

# Detecting and Quantifying Crypto Wash Trading

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## Abstract

We introduce systematic tests exploiting robust statistical and behavioral patterns in trading to detect fake transactions on 29 cryptocurrency exchanges. Regulated exchanges feature patterns consistently observed in financial markets and nature; abnormal first-significant-digit distributions, size rounding, and transaction tail distributions on unregulated exchanges reveal rampant manipulations unlikely driven by strategy or exchange heterogeneity. We quantify the wash trading on each unregulated exchange, which averaged over 70% of the reported volume. We further document how these fabricated volumes (trillions of dollars annually) improve exchange ranking, temporarily distort prices, and relate to exchange characteristics (e.g., age and userbase), market conditions, and regulation.

**2012 ACM Subject Classification** Security and privacy → Cryptography

**Keywords and phrases** Bitcoin, Cryptocurrency, FinTech, Forensic Finance, Fraud Detection, Regulation

**Digital Object Identifier** 10.4230/OASICS.Tokenomics.2021.10

**Category** Extended Abstract

**Related Version** *Full Version*: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3530220](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3530220)

**Funding** This research was funded in part by the Ewing Marion Kauffman Foundation and National Science Foundation of China, and the authors have no affiliation with or research support from any cryptocurrency exchanges.

**Acknowledgements** The authors are especially grateful to Deeksha Gupta, Kose John, Evgeny Lyandres, and Tao Li for repeated discussions and detailed feedback. We also thank Marlene Amstad, Mykola Babiak, Kevin Dowd, Valeria Ferrar, Itay Goldstein, Hanna Halaburda, Angel Hernando-Veciana, Andrew Karolyi, Dongyongp Lee, Minhyuk Lee, Jiasun Li, Laura Xiaolei Liu, Roger Loh, Emmanouil Platanakis, Fahad Saleh, Amin Shams, Donghwa Shin, Rajeev Singhal, Baolian Wang, Shang-jin Wei, Wei Xiong, Scott Yonker and seminar and conference participants and reviewers at the Alibaba Group Luohan Academy Webinar, Australasian Banking and Finance Conference, Behavioral Finance/Corporate Finance/Digital Finance (BF/DF/CF) Seminar Group, Cornell University, Cowles Foundation for Research In Economics Conference on the Economics of Cryptocurrencies, 11th CSBF Conference (National Taiwan University), Cowles Foundation Economics of Cryptocurrencies (Macroeconomics) Conference, 1st Crypto and Blockchain Economics Research Conference, Durham University Department of Economics and Finance, Econometric Society World Congress (Bocconi University), 2021 Eastern Finance Association Annual Meeting, IIF International Research Conference & Award Summit, 13th International Risk Management Conference, Inaugural Machine Learning Conference: “Human Sovereignty and Machine Efficiency



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3rd International Conference on Blockchain Economics, Security and Protocols (Tokenomics 2021).

Editors: Vincent Gramoli, Hanna Halaburda, and Rafael Pass; Article No. 10; pp. 10:1–10:6

OpenAccess Series in Informatics



OASICS Schloss Dagstuhl – Leibniz-Zentrum für Informatik, Dagstuhl Publishing, Germany

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in the Law,” 18th Paris December Finance Meeting, Paris FinTech and Crypto Webinar, 60th Southwestern Finance Association Meeting, Sun Yat-sen University, 3rd Toronto FinTech Conference, Tsinghua University PBC School of Finance, 3rd UWA Blockchain and Cryptocurrency Conference, 11th Financial Markets and Corporate Governance Conference, European Financial Management Association Annual Meeting 2021, China International Conference in Finance 2021, 17th Asia-Pacific Association of Derivatives Annual Conference, World Finance Conference 2021, 2021 Financial Management Association Annual Meeting, 3rd International Conference on Blockchain Economics (Tokenomics2021), 2021 Global AI Finance Research Conference, Xi’an Jiaotong University, and the Zhongnan University of Economics and Law for helpful comments.

### 1 Crypto Wash Trading

The market capitalization of all cryptocurrencies exceeded 1.5 trillion USD in Feb 2021, and the total trading volume is 8.8 trillion USD in the first quarter of 2020 alone [6]. Both financial institutions and retail investors have significant exposure to the cryptocurrency industry.<sup>1</sup> Meanwhile, crypto exchanges, arguably the most profitable players in the ecosystem, remain mostly unregulated with less than 1% transactions taking place on regulated crypto exchanges in 2019 as we posted the first draft of the paper. In the process of vying for dominance in this lightly regulated market, some exchanges are suspected of gaining an advantage in ways ethically and legally questionable [11, 3]. One form of such market manipulation is Wash trading – investors simultaneously selling and buying the same financial assets to create artificial activity in the marketplace, which is known to distort price, volume, and volatility, and reduce investors’ confidence and participation in financial markets [1].

Against such a backdrop, we conduct the first academic study of wash trading and misreporting on cryptocurrency exchanges. By inspecting the distribution of trade size whose first significant digit should follow Benford’s law, should exhibit clustering at round numbers, and whose tail distribution is traditionally described by power law (Pareto-Levy law), we find that most unregulated exchanges wash trade (fabricating trades and acting as the counterparty on both sides to inflate volume).<sup>2</sup> We also estimate that unregulated exchanges on average inflate over 70% of the reported volumes in our sample. Furthermore, we provide suggestive evidence that the misreporting (generically referred to as wash trading) improves their ranking and prominence within the industry, relates to short-term price dispersion across exchanges, occurs more on newly established exchanges with smaller userbases, and has implications for the long-term industrial organization, development, and regulations.

While industry reports in 2018-2019 constitute whistle-blowers, their analyses are often imprecise, ad hoc, unscalable, and non-transparent [4]. Practitioners were unsure if wash trading only concerns a few specific exchanges with legal cases or was widespread; neither did they know how regulations play a role. Our goal is not to identify a specific wash trade, but to rigorously establish that wash trading is a rampant, industry-wide issue for the cryptocurrency market. We are among the earliest to provide evidence for the efficacy

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<sup>1</sup> Surveys reveal that 22% institutional investors have invested in cryptocurrencies [10] and by April 2019 9% of adults have owned Bitcoins in particular [2]. In the UK, 25% consumers could identify “cryptocurrency” and 3% had bought them [5]. Between 2016 and 2018, Bitcoin ownership increased from 3% to 5% [7]

<sup>2</sup> Wash trading is, according to the U.S. Commodity Exchange Act, “Entering into, or purporting to enter into, transactions to give the appearance that purchases and sales have been made, without incurring market risk or changing the trader’s market position.” Definition of wash trading from US Commodity Exchange Act can be found at [https://www.cftc.gov/ConsumerProtection/EducationCenter/CFTCGlossary/glossary\\_wxyz.html](https://www.cftc.gov/ConsumerProtection/EducationCenter/CFTCGlossary/glossary_wxyz.html)

of regulation in this industry, which has implications for investor protection and financial stability.<sup>3</sup> Our findings also likely have consequences for ongoing lawsuits and empirical research on cryptocurrencies which frequently reference transaction volumes. Finally, they serve as illustrations of the usefulness of statistical and behavioral principles for forensic finance, with regulatory implications for FinTech and beyond.

Wash trading on crypto exchanges warrants our attention for several reasons. First, crypto exchanges play essential roles in the industry, providing liquidity and facilitating price discovery just like traditional exchanges. Many crypto exchanges have expanded into upstream (e.g., mining) and downstream (e.g., payment) sectors, consequently wielding great influence as a complex of trading platforms, custodians, banks, and clearinghouses. Naturally, crypto exchanges constitute an anchoring point for understanding the ecosystem from academic, industrial, and regulatory perspectives. Second, because liquidity begets liquidity, crypto exchanges have strong economic incentives to inflate trading volumes to increase brand awareness and ranks on third-party aggregator websites or media (e.g., CoinMarketCap, CoinGecko, Bitcointalk, and Reddit), which in turn increases the exchanges' profits from transaction fees. Third, while wash trading is largely prohibited in most financial markets and developed economies [8], cryptocurrencies are particularly prone to wash trading, under limited regulatory oversight.

We collect cryptocurrency transaction information on 29 major exchanges from the proprietary database maintained by TokenInsight ([www.tokeninsight.com](http://www.tokeninsight.com)), a data provider who offers consulting, rating, and research reports for the cryptocurrency-related business. We adopt the definition of regulated exchanges from the state of New York, which has one of the earliest regulatory frameworks in the world.<sup>4</sup> We then use web traffic ranking as a proxy for brand awareness and reputation to further categorize unregulated exchanges for easy reference: "Tier-1" for exchanges ranking in the top 700 in the finance/investment section of SimilarWeb.com and "Tier-2" for the rest of unregulated exchanges on our data (all ranking outside top 960). Our data cover the period from 00:00 July 09th, 2019 (when TokenInsight started to collect transaction information from these exchanges) to 23:59 November 03rd, 2019 (the time we wrote the first draft). Our data also contain variables including aggregate trading volume, reputation metrics, and exchange characteristics such as exchange age. For each exchange, we examine several most widely recognized and heavily traded cryptocurrencies against US dollars (USD), including Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Ripple (XRP).

We are fully aware of the challenges of forensic finance and employ multiple approaches that have been successfully applied in numerous fields in sciences and social sciences and are shown to be unlikely affected by dispersed traders' strategies, exchange characteristics, or specificities of the asset class. To start, we examine the first significant digit for each

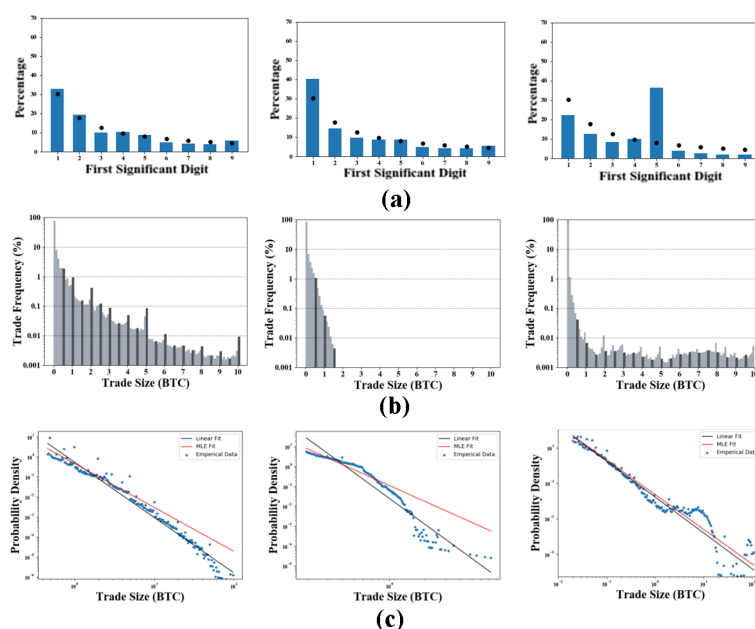
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<sup>3</sup> After we publicly circulated our study in late 2019, several ranking websites changed their matrices from purely volume-based to more sophisticated multi-dimensional ranking models, with at least one website doing so in response to our research finding. Regulators also increased scrutiny on wash trading behavior: Canada-based crypto trading platform Coinsquare has agreed to settle with the Ontario Securities Commission for wash trading charge; Coinbase was fined before IPO for wash trading several years earlier.

<sup>4</sup> Regulated exchanges are issued BitLicenses and are regulated by the New York State Department of Financial Services. Bitlicence carries some of the most stringent requirements. Our main results are robust to alternative classifications of regulated exchanges. As of June 2020, NYDFS has issued licenses to 25 regulated entities, six of which provide crypto exchange service. They are Itbit, Coinbase, Bitstamp, Bitflyer, Gemini, and Bakkt (futures and options only). Further information can be found at: [https://www.dfs.ny.gov/apps\\_and\\_licensing/virtual\\_currency\\_businesses/regulated\\_entities](https://www.dfs.ny.gov/apps_and_licensing/virtual_currency_businesses/regulated_entities). (Last accessed: July 3, 2020)

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transaction and check its frequency distribution on each exchange against Benford’s law – the well-known statistical benchmark in natural sciences and social sciences and widely used to detect frauds in macroeconomic, accounting and engineering fields. We next exploit a classical behavioral regularity in trading: clustering at certain transaction sizes. Round numbers are routinely used as cognitive reference points in individuals’ decision-making. Rounding is commonly observed in finance, including analysts’ forecasts or LIBOR submissions. Our third test explores whether the distributions of observed trade size have fat tails characterized by the power law as seen in traditional financial markets and other economic settings. We fit a power-law distribution and estimate the exponent parameters in addition to graphically inspecting the tail distributions on a log-log scale. We consistently find anomalous trading patterns only on unregulated exchanges, with Tier-1 exchanges failing more than 20% of the tests and Tier-2 exchanges failing more than 60%. The findings remain robust when under joint hypothesis tests.



■ **Figure 1** First-significant-digit, Trade-size Clustering, and Tail Distribution of Trade Size. The figure demonstrates the BTC/USD distribution drawn from sample exchanges compared with the benchmarks. Three exchanges are shown in the figure, one from each category (regulated exchange-left, Tier 1 unregulated exchanges-center, Tier 2 unregulated exchanges-right). Panel (a) are the first-significant-digit distributions and comparisons with Benford’s law. Black dots represent distributions derived from Benford’s law. Distributions of trading data are reported in bar charts. Panel (b) shows the clustering effect in trade-size distributions histograms on exchanges. In each histogram, we highlight every 5th and 10th bin to illustrate the clustering effect around round trade sizes. Panel (c) displays tails of trade-size distributions and the fitted power-law lines on log-log plots. Fitted power-law lines are plotted with parameters estimated by Ordinary Least Square (OLS) and Maximum Likelihood Estimation (MLE), shown in black and red lines, respectively. Blue dots represent empirical data points for trade-size frequencies.

As Figure 1 shows, the example unregulated exchanges deviate from all three benchmarks, Benford's Law, clustering effect, and power law, significantly. This holds for all four currency pairs on majority unregulated exchanges. While current business incentives and ranking systems fuel the rampant wash trading on unregulated exchanges, the regulated exchanges, having committed considerable resources towards compliance and license acquisition and facing severe punishments for market manipulation [9], conduct little wash trading.

Besides identifying exchanges that wash trade, we quantify the fractions of fake volume by taking advantage of the rounding regularity. A benchmark ratio (based on calculations from the regulated exchanges) of unrounded trades to authentic trades with round sizes are calculated. The extra unrounded trades above the ratio naturally constitute wash trades on unregulated exchanges. We find that the wash trading volume on average is as high as 77.5% of the total trading volume on the unregulated exchanges, with a median of 79.1%. In particular, wash trades on the twelve Tier-2 exchanges are estimated to be more than 80% of the total trade volume, which is still over 70% after accounting for observable exchange heterogeneity. Combined with the reported volumes in Helms' article [6], these estimates translate into wash trading of over 4.5 Trillion USD in spot markets and over 1.5 Trillion USD in derivatives markets in the first quarter of 2020 alone. To mitigate the influence of heterogeneity of traders and algorithmic trading strategies across various exchanges, we validate the roundness-ratio estimation and conduct a number of robustness tests to allay selection concerns.

■ **Table 1** Aggregated Wash Trading Percentage. The table presents the simple averaged and volume-weighted wash trading percentage for each exchange category.

	Wash Trade Percentage Without Control Variables		Wash Trade Percentage With Control Variables	
	Equal-weighted Average	Volume-weighted Average	Equal-weighted Average	Volume-weighted Average
Unregulated	70.85	77.50	60.96	71.43
Unregulated Tier-1	53.41	61.86	46.95	63.62
Unregulated Tier-2	81.76	86.26	70.96	76.96

We then study exchange characteristics that correlate with wash trading and investigate the impact of wash trading on market outcomes such as exchange ranking. In addition, we obtain proprietary data on historical ranking and trading volume information from CoinMarketCap and show that exchange ranking depends on wash trading (70% wash trading of total reported volume moves an exchange's rank up by 46 positions). We find that an exchange's wash trading is positively correlated with its cryptocurrency prices over the short term. We also find that exchanges with longer establishment history and larger userbase wash trade less. Less prominent exchanges, in contrast, have short-term incentives for wash trading without drawing too much attention. Moreover, wash trading is positively predicted by returns and negatively by price volatility.

To sum up, as the first comprehensive study of the pervasive crypto wash trading, our paper not only provides a cautionary tale to regulators around the globe but also reminds the readers of the disciplining or screening effects of regulation in emerging industries, the importance of using wash-trading-adjusted volume in certain empirical studies, and the utility of statistical tools and behavioral benchmarks for forensic finance and fraud detection. We offer a concrete set of tools for exchange regulation and third-party supervision in the crypto market for convincingly exposing wash trading and potentially combating non-compliant exchanges. Admittedly, the tests we introduce are not exhaustive, and wash traders may

adjust their strategies in response to these tests. Our tools nevertheless serve as valid detection of wash trading historically and thus make fabrications more difficult and facilitate regulatory resource allocation.

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