings:

- Wash trades Granger-cause BTC price, liquidity, and volatility.
- Cointegration shows long-term co-movement with market variables.
- Wash trades drop after increases in legitimate volume.

Table 4 - Panel A. How do wash traders decide when to wash-trade? This panel presents coefficients from a **Johansen test** examining variables of liq_t, vol_t, $nonwash_t$, $total_t$ and $wash_t$. Time period is from 26th June 2011 to 20th May 2013. Variable definitions are detailed in Table 1.

Hypothesized No. of Cointegrating Equations	Trace Statistic	0.95 Critical Value	0.95 Critical Value Max-Eigen	Pass/Fail (95% Significance)
At most 0	4.4e+04	60	30	Pass
At most 1	3e+04	40	24	Pass
At most 2	1.6e+04	24	18	Pass
At most 3	5.3e+03	12	11	Pass
At most 4	−2.1e+02	4.1	4.1	Fail

Panel B. How do wash traders decide when to wash-trade? This panel presents coefficients from a **Granger Causality Panel** examining variables of liq_t, vol_t, $nonwash_t$, $total_t$ and $wash_t$. Time period is from 26th June 2011 to 20th May 2013. Variable definitions are detailed in Table 1.

Independent	Dependent	Lag	F-test p-value	Result

Do Wash Trades Spill Over to Other Platforms?

Method: Regression + Engle-Granger cointegration using on-chain and cross-exchange data.

Findings:

- Strongest on-chain correlation during high-wash periods.
- Cointegration suggests spillovers from Mt. Gox to broader market.
- Wash trades may trigger cross-exchange and wallet activity.

Table 5 - Panel A. Do wash trades correlate with on-chain transactions? This panel presents coefficients from OLS regressions examining changes in non-wash trade volume to on-chain transaction volume. $nonwash_t$ and $onchain_t$ second-level data and accumulated to $t = 30$ minutes. Quartiles refer to whether the wash-trades are in the highest volume arranged to the lowest volume, with Quartile 4 being the highest trade volume and Quartile 1 being the lowest. Time period is from 16th September 2011 to 1st June 2012. p-values are shown in parentheses. Variable definitions are detailed in Table 1. *, **, *** represent significance at the 10%, 5% and 1% level.

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
$nonwash_t$	0.447	−0.186	2.2***	−0.199
	0.475	0.68	5.27e-05	0.424
constant	2.4e+04***	2.16e+04***	2.3e+04***	1.95e+04***
	8.06e-120	7.12e-89	9.49e-46	9.07e-58
adj r^2	−0.000166	−0.000283	0.0052	−0.000122
n	2.96e+03	2.94e+03	2.94e+03	2.96e+03

Panel B. Do wash trades correlate with on-chain transactions? This panel presents coefficients from a two-step Engel-Granger cointegration examining changes in non-wash trade volume to on-chain transaction volume.

Do Other Asset Markets Affect Wash Trading?

Method: VAR with S&P 500, Gold, VIX, EUR/USD (30-min intervals).

Findings:

- Wash trading declines when other asset classes are active.
- Suggests traders strategically avoid competition for attention.

Table 6 - Panel A. Do wash trades correlate with other asset movements? This panel presents coefficients from IRFs derived from VAR examining changes in wash trade volume $wash_t$ to other variables based on EURO-USD spot, Gold spot, SNP500 index and VIX. The prefixes represent each of the 4 assets respectively, and the suffixes - liq_t represents % change in liquidity, vol_t represents % change in realized volatility, $close_t$ represents % change in price, $tick_t$ represents % change in tick count and $volume_t$ represents % change in volume. The variables are seconds-level and accumulated to $t = 30$ minutes. Time period is from 26th June 2011 to 20th May 2013. Variable definitions are detailed in Table 1.

Lag	(1) % IRF of $wash_t$ to $eur\text{-}vol_t$	(2) % IRF of $wash_t$ to $eur\text{-}liq_t$	(3) % IRF of $wash_t$ to $eur\text{-}tick_t$	(4) % IRF of $wash_t$ to $eur\text{-}close_t$	(5) % IRF of $wash_t$ to $gold\text{-}vol_t$	(6) % IRF of $wash_t$ to $gold\text{-}liq_t$	(7) % IRF of $wash_t$ to $gold\text{-}tick_t$	(8) % IRF of $wash_t$ to $gold\text{-}close_t$
1	−199	−133	−260	−157	−212	−32.3	−171	−247
2	−105	−546	−3.88	−109	−123	7.88	126	−170
3	−254	−261	−199	3.11e+03	−94	−163	−247	−143
4	−47.8	−180	−30.2	−154	3.2e+03	2.92e+03	−173	−120

Does Media Attention Amplify Wash Trades?

Method: VAR with Google Trends (above/below median attention).

Findings:

- High media periods: faster impact of wash trades on real volume.
- Effects dissipate quickly—shorter-lived manipulation.
- Traders may exploit brief hype windows.

Table 7. Does media attention affect the effect of wash trades on market activity? This panel presents coefficients from IRFs derived from VAR examining changes in wash trade volume $wash_t$, non-wash trade volume $nonwash_t$, total trade volume $total_t$, liquidity liq_t, volatility vol_t. The variables are seconds-level and accumulated to $t =$ 30 minutes. They are then accumulated to weekly intervals. Weeks that do not have stationary data trends are dropped, thus, there are $n = 83$ points. *google* is a weekly datapoint and the median media popularity is based on whether the *google* for that week is higher or lower than the median. Columns (1)-(4) are for those below median media popularity, columns (5)-(8) are for those above median media popularity. Time period is from 26th June 2011 to 20th May 2013. Future time periods of $t+1$ to $t+10$ are shown and the sum is shown in the 11th row. Variable definitions are detailed in Table 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	% IRF of $total_t$ to $wash_t$	% IRF of $nonwash_t$ to $wash_t$	% IRF of $wash_t$ to $total_t$	% IRF of $wash_t$ to $nonwash_t$	% IRF of $total_t$ to $wash_t$	% IRF of $nonwash_t$ to $wash_t$	% IRF of $wash_t$ to $total_t$	% IRF of $wash_t$ to $nonwash_t$
	———**-Below median media popularity ———**				———**-Above median media popularity ———**			

Do Wash Traders Exploit Exogeneous Demand Shocks?

Method: IRF analysis around Pot Day (April 20, 2012, Silk Road event).

Findings:

- Wash trading rises before Pot Day, declines after.
- Reduced post-event impact on real volume.
- Suggests traders time manipulation around external demand surges.

	(1) % IRF of $total_t$ to $wash_t$	(2) % IRF of $nonwash_t$ to $wash_t$	(3) % IRF of $wash_t$ to $total_t$	(4) % IRF of $wash_t$ to $nonwash_t$	(5) % IRF of $total_t$ to $wash_t$	(6) % IRF of $nonwash_t$ to $wash_t$	(7) % IRF of $wash_t$ to $total_t$	(8) % IRF of $wash_t$ to $nonwash_t$
	——2 weeks before Pot Day——				**——2 weeks after Pot Day——**			
1	6.48e+04	7.79e+04			1.3e+04	1.32e+04		
2	−212	−197	−219	−143	−1.13e+03	−1.21e+03	−194	−9.34e+03
3	2.03e+04	4.24e+03	−6.98e+03	−2.7e+04	1.13e+04	1.14e+04	1.090e+05	874
4	−1.84e+03	−8.97e+03	4.03e+03	2.9e+03	−1.12e+03	−1.33e+03	−289	−1.26e+04
5	−957	−760	152	501	9.97e+03	1.05e+04	6.43e+04	795
6	1.01e+04	−7.46e+03	1.44e+04	6.27e+03	−1.3e+03	−1.43e+03	−365	−1.57e+04
7	−780	458	650	865	8.79e+03	9.66e+03	5.23e+04	698
8	−1.22e+03	1.24e+03	3.74e+03	3.52e+03	−1.53e+03	−1.43e+03	−461	−1.57e+04
9	−658	8.79e+03	2.92e+03	2.67e+03	7.89e+03	8.63e+03	3.4e+04	564

Wash Traders are Strategic - Legal, Detection, AI

Thank You! 🙏

For the full paper and appendix, visit:

hunterng.com

Questions or comments?

Email: hng@gc.cuny.edu

Thank you!

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