Cryptocurrency Pump-and-Dump Schemes

Tao Li, Donghwa Shin, and Baolian Wang*

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Abstract

We document numerous occurrences of pump-and-dump schemes (P&Ds) targeting cryptocurrencies, which tend to trigger short-term episodes that feature significant increases in prices, volume, and volatility, followed by quick reversals. The evidence we document, including price run-ups before P&Ds start, suggests the possibility of wealth transfers from outsiders to insiders. Our findings based on wallet-level data are consistent with the reasoning that gambling preferences, overconfidence, and naïve reinforcement learning help explain P&D participation. Finally, exploiting two natural experiments in which exchanges altered P&D policies, we find evidence consistent with the idea that P&Ds contribute to reduced cryptocurrency liquidity and lower prices.

JEL classification: G14, G18, G28, G41

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* Shin is from the University of North Carolina at Chapel Hill, Kenan-Flagler Business School, Email: Donghwa_Shin@kenan-flagler.unc.edu, Phone: 609-613-7699. Li is from the University of Florida, Warrington College of Business, Email: tao.li@warrington.ufl.edu, Phone: 352-392-6654. Wang is from the University of Florida, Warrington College of Business, Email: baolian.wang@warrington.ufl.edu, Phone: 352-392-6649. We thank the editor, Hendrik Bessembinder, and two referees for their valuable feedback. We have benefited greatly from comments and suggestions made by Vikas Agarwal, Brad Barber, Natalie Bachas, Nicholas Barberis, Kent Daniel, Itzhak Ben-David, Utpal Bhattacharya, Justin Birru, Patrick Bolton, David Brown, Markus Brunnermeier, Chris Burniske, Will Cong, Vyacheslav Fos, Simon Gervais, Kathleen Weiss Hanley, Campbell Harvey, Byoung Hwang, Jennifer Huang, Robert Jarrow, Wei Jiang, Lawrence Jin, Andrew Karolyi, Jiasun Li, Ye Li, Stefan Nagel, Andy Naranjo, David Ng, Mahendrarajah Nimalendran, Jun Pan, Jay Ritter, Harley Ryan, Harald Uhlig, Yizhou Xiao, Wei Xiong, David Yermack, Motohiro Yogo, Scott Yonker, and seminar participants at the U.S. Securities and Exchange Commission, the Cheung Kong Graduate School of Business, Cornell University, Fudan University (Fanhai), Korea University, Princeton University, Renmin University, the Shanghai Advanced Institute of Finance, the University of South Florida, the AEA, the LSE Paul Woolley Centre Conference, the CBER Conference, the Crypto Day Conference (Georgetown University), the GSU FinTech Conference, the University Blockchain Research Initiative Conference (UC Berkeley), the ABFER, the Annual Symposium in Financial Economics (ABFER, CEPR and CUHK), the Chicago Financial Institutions Conference, the CICF, the China Fintech Research Conference (Tsinghua University), and the Toronto FinTech conference. We thank Yiming Chen, Chase Maxwell, Gunsu Son, Chuyi Sun, Sishun Wang, Zirui Wang, Wei Yang, and Jiawei Yu for their excellent research assistance. All errors are our own. Shin acknowledges financial support from the Kenan Institute.

I. Introduction

This paper studies cryptocurrency "pump-and-dump" schemes (P&Ds). A P&D, more generally, is a form of price manipulation that involves artificially inflating the price of a cheaply purchased asset before selling it at a higher price. Once the asset is "dumped," its price falls, and some investors lose money. Such schemes were observed in microcap stocks (e.g., Aggarwal and Wu (2006)) and have recently become popular in the cryptocurrency market (Shifflett and Vigna (2018)). We focus on cryptocurrency P&Ds because, while the U.S. Securities and Exchange Commission (SEC) deems P&Ds illegal in the stock market, there is little or no regulation of P&Ds in the cryptocurrency market.[1] In this paper, we aim to understand how P&Ds work in the cryptocurrency space and assess the consequences of P&D activities.

In the cryptocurrency market, P&Ds are often initiated through "pump groups" over encrypted messaging apps such as Telegram. Our research indicates that a typical pump group consists of two parties: a "manipulator" who coordinates P&Ds, and investors who are invited to participate as members of the channel. To attract investors, manipulators might advertise such schemes on social media platforms. A Telegram channel operator can post messages for other members to read. For a planned pump, the operator would announce a target date, time, and exchange, usually at least one day in advance. According to our data, however, these manipulators usually do not disclose the identity of the targeted cryptocurrency until the scheduled time. Members typically receive multiple reminder messages before the announcement of the cryptocurrency symbol. As we argue in this paper, a typical cryptocurrency P&D seems to last only several minutes, leaving little time for non-members to participate.

[1] Many cryptocurrencies are difficult to justify as investment or consumer products and do not fall easily under existing securities or consumer protection laws. Regulating cryptocurrencies potentially also requires greater global coordination than when regulating other assets because they are typically traded globally.

Recent studies have documented various forms of market manipulation involving cryptocurrencies, including price manipulation (e.g., Griffin and Shams (2020)) and wash trading (e.g., Cong, Li, Tang, and Yang (2023)), as well as the use of cryptocurrencies in illicit activities (e.g., Foley, Karlsten, and Putnins (2019)). Given this evidence and the increasing adoption of cryptocurrencies as investment products, cryptocurrency P&D schemes merit critical research attention. In addition, our setting provides several advantages for investigating P&Ds that the stock market lacks. First, in the cryptocurrency market, a typical P&D episode lasts only several minutes, while such an episode in the stock market frequently lasts months (Aggarwal and Wu (2006), Hackethal, Leuz, Meyer, Muhn, and Soltes (2019)). Many other factors can cloud inferences when pumps last that long.

Second, there is typically no false information release or company action associated with a P&D in the cryptocurrency market, reducing the occurrence of information- or action-based manipulation (Allen and Gale (1992)).[2] In the stock market, P&Ds are often associated with the release of false information or other actions (Aggarwal and Wu (2006), Putnins (2012), Hackethal et al. (2019)). By contrast, most of the Telegram channels in our sample include the word "pump" in their aliases, and members likely understand that P&Ds involve no news on fundamentals.

In trade-based price-manipulation theories, where a manipulator cannot act in ways other than buying and selling assets, a manipulator needs first to buy a target asset to "pump" its price (Allen and Gale, (1992)). As outside investors follow, the manipulator can sell at a higher price to make profits. Manipulators can profit only if the price impact is greater when they buy than when

[2] Allen and Gale (1992) classify manipulation into information-, action-, or trade-based manipulation. The first type relies on spreading false information (Enron), the second on non-trade actions that can affect stock prices (such as a purported takeover bid), and the third on direct manipulation of stock prices through trading. Access to private information can both generate incentives and enable insiders to manipulate asset markets through strategically distorted announcements (Benabou and Laroque (1992)). The cryptocurrency P&Ds we study in this paper are not associated with company information releases or other actions and, therefore, cannot be explained by information- or action-based manipulation theory.

they sell; otherwise, this strategy is self-defeating (Friedman (1953)).[3] Our findings suggest that other investors' purchases, instead of the manipulators' purchases, are the likely drivers behind the large price increases. These findings diverge from an assumption that underlies existing trade-based manipulation theories, according to which manipulators must buy to increase asset prices, implying the presence of a new type of manipulation beyond those considered by Allen and Gale (1992).

Third, identifying P&Ds appears to be easier in the cryptocurrency market than in stock markets. The literature has focused on studying stock P&Ds that were investigated on an ex-post basis by regulators (Aggarwal and Wu (2006), Hackethal et al. (2019)) or on the "stock pools" of the 1920s, which perhaps represent the most infamous case of alleged stock manipulation. The ex-post investigated cases may not be representative, and the existing literature shows that "stock pools" engage in informed trading rather than manipulation (e.g., Mahoney (1999), Jiang, Mahoney, and Mei (2005)). In the cryptocurrency market, by contrast, manipulators often organize pump groups and disclose their pump plans in real time using encryption-enabled messaging apps, which allow them to hide their identities. This feature enables us to identify a sample of P&Ds, pinpoint their timing, and conduct detailed analyses.

Our findings reveal several patterns that indicate how pump groups choose their target cryptocurrencies. First, they target a small number of exchanges that lack or have weak "Know Your Customer" requirements. These target exchanges also list many cryptocurrencies, perhaps reflecting the fact that pump organizers need to hide the identities of their target currencies (but

[3] Some studies show that such a strategy can be profitable, as it is when investors cannot distinguish between informed trading and a manipulator and believe it is likely that the manipulator is informed (Allen and Gale (1992)), when price momentum enables a manipulator to establish a price trend and then to profit from trading against it, or when investors exhibit the disposition effect and are reluctant to sell plummeting assets (Mei, Wu, and Zhou (2004)). Jarrow (1992) and Huberman and Stanzl (2004) derive conditions in which price manipulation does not occur, and both studies show that market-manipulation strategies can exist under reasonable conditions.

not the exchanges) until they make scheduled announcements. Second, differing from stock markets, where pumpers typically target small stocks, cryptocurrency pumpers often target a wide range of cryptocurrencies, some of which are large, although not as large as Bitcoin and Ethereum. Many target cryptocurrencies in our sample have a market capitalization that is comparable to that of medium-sized CRSP stocks. We also find that pumped cryptocurrencies are more likely to be targeted repeatedly but predicting the next target is difficult. Third, larger pump groups are more likely to target large and more liquid cryptocurrencies, and organizers of larger pump groups also tend to earn higher profits.

Using a sample of 500 hand-collected P&Ds that were carried out on three major centralized exchanges (CEXs), we document several stylized facts. First, we find that following P&D announcements, prices, volume, and volatility of pumped cryptocurrencies increase significantly. On average, prices increase more than 25%, while trading volume increases more than 100-fold. After an hour, though, most of the initial effects disappear. Nonetheless, our analysis suggests significant aggregate P&D-related trading volume. From ten minutes before a pump starts to 30 minutes after, the total trading volume in our sample P&Ds is around $300 million. On average, trading volume on a P&D date accounts for 6% and 50% of the total volume, respectively, within a window of -100 days to +100 days around P&Ds that occur on the CEXs and PancakeSwap, a leading decentralized exchange (DEX).

The above findings, although stronger for smaller cryptocurrencies, hold even for large cryptocurrencies. We sort all pumped cryptocurrencies on the CEXs into quintiles by market capitalization. The average (median) market capitalization of the largest quintile is $144 million ($68 million), which is comparable to the median market capitalization of CRSP stocks during our sample period. Even among this group, on average prices increase 18% and trading volume increases 114 times. We find qualitatively similar patterns when examining 1,496 P&Ds that occurred on PancakeSwap.

We also document that prices of pumped cryptocurrencies typically begin rising several minutes before a P&D starts. The average price run-up is around 5% for P&Ds on the CEXs and 20% for P&Ds on PancakeSwap, at abnormally high volumes, likely reflecting the fact that pump-group organizers can buy pumped cryptocurrencies in advance.

Reading related messages posted on social media, we also find that some pump-group organizers offer premium memberships to allow certain investors to receive pump signals before others do. We deem investors who buy in advance "insiders" and the rest "outsiders." We estimate that during our sample period, insiders realize large returns, ranging from 18% on the CEXs to 152% on PancakeSwap, and make one Bitcoin (about $10,000) and 2.9 Binance Coin (about $1,300), respectively, from an average P&D on the CEXs and PancakeSwap. Despite their short duration of only a few minutes, these P&Ds seem to result in considerable insider profits, given that thousands occur per year. The wealth transfer between outsiders is perhaps higher, as most abnormal trading volume likely occurs between them.

The quick reversal that occurs during a P&D suggests that an outside investor needs to buy and sell very quickly to make a profit. Our analyses show that, on average, only investors who buy in the first 20 or 30 seconds after a P&D begins can earn a profit, and they can do so only if they do not hold their cryptocurrencies for long. We also find that some outsiders receive pump signals systematically earlier than other outsiders. All these findings make it puzzling as to why outsiders, especially those who receive signals systematically later, are willing to participate in P&D schemes.

We conjecture that one possible explanation comes from P&Ds attracting overconfident investors who believe that they can time the market more accurately than others can (Scheinkman and Xiong (2003), Daniel and Hirshleifer (2015)). In other words, they think that they can take advantage of others by riding the pump but they may end up losing money. Another mechanism that might be involved is investors' gambling preferences. The short-term returns on pumped cryptocurrencies are often high and salient, and investors may overweight the probability that they will obtain such returns in their decision-making (Barberis and Huang (2008), Barberis (2013), Bordalo, Gennaioli, and Shleifer (2012, 2013)). Utilizing our PancakeSwap data, which include investor identifiers, we find evidence consistent with both conjectures. Conditional on participation, investors who achieve higher past P&D performance are more likely to participate in future P&Ds and lose more money when doing so. We interpret these results as consistent with naïve reinforcement learning (Kaustia and Knupfer (2008), Chiang, Hirshleifer, Qian, and Sherman (2011), Anagol, Balasubramaniam, and Ramadorai (2021)).

Are there, in addition to wealth transfers, any other consequences of P&Ds? Although buy-and-hold investors who maintain reasonably long horizons may not be directly affected, exposure to scandals may erode investor trust, as documented in traditional financial markets (Giannetti and Wang (2016), Gurun, Stoffman, and Yonker (2018)). We investigate the economic consequences of P&Ds using two natural experiments in which two cryptocurrency exchanges changed their policies toward P&Ds. On November 24, 2017, Bittrex announced that it would ban P&Ds. On October 10, 2018, Yobit announced that it would pump cryptocurrencies listed on the exchange randomly. These changes likely affected only the cryptocurrencies traded on the event exchanges, not those traded on other exchanges.

We employ a difference-in-differences approach and find evidence consistent with the reasoning that P&Ds contribute to reduced cryptocurrency liquidity and lower prices. After the Bittrex ban, prices (volumes) of cryptocurrencies listed on Bittrex increased by 6.3%–15.1%

(22.5%–36.0%) relative to those of other cryptocurrencies. In contrast, following Yobit's pump scheme, the prices (volumes) of cryptocurrencies listed on Yobit dropped by 12.1%–15.5% (34.3%–44.3%). For cryptocurrencies that are cross-listed on Bittrex and other exchanges, the Bittrex ban was followed by greater volumes on Bittrex than on other exchanges, while the Yobit pump scheme was followed by lower volumes on Yobit than on other exchanges. Such a volume redistribution is consistent with the notion that the average investor may be averse to P&Ds.

Our paper contributes to the price-manipulation literature. It is difficult for purely trade-based manipulation to be profitable (Friedman (1953)). Profitable manipulation often involves the release of false information or trading in an underlying market to benefit large derivatives positions. For the latter, if manipulators take large positions in derivatives contracts, they can make profits even if they lose in the underlying market.[4] The cryptocurrency P&Ds we study in this paper, however, do not involve the release of false information or derivatives trading. When these schemes work it seems to be because manipulators encourage other investors to buy cryptocurrencies and drive up their prices. Therefore, we believe that cryptocurrency P&Ds represent a new type of manipulation.

Our findings also contribute to the burgeoning literature on the application of blockchain technology in finance.[5] Most of these studies focus on blockchain system design or blockchain-based financing. Diverging from all these papers, we study cryptocurrency P&Ds. Ours is one of the first academic studies to leverage wallet information from DEXs to analyze investor behavior

[4] Price manipulation has been documented in the stock market (Aggarwal and Wu (2006), Ben-David, Franzoni, Landier, and Moussawi (2013), Ni, Pearson, and Poteshman (2005), Comerton-Forde and Putnins (2015), Henderson, Pearson, and Wang (2020)); derivatives markets, including the equity and index options markets (Griffin and Shams (2018)); futures markets (Merrick, Naik, and Yadav (2005)); and the LIBOR market (Snider and Youle (2010)). Manipulation has also been documented in emerging stock markets, such as in Pakistan and China (Khwaja and Mian (2005), Chen, Gao, He, Jiang, and Xiong (2019)).

[5] The literature is too voluminous to cite. Notable studies include Cong and He (2019), Howell, Niessner, and Yermack (2020), Griffin and Shams (2020), Foley et al. (2019), Makarov and Schoar (2020), and Liu and Tsyvinski (2021). See also Part A1 of the Internet Appendix for a discussion of academic research on cryptocurrency trading.

in the cryptocurrency market. With the growing popularity of trading on DEXs, we expect more studies to come.

Several concurrent papers also study cryptocurrency P&Ds. Xu and Livshits (2019) study how P&D events can be predicted, and Kamps and Kleinberg (2018) study techniques designed to detect pumps ex post. Hamrick, Rouhi, Mukherjee, Feder, Gandal, Moore, and Vasek (2019) examine which factors affect returns on pumped cryptocurrencies. Their main finding is that a cryptocurrency's market capitalization is the most important factor, consistent with our finding that P&Ds are associated with a larger increase in illiquid cryptocurrencies' prices than those of liquid cryptocurrencies. We use the actual timing of each P&D. Differing from us, however, Hamrick et al. (2019) infer the timing of P&Ds based on significant price changes. Such inferences may overestimate the effects of P&Ds. In addition, we collect our cryptocurrency trading data on a trade-by-trade basis from the target exchanges, while Hamrick et al. (2019) use data at five-minute intervals and Xu and Livshits (2019) use data at one-hour intervals. Both of their datasets are aggregated across *all* exchanges. As we show later in this paper, most P&D effects occur in seconds and concentrate on target exchanges. Data at five-minute or one-hour intervals or data aggregated across exchanges are unlikely to capture the effects accurately. The granularity of our data enables us to pin down the effects of P&Ds more accurately.

Dhawan and Putnins (2023), using very similar CEX price and volume data, confirm our findings on price and volume patterns around P&Ds. They test investors' motives for participating in P&Ds using market-level or pump-level proxies.[6] Much like us, they also provide interpretations based on overconfidence and gambling preferences. As Dhawan and Putnins (2023) acknowledge, however, it is challenging to test investors' motives for participating in P&Ds without granular

[6] Our paper was first posted on the Social Science Research Network (SSRN) on October 23, 2018, whereas the initial version of Dhawan and Putnins (2023) was posted on the SSRN on September 24, 2020 (https://ssrn.com/abstract=3670714).

individual-level data. Instead, we leverage investor-wallet-level trading data obtained from a blockchain to conduct more direct tests. We find that, in addition to succumbing to overconfidence and gambling preferences, some P&D participants exhibit trading behavior that is consistent with naïve reinforcement learning, resulting in repeat participation. We also examine market reactions to the Bittrex P&D ban and the Yobit pump scheme, which those studies on cryptocurrency P&Ds do not study.

Our study could also inform the development of cryptocurrency regulations. First, our findings surrounding the Bittrex ban and the Yobit pump scheme are consistent with the notion that P&Ds may generate negative externalities. Second, price run-ups before P&Ds suggest the possibility of insiders taking advantage of outsiders. Third, we find that the number of Bittrex P&Ds dropped sharply after the exchange announced to ban P&Ds, suggesting that banning P&Ds is technologically feasible. An exchange may be able to distinguish itself by preventing manipulation. Even if one thinks of the space in which cryptocurrency P&Ds are carried out as a casino, she may still prefer to see transparent rules. Moreover, the cryptocurrency market is perhaps not a socially optimal venue for such amusement.

Our paper also sheds light on manipulation and financial fraud. Our findings are consistent with the reasoning that some investors knowingly participate in P&Ds and may be willing to pay prices that exceed fundamentals, given the rapid price increases around P&Ds, because they believe they can sell to less sophisticated investors at higher prices. A similar mechanism may also play a role in other fraudulent schemes, such as Ponzi schemes and pyramid schemes. Investors in these fraudulent schemes may not choose to exit immediately after learning about them if they underestimate the probability that they will end in the last round. Our findings also relate to the literature on how social interactions affect asset prices (Han, Hirshleifer, and Walden (2022), Pedersen (2022)). Related to P&D events is the "meme" investment phenomenon (Bradley, Hanousek, Jame, and Xiao (2024), Li, Shin, Sun, and Wang (2022)). Both our findings and the meme investment phenomenon underscore the important role that social media play in retail investor coordination, a topic that deserves in-depth research.

II. Institutional Background on P&D Schemes

In the cryptocurrency market, operators of P&Ds often organize "pump groups" using encrypted messaging apps such as Telegram. Telegram is considered one of the most heavily encrypted messaging platforms, and users can use aliases. These features make it difficult to track who is involved in P&D schemes.

Another unique feature of Telegram is that it allows operators to create channels to broadcast messages. Members can join a channel free of charge and access the entire message history. Each message, timestamped to the second, has its view counter that shows how many users have viewed it. To attract participants, P&D operators often advertise their pump groups on social media platforms, such as Reddit and BitcoinTalk, and they often urge their participants to do the same.[7]

Figure 1 illustrates how a typical P&D works. On July 4, 2018, a pump group called "Big Pump Signal" announced that they would pump a cryptocurrency at 7 p.m. Coordinated Universal Time (UTC; in this case, the UTC time was 3 p.m. EDT) on Binance. One and a half hours before the pump, the operator of the Telegram channel reminded its more than 70,000 followers of the

[7] See Figure 1 for an example in which the P&D operator urged the participants to "spreading news" on social media. While some P&D organizers may announce P&Ds to attract social media followers and generate income from those followers, we find no evidence that such a motive is of first-order importance during our sample period.

event and encouraged them to reach out to other investors. The members were reminded again 34, 20, 10, 5, and 2 minutes before the pump.

[Insert Figure 1 here.]

At 6:59:57 p.m. UTC, three seconds before the scheduled time, the ticker of the target cryptocurrency, NXS (Nexus), was announced.[8] Telegram's record of the event shows that about 28,800 followers viewed the message. The price of Nexus jumped 52.0% immediately before plummeting 24.5% from the peak after ten minutes. During this time, 4,153 trades worth about $1.5 million were executed, compared with minimal trading during the hour before the announcement.[9]

We find that not all group members obtain pump signals at the same time. Tiered access to pump signals occurs commonly in many groups. High-ranking members may be sent a signal several seconds earlier than others receive it. In some channels, members can pay a fee to become VIP members. The operators may also incentivize members to invite new members to join by offering premium memberships. For example, "Mega Pump Group," a pump group with more than 15,000 followers on Telegram, sends pump signals 0.5 (3.5) seconds earlier to members who have successfully invited at least four (50) members to join. The existence of VIP members is not necessarily common knowledge, as we observe in some complaints about front-running on social media platforms.[10]

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[8] P&Ds on DEXs follow a similar process. In addition to revealing token tickers and names, pump organizers usually also reveal contract addresses. We provide an example in Part A2 of the Internet Appendix.

[9] We provide details on cryptocurrency trading in Part A1 of the Internet Appendix.

[10] In Figure A2 of the Internet Appendix, we present Reddit snapshots and their corresponding website links as evidence of the existence of VIP members in some P&D channels as well as complaints about front-running. Reddit is considered a popular platform where investors discuss cryptocurrency-related topics, including those about P&Ds. For example, one P&D channel charged VIP members 0.038 Bitcoin for five months plus one month of free membership. Some Reddit users, recognizing their disadvantage in participating in P&Ds, have expressed frustrations with organizers. For instance, the user posting as "humbrie" states, "You may have a lucky shot, but actually you will get burned heavenly as a normal group member. The leaders have always an advantage over you and the other lemmings." Similarly, the user posting as "xXdDrifterXx" remarks, "Very true. Unless you were the one who creates the group, better stay away from invitations from strangers you meet on the internet. If you do join, you deserve the hard lesson you will get." In addition to complaining

III. Data

We obtained a list of P&D events, cryptocurrency trading data, and additional cryptocurrency-level variables from several sources. We discuss these datasets in detail below.[11]

A. P&D events

We collected data manually in two separate batches: first in September 2018 on CEXs and then in January 2022 on DEXs. We first collected a list of pump groups from Reddit and BitcoinTalk, two popular cryptocurrency message boards. Pump groups typically advertise on these boards to attract participants. For completeness, we also conducted an internet search for additional advertisements posted by such groups. With CEXs, we initially identified 210 Telegram groups that engage in P&Ds, 129 of which were still accessible as of September 2018. Forty-nine of the 129 groups did not initiate any pumps. With DEXs, we initially identified 151 Telegram groups, 134 of which were accessible as of January 2022. Eleven of them did not initiate any pumps.[12]

We read all messages posted on these Telegram channels. For each P&D event, we collected the target cryptocurrency's identifiers, target exchange, announcement time, initially scheduled time, number of viewers of the announcement, and target return if available. All timestamps in this paper are based on the UTC scale. In cases where multiple channels target a

about organizers, some users also criticize their would-be associates, such as VIP members. For example, the user posting as "SkyDefender" asserts, "So who won? Admin and his friends/family who bought earlier and their sell order was ready." Another user posting as "TNGSystems" remarks, "By this point, the admins & insiders have already set their SL orders at, you know, maybe current price+150%. The admin & insiders orders are filled and they walk away with huge profits."

[11] Separate data sources may use distinct cryptocurrency identifiers, and we matched them manually by cryptocurrency symbol and name. In Part A3 of the Internet Appendix, we discuss the details relating to matching cryptocurrencies across multiple datasets.

[12] We also identified a small number of Discord pump groups. We do not include them in our sample because Discord groups are generally smaller and we would have had to be invited to access them.

cryptocurrency at the same scheduled time, we use the earliest announcement time for our analysis. As we document later in the paper, the sharp changes in cryptocurrency price and trading volume occur around the time of an announcement, indicating that our data on P&D announcement times are accurate.

For CEXs, we identified 3,412 P&D announcements from 80 Telegram channels from May 2017 through August 2018. For DEXs, we identified 2,404 P&D announcements from 123 Telegram channels from September 2020 through December 2021. Many P&Ds are coordinated across more than one channel. The total number of unique P&Ds on CEXs is 1,747, and the corresponding number on DEXs is 1,496. The large number of P&D events suggests that P&Ds occur frequently in the cryptocurrency market.[13]

The targeted CEXs include Binance, Bittrex, Yobit, Cryptopia, HitBTC, Poloniex, and CoinExchange. We restrict our attention to the 1,040 P&Ds targeting cryptocurrencies on Binance, Bittrex, and Yobit. This choice is motivated by the small number of P&Ds on HitBTC, Poloniex, and CoinExchange as well as by the lack of available trading data from Cryptopia.[14] Binance, Bittrex, and Yobit were among the largest cryptocurrency exchanges in the world. As of September 2018, they were ranked first, 36th, and 27th by trading volume, respectively, on CoinMarketCap. All the DEX P&Ds took place on PancakeSwap.

[13] Some CEXs may have incentives to organize P&Ds because such activities increase trading volume and profits, and the exchanges have abundant resources at their disposal (e.g., client funds) to pump cryptocurrencies. It is, however, challenging to identify exchange-organized P&Ds because exchanges may not want to publicize their pump activities. Yobit is an exception. On October 10, 2018, Yobit announced on its website and official Twitter page that it would pump cryptocurrencies listed on the exchange randomly. This is one of the two events that we use in Section V to gauge the economic consequences of P&Ds. While it is difficult to collect the entire history of Yobit's planned pumps, in Figure A9, we provide several screenshots of Yobit's P&D activities.

[14] In our sample, only four announcements target HitBTC, while there are 54 and 44 announcements, respectively, for Poloniex and CoinExchange. We collected information on 690 P&Ds on Cryptopia. Cryptopia did not, however, allow third parties to download tick-level trading data that were older than one week. To the best of our knowledge, no data provider has collected its trading data either, potentially as a result of Cryptopia's small size. Before shutting down in January 2019 after suffering a hack that stole around $16 million, Cryptopia was ranked 77th among all cryptocurrencies, according to CoinMarketCap.

Our evidence supports the notion that the targeted CEXs were not chosen randomly. First, none of the targeted exchanges imposed "Know Your Customer" requirements. Another common feature of these three exchanges is that they all listed a reasonably large number of listed cryptocurrencies. Based on data from CoinAPI, 147, 204, and 1,261 cryptocurrencies were involved in at least one trade in August 2018 on Binance, Bittrex, and Yobit, respectively.[15] Based on the number of listed cryptocurrencies, these three exchanges were all among the ten largest exchanges at that time. As pump groups conduct pumps regularly and do not switch exchanges frequently, they are more likely to target exchanges with sufficiently many prospective targets, where they can hide the identity of their target cryptocurrency until they make pump announcements.

Similarly, our evidence suggests that PancakeSwap was not chosen at random either. Because a typical P&D scheme concludes within several minutes, a viable DEX venue needs to achieve high transaction speed at low cost (charging gas fees to miners and transaction fees to liquidity providers). PancakeSwap features both high speeds (the average block time on its underlying blockchain, Binance Smart Chain, is roughly 3 seconds) and low costs (a gas fee of approximately $0.5 per trade and a 0.25% transaction fee).[16] In contrast, Uniswap, another popular DEX, achieves much lower transaction speed and involves higher costs.[17] Indeed, we did not find any P&Ds on Uniswap.

[15] We thank Amin Shams for providing us with these data.

[16] In February 2022, Binance Smart Chain rebranded to BNB Chain. We use Binance Smart Chain in our setting as the name change occurred after our sample period ended.

[17] According to Ethereum.org, on average a block is created in 12–14 seconds in the Ethereum blockchain where Uniswap is deployed. In 2021, the average token swap-related gas fee on Uniswap was higher than $38. We provide additional details in Part A4 of the Internet Appendix.

B. Trading data

We obtained trade-by-trade data on cryptocurrencies listed on Binance, Bittrex, and Yobit from two sources. For Binance cryptocurrencies, we downloaded data using its public application programming interface (API). Binance's API enabled us to retrieve the entire history of cryptocurrency trading data, but the APIs provided by Bittrex and Yobit allow access only to the preceding 24 hours' worth of data. We thus purchased these trading data from Kaiko, which obtains the data by querying the APIs on a daily basis.

The structure of the CEX data is similar to that of trade files in the NYSE Trade and Quote (TAQ) database. For each transaction, we have the ticker symbol pair (e.g., NXS/BTC), execution price, quantity, and timestamp. All three exchanges cover active and delisted cryptocurrencies and therefore are not subject to survivorship bias.

We collected DEX transactions that occurred on Binance Smart Chain during the sample period. An advantage of using DEX data is the availability of each trader's wallet address. PancakeSwap is the leading DEX deployed on Binance Smart Chain and one of the largest DEXs globally.[18] The sample includes 14.8 million wallets that were ever used to trade on PancakeSwap, 395.3 million trades and over half a million cryptocurrency addresses. In Part A5 of the Internet Appendix, we provide additional details regarding how we process the blockchain data.

C. Other data

For cryptocurrencies trading on the CEXs involved in our study, we obtained daily prices (volume-weighted across exchanges), total volume, and market capitalization from CoinMarketCap. CoinMarketCap does not cover all cryptocurrencies but tends to feature larger

[18] Since early 2021, PancakeSwap has consistently ranked among the top DEXs globally in trading volume, according to DeFiLlama (https://defillama.com/).

and more liquid ones. Our data indicating whether a cryptocurrency is a coin or token came mainly from CoinMarketCap.[19] If a cryptocurrency is not featured on CoinMarketCap, we collected the information from BitcoinTalk. From CryptoCompare, which aggregates the number of users on Reddit, Twitter, Facebook, and its own website, we manually collected a social media index for each cryptocurrency.

D. Summary statistics and targeted cryptocurrencies

After merging the above data with trading data, our CEX sample includes 500 distinct P&Ds involving 239 unique cryptocurrencies. The total number of unique P&Ds on PancakeSwap is 1,496, involving 871 unique cryptocurrencies. On the CEXs, all the P&Ds involve Bitcoin as the base currency, while on PancakeSwap, the base currency is Binance Coin (BNB).[20]

In Table 1, Panel A, we report the characteristics of our P&D events. For the three CEXs, 1.6 Telegram channels coordinate on average one P&D, suggesting that coordination is popular. On average, the total number of viewers across these channels in a pump is 5,942, with Binance pumps attracting the most viewers and Yobit pumps the least. On average, P&Ds are announced 24.5 seconds (the median is 5.2 seconds) after the scheduled time. The earliest channel receives the signal about 3 seconds earlier than the average. In 229 P&Ds, pump groups specify the returns they target. If a target return is specified as a range—for example, from 200% to 300%—or it differs across channels, we use the lower bound. The target returns are 212% on average. The average target returns on Yobit cryptocurrencies (233%) are much higher than those on Binance

[19] A coin is a digital equivalent of money and is native to its blockchain. Coins are like money: they are fungible, divisible, portable, and limited in supply. A token is a digital asset issued by a particular project, which provides a specific set of rights to its holders, including access to a platform or network, the right to create or develop features for an ecosystem, and the right to vote, among others. Tokens typically operate on existing blockchain platforms, such as Binance Smart Chain. Therefore, most cryptocurrencies that trade on PancakeSwap are tokens.

[20] In seven P&Ds, both Bitcoin pairs and Ethereum pairs are targeted. We therefore focus on Bitcoin pairs in our main analysis when examining the CEXs. In an additional analysis, we also examine Ethereum pairs.

cryptocurrencies (69%), likely because Yobit cryptocurrencies are generally smaller and less liquid. The P&Ds on PancakeSwap look similar, except that the average target returns are significantly higher, again likely because its listed cryptocurrencies tend to be smaller.

[Insert Table 1 here.]

In Table 1, Panel B we report summary statistics for the targeted and non-targeted cryptocurrencies. For each characteristic on each day on which at least one pump occurs, we calculate the average value of target and non-target cryptocurrencies. We then compute the time-series averages. The differences between target and non-target cryptocurrencies and their associated *t*-values are calculated using these time-series averages. The characteristics of non-target cryptocurrencies inform us of the average cryptocurrency's characteristics, as most cryptocurrencies are not pumped on any given day.

For the CEXs, the cryptocurrency characteristics we report are logarithmic trading volume, log market capitalization (in dollars), return volatility, preceding-seven-day returns, a token dummy, a pumped-before dummy, cryptocurrency age, social media index, and the frequency of CoinMarketCap coverage. Trading volume and volatility are calculated over the period running from day -37 to day -8. On the CEXs, Bitcoin is the most widely used base currency and all PancakeSwap P&Ds target trading pairs involving Binance Coin (BNB). Therefore, we report trading volume in Bitcoin for the CEXs and in BNB for PancakeSwap. Market capitalization is available only when CoinMarketCap covers a cryptocurrency. The token dummy equals one if a cryptocurrency is a digital token issued by a particular project and zero if it is a coin. The pumped before dummy equals one if a cryptocurrency was pumped previously and zero otherwise. Cryptocurrency age indicates the number of years since it was first covered by CoinMarketCap.

The analysis of PancakeSwap tokens requires a different approach. First, we omit several characteristics because they are not applicable to DEXs. Second, we calculate trading volume and volatility over the period running from day -37 to day -2 because most of the cryptocurrencies on PancakeSwap are so young, and omitting the last seven days will eliminate many of them from the analysis.

We report several findings. First, on average, 2.16 cryptocurrencies per day are pumped on the CEXs, while 6.29 are pumped on PancakeSwap. On the CEXs, the likelihood that a cryptocurrency will be pumped on a given day is 0.3%, which is equivalent to about once a year. The corresponding probability with respect to PancakeSwap is much lower, given the large number of cryptocurrencies traded on that platform. Second, the targeted cryptocurrencies trade on average at higher volume and are less volatile. The average targeted cryptocurrencies earn similar preceding-seven-day returns on the CEXs but higher preceding-seven-day returns on PancakeSwap. Third, the targeted cryptocurrencies are more likely to have been targeted before than the non-targeted ones, which suggests that pump groups' target choices are persistent. We note, however, that although targeted cryptocurrencies differ from non-targeted ones, predicting the next target is not an easy task because the total number of cryptocurrencies is large and the daily unconditional target probability is low.

Although we find that the average targeted cryptocurrency is small, especially on PancakeSwap, not all the targeted cryptocurrencies are small. CoinMarketCap covers 59.0% of targeted cryptocurrencies on the three CEXs. Conditional on CoinMarketCap coverage, their market capitalization is similar to that of other covered cryptocurrencies. For covered cryptocurrencies, the average market capitalization is about $10 million (exp(16.078)), which is comparable to that of U.S. common stocks in the 10th percentile during our sample period.[21]

IV. Empirical Results for P&Ds

In this section, we first report the cryptocurrency price and trading patterns following P&Ds using the standard event-study method. We report all the results without adjusting for market effects. We find that adjusting for market effects has little influence on our results. At the end of the section, we also investigate why investors participate in P&Ds.

A. Can P&Ds move cryptocurrency prices?

In Figure 2 we report cumulative returns, abnormal volume, and the volatility of the cryptocurrencies targeted by P&D groups for each ten-second interval from 600 seconds before to 600 seconds after the announcement of a P&D. Panel A covers the CEXs and Panel B covers PancakeSwap. The X-axis represents time. Time 0 indicates the ten-second interval running from 0 to 10 seconds, where 0 is the announcement time. The solid lines show the means across all P&Ds and the dashed lines indicate 95% confidence intervals. Cumulative returns are calculated as the logarithmic change in the price from 600 seconds before a P&D announcement. We use log returns to mitigate the effects of extreme returns. Abnormal volume is calculated as log (1+10-second volume/average 10-second volume over day -37 to day -8) for P&Ds on the CEXs and as log (1+10-second volume/average 10-second volume over day -37 to day -2) for P&Ds on PancakeSwap. We include more days for PancakeSwap P&Ds because of the extremely young age

[21] Both trading volume and P&Ds concentrate from 12:00 to 22:00 UTC (daytime in the U.S.). Part A6 of the Internet Appendix presents the distribution of our sample P&Ds and trading volume by hour and exchange. Although the three CEXs are located on three continents, P&Ds and trading volume distributions by hour look remarkably similar. The distributions are also similar for PancakeSwap. In Part A7 of the Internet Appendix, we discuss issues that might arise with our data and explain how we address them.

of many of its cryptocurrencies. Volume is measured by the number of cryptocurrencies traded. Volatility is measured as the absolute value of returns in each ten-second interval. To minimize the effects of extremely large returns, we measure volatility as the absolute value of returns rather than squared returns.

[Insert Figure 2 here.]

Figure 2 illustrates that following P&D announcements, cryptocurrency prices and trading volumes on average increase significantly for both the CEXs and PancakesSwap. It is noteworthy that the changes start before announcements, suggesting some information leakage. Such leaks are likely driven by VIP members of pump groups who tend to receive signals in advance, by pump group operators who may trade directly, or both.

We find that insiders, who know a cryptocurrency's identity and the timing of a pump in advance, would earn a nearly 25% return if they buy target cryptocurrencies on the CEXs ten minutes before announcements and hold until one minute after announcements. On PancakeSwap, the average return is 114%. The second and third graphs display abnormal volumes and volatility, respectively. At the maximum, the ten-second volume is 128 and 167 times higher than the average in the baseline period for the CEXs and PancakeSwap, respectively; the average ten-second absolute return reaches 15% and 43% for the CEXs and PancakeSwap, respectively.

Although cryptocurrencies on PancakeSwap are typically significantly smaller than those on the CEXs, the patterns appear to be similar, except that PancakeSwap P&Ds on average exhibit steeper price and volume increases. The results for returns, trading volume, and volatility all suggest that P&Ds are followed by significant short-term changes in cryptocurrency prices and trading. Ten minutes after an announcement, the price, trading volume, and volatility of an average target cryptocurrency are still significantly higher than their pre-announcement levels, although reversals of volume and volatility are quicker than that of price.

In Figure 3 we present the returns, trading volume, and volatility patterns over a longer period—from seven days before an announcement to seven days after. Outside of the short period around a P&D, trading typically decreases sharply, preventing us from accurately calculating these variables based on ten-second data. Therefore, we calculate price, volume, and volatility over one-hour intervals for this longer-term analysis. On average, volume and volatility return to their original levels within one to two days, while price takes slightly longer to revert. In generating the price graphs, if a cryptocurrency is not traded in a given period we carry the last available trade price. This method tends to underestimate the speed of price reversal. Overall, given that trading volume returns quickly to the normal level, on average there is little liquidity for trading against a continual price reversal.

[Insert Figure 3 here.]

B. P&D effects by market capitalization

In this subsection, we examine whether the prices of big cryptocurrencies move after P&Ds. The average cryptocurrency on the CEXs is much bigger than that on PancakeSwap, so we focus on the CEX P&Ds in this analysis. We sort all the pumped cryptocurrencies on the CEXs into five groups based on market capitalization. Market capitalization is measured eight days before a pump. We replicate the analysis shown in Figure 2 for each of these five groups. To save space, we report in Figure 4 the results only for the largest group. The results for the other groups are reported in Part A8 of the Internet Appendix. The largest group carries an average (median) market capitalization of $144 million ($68.0 million), which is comparable to the median of the CRSP firm-size distribution during our sample period (about $100 million). Our results indicate that price and volume changes following P&Ds are generally more pronounced for smaller cryptocurrencies than for larger ones. Even among the largest pumped cryptocurrencies, however, P&Ds are followed by significant changes in price and volume, suggesting that the relationship between P&D schemes and trades also applies to large cryptocurrencies.[22]

We note that P&D-related trading volume is economically significant. Table A1 of the Internet Appendix shows that trading volume on a P&D date accounts on average for 6% and 50% of the total volume during a period of -100 days to +100 days around P&Ds that occur on the CEXs and PancakeSwap, respectively. The economic significance is larger for smaller cryptocurrencies. For targets in the bottom volume quintile, the average percentage of trading volume attributed to P&Ds is over 13% and 91% for the CEXs and PancakeSwap, respectively.

[Insert Figure 4 here.]

C. Spillovers to Ethereum pairs and other exchanges

For P&Ds on the three CEXs, in previously reported analyses we focus only on Bitcoin (BTC) pairs traded on the target exchanges because P&Ds target them specifically. In this subsection, we investigate the effects of P&D spillovers to Ethereum (ETH) pairs, the second most commonly traded pairs. We also examine whether there is any spillover effect on the same cryptocurrencies traded on the other two exchanges.

A spillover effect on the ETH pair is likely to be significant because the limits to arbitrage between a BTC pair and an ETH pair on the same exchange are generally low. Investors can buy BTC pairs and sell them as ETH pairs and vice versa. BTC/ETH pairs are listed on all three CEXs

[22] In Part A9 of the Internet Appendix, our analysis indicates that these results are not likely driven by a small number of P&Ds, because cryptocurrency prices tend to increase in most P&Ds.

we study and are highly liquid, facilitating exchange between these two base currencies. We also conjecture that the spillover to other exchanges might be low because of stronger limits to arbitrage. Trades typically happen instantly within an exchange, but once a cryptocurrency must be transferred to another exchange, settlement of that transaction generally takes much longer, in part reflecting the mining process. For example, settling a Bitcoin transfer can take up to an hour or even days, which makes exploiting mispricing opportunities across exchanges difficult. This is consistent with findings reported in Makarov and Schoar (2020), who show many recurrent arbitrage opportunities involving Bitcoin and Ethereum pairs across exchanges.

Our sample includes 92 pumped cryptocurrencies that have also traded ETH pairs and 89 pumped cryptocurrencies that are cross-listed on one or two other exchanges. Figure 5 displays the patterns for these ETH pairs and cross-listed cryptocurrencies. If a cryptocurrency is cross-listed on two other exchanges in addition to the target exchange, we take the average of returns, abnormal volume, and volatility across the two exchanges. Figure 5, Panel A shows that the average return, abnormal volume, and volatility of the ETH pairs are comparable to those of the BTC pairs, but the average return, abnormal volume, and volatility of the pumped cryptocurrencies traded on the other exchanges are all much lower than those of the cryptocurrencies traded on the target exchanges, as shown in Figure 5, Panel B. The results reported in Figure 5 and Figure 2, Panel A are not directly comparable, as the sample compositions differ. In Part A10 of the Internet Appendix, we present an analysis in which we restrict our data to the same sample and find similar results.

[Insert Figure 5 here.]

Overall, the results reported in Figure 5 and Part A10 of the Internet Appendix support our conjecture about substantial spillover to ETH prices, but the spillover to other exchanges is less significant. This is consistent with our previous discussion of relatively low limits to arbitrage between BTC pairs and ETH pairs and relatively high limits to arbitrage across exchanges. The spillover to ETH pairs indicates that P&Ds can affect investors who do not participate directly in P&Ds. The quick reversal shown in Figure 2 and weaker spillover to other exchanges shown in Figure 5, Panel B imply that the price increases are likely not supported by changes in cryptocurrency fundamentals.

D. Performance by purchase time

We can infer from the results reported in Figure 2 how investor performance depends on the timing of buying and selling. This inference reflects the perspective of a small investor whose trade does not move the market. In this subsection we investigate this question from an average real-world investor's perspective and account for real-time liquidity. For PancakeSwap, this task is straightforward because we have investor identifiers and trading records and therefore can calculate every purchase's realized returns directly. For purchases that have not been sold ten minutes after a P&D starts, we assume that they can be sold at the price that was effective at that time. The results are qualitatively similar if we extend the period to one hour or the end of the day.

For the CEXs, we have all the trading records but no investor identifiers, and thus we cannot match the purchases and sales of the same investors. Hence, we infer the "achievable" returns. We illustrate how the inference is made using the following example. Suppose the total volume for cryptocurrency ABC in the first ten-second interval after a P&D announcement is N and the volume-weighted average price is P. Assume that all these investors follow the same strategy by waiting for D seconds before they start to sell. We also assume that, when they sell, they are the only sellers on the market and can trade at the volume-weighted average price until they sell all of their purchased cryptocurrencies.

[Insert Table 2 here.]

We report the results of this exercise in Table 2. Note that the returns are calculated before exchange commissions, which range from 0.2% to 0.5% per round trade plus gas fees of roughly $1 per round trade for PancakeSwap. Incorporating transaction costs does not appear to materially affect our results. In addition to the six ten-second intervals after a P&D, we also include a "Before P&D" interval, which is the ten-minute window before a P&D announcement. We use this interval to evaluate how insiders perform. In Panel A we report the mean returns for each purchase time–delay combination across P&Ds on the CEXs. In Panel B, we report the mean returns for each purchase time on PancakeSwap. For PancakeSwap pumps, we need not make assumptions about selling delays because we observe the actual trades.

We find that returns seem to depend critically on when an investor buys into a P&D. On PancakeSwap, an average investor who buys before a P&D realizes a 152% return. On average, investors can make money if they buy within 30 seconds after a P&D, but not later. The inferences for the CEX P&Ds are similar. Investors who buy before a P&D earn high returns on average. If they start to sell immediately after an announcement, the average return will be 13.5%. These investors' average return, at 17.7%, is highest if they sell after a delay of 10 seconds. The other groups' average returns are much lower. Investors who buy in the first ten seconds after a P&D will earn a positive average return. With optimal timing, their average return is 6.5%. The next group whose members buy in the second ten-second interval cannot delay selling by more than ten seconds to earn statistically significant profits. The remaining groups, on average, cannot make money at all.

Overall, the results reported in Table 2 suggest that, to earn positive returns from P&Ds, an outsider has to buy cryptocurrencies in the first 20 or 30 seconds and make sure that he can sell before it is too late. Most others lose money.

The consistently positive performance achieved by investors in the "Before P&D" interval (i.e., ten minutes before a P&D) suggests the occurrence of wealth transfers from later participants to these early investors. We deem the former insiders and the latter outsiders. During our sample period, for an average PancakeSwap P&D insiders make about 2.9 BNB (about $1,300), while for an average CEX P&D insiders make 1 Bitcoin (about $10,000).

E. Other sources of asymmetry

As noted above, not all pump outsiders obtain pump signals at the same time. Some receive signals earlier than others. We do not, however, observe the times at which VIP members receive their signals, and thus we cannot evaluate the benefits VIP members may enjoy. In this subsection, we investigate whether participants in some Telegram channels receive signals systematically later than others.

The results are reported in Table 3. In Panel A we report delays in announcements, which are measured by the number of seconds that elapse after a scheduled pump time. A negative number indicates that the announcement time is ahead of schedule. We report the largest ten pump groups (measured by the number of all P&Ds in which they participate) and an aggregate number for all other channels. The delay is capped at ±30 seconds, as the statistics reported in Table 2 indicate that the marginal effect of delays beyond 30 seconds weakens considerably. This also helps us avoid undue influence by a small number of large deviations from the scheduled time.

[Insert Table 3 here.]

We conduct the analyses for the CEXs and PancakeSwap separately. For the CEXs, in the two columns headed by "All," we report the results based on all the P&Ds in our sample, while in the columns headed by "With trading data" we report the results based on our final sample, for which we require trading data to be available. The results reported in the "All" columns show that the average delay for PumpZone is only 0.73 seconds, while it is 11.29 seconds for Premium Yobit Pump. The results based on our final sample are similar. This suggests the presence of significant heterogeneity in receiving pump signals across groups. The PancakeSwap sample indicates similar heterogeneity.

In Panel B we present the results obtained by investigating whether there is any persistence in delays. We regress a channel's delay in receiving a P&D signal on its lagged delay. We use one specification without P&D fixed effects and another with such fixed effects. All our results suggest significant persistence in the delay in receiving signals. Overall, although we cannot judge whether the observed heterogeneity in signal reception is an intentional outcome, the results reported in Table 3 provide some evidence of additional asymmetry in addition to what occurs between insiders and outsiders.

F. Pump-group size

In this subsection we analyze the relationship between pump-group size and P&D outcomes. This analysis helps us shed light on whether pump-group operators behave strategically. To insiders, a P&D's success relies on participation by channel members. In Table 4 we report the results of our examination of whether insiders operating bigger pump channels earn higher profits and how the size of a pump channel affects insider behavior. We conduct our analysis at the P&D

level. For pumps organized by multiple channels, we take the sum of all the participating pump groups.

[Insert Table 4 here.]

As shown in columns 1 and 2 of Table 4, pumps organized by larger channels are, on average, associated with higher profits for insiders. Insider profits are profits earned by investors who purchase during the ten-minute period before a pump announcement.[23] We winsorize insider profits at the 1% level on both tails to mitigate the effects of outliers. The results suggest that insiders operating larger channels tend to earn higher profits. Based on the estimates, a 100% increase in log channel size is associated with an increase of 0.10 BTC and 0.70 BNB for P&Ds on the CEXs and PancakeSwap, respectively. Given that the corresponding average insider profits are 1 BTC and 2.9 BNB for our sample P&Ds, the effect appears substantial.

Insiders with more channel followers can potentially generate higher profits through higher pump returns, higher trading volume, or both. The results reported in columns 3–8 suggest that larger channels are more likely to target larger cryptocurrencies (measured by higher past volume), and pumps organized by larger channels are associated with higher trading volume and higher pump returns, although the estimate derived from the return regression is not statistically significant for the CEXs.[24] As in Figure 3, we measure pump returns as the ratio of the highest price achieved within ten minutes after a pump announcement to the price ten minutes before the announcement minus one. Pump volume is measured as the total volume (in BTC for the CEXs and in BNB for PancakeSwap) in the 30-minute period after the announcement. Based on the

[23] An investor's profit during a P&D is calculated as (Value of sell orders – Value of buy orders + (Buy volume – Sell volume) × Price) as of 10-minutes after the P&D announcement.
[24] A hierarchical structure—organizers, premium members, regular members, and outsiders—of P&Ds exists, and it appears to allow a P&D to target large cryptocurrencies. We find suggestive evidence that collaboration across channels could enable large-scale P&Ds. We refer the reader to Internet Appendix Part A11 for additional details.

estimate reported in column 5, a 100% increase in log channel size is associated with a nearly 43% increase in pump volume.

In an untabulated analysis, we also examine whether channel size is associated with the choice of target return, price run-up, and delay for an announcement. A noteworthy result derived from this analysis is that larger channels tend to choose higher target returns. As we show in Table 1, the average target return is significantly higher than the average achieved pump return. The finding that target returns are not achieved in most cases suggests that, to lure participants, pump operators intentionally set the target returns too high and the more followers they attract the more frequently they do so.

G. Why do outsiders participate in P&Ds?

To summarize the results of our analysis thus far, we have reported three main findings. First, the average P&D is followed by significantly higher cryptocurrency prices and trading volume. Second, investor performance depends critically on when investors obtain their signals. Third, some outsiders receive signals systematically later than others. All these findings make it puzzling that an outsider is willing to participate in a P&D. In this section, we use the PancakeSwap sample to examine the mechanisms. We do not use the CEX sample because it does not provide traders' identities.

We conduct two tests. The first test examines whether investor characteristics are associated with P&D participation, while the second studies whether past P&D performance predicts future P&D participation and performance. We focus on outsiders and exclude investors who buy before an announcement.

We conjecture that it is plausible that P&Ds attract overconfident investors who believe that they can time the market better than others can (Daniel, Hirshleifer, and Subrahmanyam (1998), Barber and Odean (2000, 2001), Scheinkman and Xiong (2003), Daniel and Hirshleifer (2015)). In other words, these investors believe that they can take advantage of others by riding a pump. It is also possible that outside investors with gambling preferences are more likely to participate. The short-term returns on pumped cryptocurrencies are often very high and salient. Investors may overweight these returns in their decision-making or overestimate the skewness of the cryptocurrencies, consistent with salient thinking or prospect theory (Barberis and Huang (2008), Bordalo et al. (2012, 2013), Barberis, Mukherjee, and Wang (2016)).

Our proxy for gambling preference is the median price of all the cryptocurrencies an investor has bought. Low-priced assets may be viewed as "cheap" with high upside potential. Such a proxy has been widely used with the stock market (e.g., Kumar (2009), Birru and Wang (2016)). Another widely used gambling preference proxy is return skewness (Barberis and Huang (2008)). Unfortunately, calculating skewness requires a long sample period and hence is unavailable for many PancakeSwap cryptocurrencies, given their young age and limited liquidity. Our proxy for overconfidence is trading frequency. Overconfident investors tend to trade more frequently than others (Barber and Odean (2000, 2001), Scheinkman and Xiong (2003)). We measure trading frequency following Ben-David and Hirshleifer (2012). Specifically, we calculate the daily probability that an investor sells his positions. We also consider portfolio size, experience, and past returns. Portfolio size is the value of an investor's cryptocurrency portfolio. Experience is the time since an investor started trading on PancakeSwap. We calculate these investor characteristics at the end of each month and predict who participates in P&Ds the following month.[25]

[25] We provide additional details on how we construct these variables in Part A12 of the Internet Appendix.

In Table 5, Panel A we report the summary statistics for this sample. On average, 0.072% of investors participate in P&Ds each month. The average log (price) is -15.09 (about $0.0001), which is significantly lower than the average CRSP stock price (about $30). The average daily selling probability is 1.5%, about six times higher than the daily selling probability for retail investors on the stock market (Ben-David and Hirshleifer (2012)). The log average portfolio size is 2.74 (about $7,000), which is smaller than that of the average stock portfolio held by investors in a large U.S. discount brokerage firm (Barber and Odean (2000)) but it is still significant.

The results reported in Table 5, Panel B suggest that investors who buy relatively higher-priced cryptocurrencies are less likely to participate in P&Ds, while those who trade more frequently (at a higher selling probability) are more likely to participate. These two findings are consistent with our conjectures that investors exhibiting a gambling preference or overconfidence participate in P&Ds more often. We also find that investors who carry larger cryptocurrency portfolios or who are less experienced are more likely to participate.

[Insert Table 5 here.]

Next, we study investor learning by examining whether past P&D experience is associated with future P&D participation and performance. The analysis is performed at the investor-P&D level. For an investor who participates in a P&D, we calculate his performance in the current P&D (Ret_t) and examine whether Ret_t predicts the likelihood that this investor will participate in the next P&D organized by the same channel as well as his future P&D performance.[26] We split outsiders into two groups: "early" outsiders who buy in the first 20 seconds after a P&D announcement and late investors who trade after 20 seconds. The grouping is based on trading in the current P&D.

[26] Specifically, for each P&D we calculate an investor's return Ret_t as the raw profit divided by the maximum value of the investment during that P&D. Liu, Peng, Xiong, and Xiong (2022) use the same method to calculate stock investors' returns over a given period.

Our results are qualitatively similar if we use 10 seconds or 30 seconds to split the sample. Recall that the announcement time of a P&D is defined as the earliest announcement time among all participating channels. The early outsiders may come through channels that enjoy preferential treatment or have skills that enable them to move quickly. Hence, late outsiders likely represent a group of clear outsiders. In total, we obtain 88,556 investor-P&D pairs, of which 4,651 are early outsiders (for a mean Ret_t of -9.5%) with the remaining 83,905 being late outsiders (for a mean Ret_t of -41.0%).

[Insert Table 6 here.]

In the odd columns of Table 6 we report the results of our participation analysis. To facilitate interpretation, we use a positive-return dummy, $I(Ret_t>0)$, which equals 1 if Ret_t is positive and 0 otherwise, as our independent variable of interest. As reported in Part A13 of the Internet Appendix, using Ret_t as the independent variable yields qualitatively similar results. The coefficient on $I(Ret_t>0)$ we report is significantly positive in all four odd columns, suggesting that better past performance is associated with a higher likelihood that an investor will participate in future P&Ds. Having a positive Ret_t is associated with a likelihood that is 12.6 percentage points higher for early outsiders and 14.0 percentage points higher for late investors. Given that the unconditional probability that an investor participates in the next P&D is about 10%, these increases are economically significant for both types of outsiders.

In the even columns of Table 6 we report results pertaining to the relationship between past and future performance for early and late outsiders. For cases where these investors do not participate at t+1, Ret_{t+1} is set to zero. We conjecture that outsiders, especially the late ones, with positive Ret_t will lose more money in the next round because of their higher participation rate. The results suggest that, for early outsiders, past P&D performance does not predict future performance.

For early outsiders who earn negative Ret_t, their average Ret_{t+1} is -1.6% (t = -2.11). For early outsiders who earn positive Ret_t, their average Ret_{t+1} is -1.4% (0.2% - 1.6%, t = -1.12). For late outsiders, however, past P&D performance negatively predicts future performance. For late outsiders who earn negative Ret_t, their average Ret_{t+1} is -2.6% (t = -11.98). For late outsiders who earn positive Ret_t, their average Ret_{t+1} is -4.8% (-2.2% - 2.6%, t = -7.69), suggesting that late investors who did better in the past tend to lose more money in the future. We also note that, regardless of the value of $I(Ret_t>0)$, late outsiders on average lose money in the next P&D.

In summary, the results reported in Table 5 are consistent with the hypothesis that both investors with gambling preferences and overconfident investors are more likely than others to participate in P&Ds. The results reported in Table 6 also suggest that late investors, who comprise the vast majority of P&D participants, tend to exhibit behavior consistent with naïve reinforcement learning: those who profit from P&D schemes are more likely to believe in their own ability, participate in future P&Ds, and lose more money (Kaustia and Knupfer (2008), Chiang et al. (2011), Anagol et al. (2021)).

V. The Bittrex Ban and the Yobit Pump Scheme

In this section we examine the economic consequences of P&Ds. In Section IV we show that P&Ds are followed by short-term episodes featuring significant increases in prices, volume, and volatility, which suggests that P&Ds are associated with reduced informativeness of cryptocurrency prices. To some extent, P&Ds resemble fat-finger incidents. Instead of occurring once every few years as in traditional financial markets, during our sample period, P&Ds generally occurred multiple times every day and were planned. Evidence suggests that exposure to scandals erodes investor trust and reduces stock market participation and the use of financial intermediation services (e.g., Giannetti and Wang (2016), Gurun et al. (2018)). Do P&Ds play a similar role by weakening investors' willingness to invest in the cryptocurrency market? We study this question using two natural experiments.

A. The background

On November 24, 2017, Bittrex sent a notice to customers warning them about market-manipulation tactics. Customers could be banned or have their accounts frozen for artificially manipulating the prices of cryptocurrencies trading on its platform.[27] Bittrex's ban followed an investigation by *Business Insider* ten days earlier that found traders were colluding in groups on Telegram to inflate the prices of cryptocurrencies (Williams-Grut (2017)). On October 10, 2018, Yobit announced on its website and official Twitter page that it would pump cryptocurrencies listed on the exchange randomly.[28] This was the first (and to the best of our knowledge, the only) case in which an exchange has initiated such an action.

Both announcements appeared to affect the market significantly. Messages about pump groups on Telegram indicate that traders involved in P&D tactics had taken notice of the Bittrex warning. Many scheduled P&Ds were canceled immediately after Bittrex's announcement. We

[27] Bittrex stated that it "actively discourages any type of market manipulation, including pump groups. Consistent with our terms of service, we will suspend and close any accounts engaging in this type of activity and notify the appropriate authorities." In the same notice to customers, Bittrex also announced three other planned changes. First, the minimum trade size would increase from 50,000 Satoshi to 100,000 Satoshi. One Satoshi is 100 millionth of a bitcoin. This change increased the minimum trade size from about $0.5 to $1. We do not expect this increase in the minimum trade size to have any impact on our results because it was so small that virtually no trades were constrained even after the change. Second, the minimum tick size would increase from 1 Satoshi to about 0.1% of a cryptocurrency's price. Studies of the stock market suggest that a wider tick reduces liquidity and trading volume (Harris (1994)). We find, however, that the ban was followed by greater volume. Third, Bittrex would remove orders that are not between 50% and 200% of the last trading price after 28 days. It would also cancel buy orders at bid prices that are 12.5% or lower than the last price and cancel sell orders that are 800% or greater of the last price. Overall, these changes likely had a minimal impact on investor trading. Consistent with our argument, almost all media outlets ignored these changes and focused on the P&D ban. Below is an archived link of this announcement: https://web.archive.org/web/20201026015620/https://bittrex.zendesk.com/hc/en-us/articles/115003004171-What-are-my-trade-limits.

[28] Figure A9 of the Internet Appendix presents a snapshot of Yobit's Twitter announcement.

provide additional details in Part A14 of the Internet Appendix. In the case of Yobit, we read the hundreds of responses posted on its official Twitter page. The announcement appeared to surprise market participants. Initially, many users believed that Yobit's official Twitter account was hacked. This belief quickly dissipated as people learned that Yobit had posted the same announcement on its official website. We also find that the sentiment was predominantly negative. Of the 210 Twitter responses, we find no positive posts: 142 appear to be negative, while others are unclear or too short to tell. Two of the earliest responses are representative. One said, "Who is the genius at Yobit who thought this would be a good idea . . ." and the other said, "SEC. Pls. Stop this! We need regulations!"

B. Visualization of the two natural experiments' effects

We adopt a difference-in-differences approach to examine the effects of the two events, the Bittrex ban and Yobit's pump scheme, on the prices and trading volumes of cryptocurrencies. We compare a cryptocurrency listed on an event exchange with a propensity-score-matched cryptocurrency that is not listed on the event exchange. We drop stablecoins from both the treatment and control samples.

For each event, we consider these characteristics in propensity-score matching: market capitalization 31 days before the event, average trading volume (in Bitcoin) in the period running from 60 days to 31 days before the event, and preceding-seven-day return based on prices one and eight days before the event. We conduct our analysis based on CoinMarketCap data rather than on data from the three CEXs because the cryptocurrencies on these exchanges differ in important ways (see Table 1). The matching is performed with replacement. Cryptocurrencies with no volume in the period running from 60 days to 31 days before the event are excluded. Our final sample includes 190 treatment-control pairs for the Bittrex ban and 174 treatment-control pairs for the Yobit pump event.[29]

In Figure 6 we present the average trading volumes and prices over the period running from 14 days before the event to 14 days after. Trading volume is measured as the natural logarithm of the ratio between the trading volume on a given day and the average volume in the period running from 14 days to one day before the event. Price is calculated as the natural logarithm of the ratio between the price on a given day and the average price in the period running from 14 days to one day before the event. We conduct these transformations to mitigate the effects of cross-cryptocurrency heterogeneity in volume and price.

The patterns presented in Figure 6 suggest that the volumes and prices of the Bittrex cryptocurrencies increased relative to those of the controls following the ban and decreased relative to those of the controls following Yobit's announcement. For both events, the changes started on the event day. In the pre-event period, the treatment and control groups move in tandem on average, suggesting that the control group represents a reasonable counterfactual.

[Insert Figure 6 here.]

C. The difference-in-differences regressions

We conduct formal difference-in-differences tests and report the results in Table 7. Specifically, we estimate

$$DV_{i,t} = \beta_1 Post_t + \beta_2 Treat_i * Post_t + \alpha_i + \varepsilon_{i,t}, \quad (1)$$

where *DV* is either volume or price. $Treat_i$ equals 1 if cryptocurrency *i* is listed on the event exchange and 0 otherwise. *Post* is a dummy variable that equals 1 for periods after November 24,

[29] Part A15 of the Internet Appendix provides additional details on the sample and variable construction.

2017, for the Bittrex event (and after October 10, 2018, for the Yobit event) and 0 otherwise. α_i represents cryptocurrency fixed effects, subsuming the *Treat* dummy. β_2 is the difference-in-differences estimator.[30]

Instead of running a pooled regression with observations at the cryptocurrency-day level, we aggregate all the data and produce two observations for each cryptocurrency, one for the pre-event period and one for the post-event period (Bertrand, Duflo, and Mullainathan, 2004). Specifically, for the price regression we use the price two (seven) days before the event and two (seven) days after the event. For trading volume, we calculate the average for the week (or two weeks) before and after the event. We use shorter windows to measure the price effects to address the possibility that confounding factors exist over longer windows. The results are similar if we use longer windows.

In Table 7, Panel A we report that the coefficient on the interaction term is economically and statistically significant. Our estimates suggest that, relative to those of non-Bittrex cryptocurrencies, the prices of Bittrex cryptocurrencies on average increased by about 6.3% (15.1%) during a five-day (two-week) window after the Bittrex ban and the volume increased by 22.5% (36.0%) during a two-week (four-week) window after the ban. For the Yobit case, on average prices dropped by about 12.1% to 15.5% more, and the volume dropped by about 40% more for Yobit cryptocurrencies than non-Yobit cryptocurrencies after the announcement.[31]

[Insert Table 7 here.]

[30] Regarding the difference-in-differences tests for price and volume, our estimation is valid as long as there is no change in wash-trading activities on the event days. For Yobit's pump scheme, one would have to argue that Yobit reduced "wash-trading management" on the same day as it announced its pump scheme, which we believe is not plausible. We discuss wash trading in detail in Part A1 of the Internet Appendix.

[31] In Part A16 of the Internet Appendix, following a methodology developed recently by Rambachan and Roth (2023), we re-estimate our difference-in-differences specification while controlling for pre-trends that might have occurred. We find that controlling for pre-trends yields similar results.

D. Cryptocurrencies cross-listed on both the event exchange and other exchanges

In addition to the relative price and volume changes we have documented, we also conjecture that, for a cryptocurrency cross-listed on Bittrex (Yobit) and other exchanges, its Bittrex (Yobit) volume will increase (decrease) to a greater extent than its volume on other exchanges. Given the possibility of arbitrage, however, we do not expect that a cross-listed cryptocurrency's Bittrex/Yobit price will change more than its price on other exchanges.

In this test, we include only cryptocurrencies that are cross-listed on the event exchange and at least one other exchange. For each cryptocurrency the volumes on other exchanges equal the aggregate volume recorded on CoinMarketCap minus the volume on the event exchange. As the aggregate CoinMarketCap price is volume-weighted across all exchanges, we back out a cryptocurrency's non-event exchange price using volumes on Bittrex (Yobit) and other exchanges.[32] Equation (1) is revised as follows:

$$DV_{i,e,t} = \beta_1 Post_t + \beta_2 Treat_{i,e} * Post_t + \alpha_{i,e} + \varepsilon_{i,e,t}. \quad (2)$$

We add subscript *e* to indicate that the analysis is performed not at the cryptocurrency level (*i*) but at the cryptocurrency-exchange level (*i*,*e*). *DV*, *Treat*, and $\alpha_{i,e}$ are defined in the same way as in Equation (1), except that they are calculated at the cryptocurrency-exchange level.

The results reported in Table 7, Panel B seem to confirm our predictions. We find consistent results for volume as those reported in Panel A. There is no significant change in price, however, likely reflecting arbitrage trades causing prices of the same cryptocurrency listed across exchanges to converge. The economic magnitudes are somewhat smaller than those in the cross-cryptocurrency comparisons that are evident in Panel A. One concern with the propensity-score-matching results reported in Panel A is that cryptocurrencies listed on Bittrex/Yobit may be

[32] Specifically, for Bittrex, we use the following equation to back out the non-Bittrex price: CoinMarketCap price = Fraction of Bittrex volume × Bittrex price + Fraction of non-Bittrex volume × non-Bittrex price. The calculation for Yobit is similar.

inherently different. The results reported in Panel B address this concern because, for Panel B, we compare the same cryptocurrency across exchanges and therefore any difference has to come from differences across exchanges.

Overall, these results are consistent with the notion that P&Ds are associated with lower cryptocurrency prices and volumes. Kyle and Viswanathan (2008) propose two necessary conditions to classify a scheme as “illegal price manipulation:” (1) the scheme makes prices less accurate as signals for efficient resource allocation, and (2) it makes markets less liquid for risk transfer. Our results suggest that cryptocurrency P&Ds satisfy both conditions.

VI. Conclusion

This paper studies pump-and-dump schemes (P&Ds) in the cryptocurrency market. We find that most P&Ds are associated with short-term episodes where prices, volume, and volatility increase significantly, followed by quick reversals. We also find evidence consistent with the occurrence of significant wealth transfers from outsiders to insiders. The quick reversals imply that it is difficult for outsiders other than fast movers to earn profits in P&Ds. Standard trade-based price-manipulation theories assume that manipulators need to buy to pump asset prices (e.g., Allen and Gale (1992)). In contrast, we find that cryptocurrency P&Ds seem to be driven by uninformed speculative traders.

Our findings make it puzzling why these outsiders are willing to participate in P&Ds. We conjecture that P&Ds are likely to attract overconfident investors who believe they can time the market more accurately than others can (Scheinkman and Xiong (2003), Daniel and Hirshleifer (2015)). It is also possible that these investors are affected by the salience of extreme short-term returns and, in their decision-making, overweight the possibility that they will earn similar returns or overestimate the skewness of cryptocurrency returns (Barberis and Huang (2008), Barberis (2013), Bordalo et al. (2012, 2013)). Our results are consistent with both mechanisms. We also find evidence consistent with the idea that investors exhibit naïve reinforcement learning: outsiders who occasionally profit randomly from P&D schemes are more likely to participate in the future and lose more money in doing so.

We also conduct a difference-in-differences test using Bittrex's ban and Yobit's pump scheme to shed light on the equilibrium effects of P&Ds. Based on these two natural experiments, we find evidence that is consistent with the idea that P&Ds contribute to a decline in cryptocurrency liquidity and lower prices.

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Table 1. Summary Statistics

We report the characteristics of P&Ds in Panel A and the characteristics of pumped cryptocurrencies in Panel B. *Earliest channel's delay time* is the difference between the earliest pump announcement among all participating channels and the scheduled time. *Average delay time* is the average difference between the announcement and the scheduled time among all participating channels. *Number of channels* is the average number of channels coordinating a P&D. *Total number of viewers* is the sum of viewers across all channels in a P&D event. *Number of viewers per channel* is the average number of viewers across all channels in a P&D event. *Target return* is the pre-specified return before a P&D announcement. In Panel B, we report the characteristics of pumped cryptocurrencies and compare them with non-targeted cryptocurrencies. For each cryptocurrency characteristic, on each day with at least one pump we calculate the average value of target and non-target cryptocurrencies. We then compute the time-series average. We report log market capitalization (U.S. dollar), log trading volume, volatility, the past seven-day return, a token dummy, the frequency at which a cryptocurrency is covered by CoinMarketCap.com, cryptocurrency age, and a social media index. *Volatility* is defined as the standard deviation of daily log returns. Trading volume and volatility are calculated over the period running from day -37 to day -8 for centralized exchanges and from day -37 to day -2 for PancakeSwap. *Past seven-day return* is the return during the seven-day period before a pump. *Token dummy* equals one if a cryptocurrency is a digital token issued by a particular project and zero if it is a digital equivalent of money (a coin). *Covered by CoinMarketCap* equals one if a cryptocurrency is covered by CoinMarketCap and zero otherwise. *Cryptocurrency age* is the number of years since the cryptocurrency was first listed. *Social media index* is the logarithm of social media activity points computed by CryptoCompare.com. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Pump-and-dump events

	Centralized exchanges								Decentralized exchange	
	All (N=500)		Binance (N=76)		Bittrex (N=263)		Yobit (N=161)		PancakeSwap (N=1,496)	
Event-level	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Earliest channel's delay time (seconds)	21.7	4	20.1	5	14.0	4	34.9	3	31.4	6
Average delay time (seconds)	24.5	5.2	31.2	8	14.3	4.5	38.0	5.5	35.7	7
Number of channels	1.58	1	1.42	1	1.08	1	2.45	1	1.61	1
Total number of viewers	5,941.5	2,094	22,445.0	3,049	3,887.1	2,382	1,507.0	1,038	5,059.9	1,086
Number of viewers per channel	4,295.6	1,633	13,915.1	2,973	3,649.7	2,373	787.8	523.5	4,010.9	1,169

	Centralized exchanges								Decentralized exchange	
	All (N=788)		Binance (N=108)		Bittrex (N=285)		Yobit (N=395)		PancakeSwap (N=2,404)	
Channel-level	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Target return	211.5%	200%	69.0%	51.2%	246.9%	100%	233.0%	200%	1,371.2%	1,000%

Panel B. Characteristics of cryptocurrencies

	Target cryptocurrency	Non-target cryptocurrency	Difference	*t*-stat. of Diff.
Centralized exchanges (Binance, Bittrex, and Yobit)				
Log(Market capitalization (dollars))	16.078	16.297	-0.219*	-1.72
Log(Volume (Bitcoin))	4.538	3.345	1.193***	5.96
Volatility	12.83%	14.07%	-1.24%***	-3.13
Past seven-day return	-3.78%	-2.16%	-1.62%	-1.44
Token dummy	0.317	0.175	0.142***	6.09
Pumped before	0.578	0.109	0.469***	20.05
Covered by CoinMarketCap	0.590	0.524	0.066***	3.10
Cryptocurrency age (years)	0.771	0.630	0.141***	5.82
Social media index	8.253	8.517	-0.265***	-3.36
Average number of cryptocurrencies per day	2.16	683.80		
Decentralized exchange (PancakeSwap)				
Log(Volume (Binance Coin))	3.247	0.982	2.266***	14.11
Volatility	42.38%	56.13%	-13.75%***	-3.06
Past seven-day return	5.12%	-28.65%	33.78%***	8.59
Pumped before	0.482	0.001	0.481***	19.05
Cryptocurrency age (years)	0.103	0.098	0.005	0.71
Average number of cryptocurrencies per day	6.29	111,517.82		

Table 2. Trade Performance by Purchase Time

In this table we report the returns (in percentages) by purchase time. We consider six ten-second intervals after a P&D starts and one “Before P&D” interval, which is the ten-minute interval before a P&D. These are shown in each column. For P&Ds on PancakeSwap, we calculate returns directly because we observe every participant’s trading history. For the P&Ds on the centralized exchanges (Binance, Bittrex, and Yobit), we estimate the returns for each purchase time-delay combination. Each row displays the results by delay time. Time 0 indicates sales immediately after the ten-second interval after a purchase. For a combination of purchase time–delay, we assume that an investor buys cryptocurrencies at the volume-weighted average price during the purchase time interval and starts to sell after the delay. We further assume that when the investor decides to sell, he is the only seller and can trade at the volume-weighted average price until he fully unwinds his initial purchase. All the returns are calculated before considering exchange commissions (and gas fees for P&Ds on PancakeSwap). *t*-values are reported in parentheses.

Panel A. Centralized exchanges

	Purchase time, in seconds						
Delay time	Before P&D	10	20	30	40	50	60
0	13.510	5.698	1.292	-0.149	-0.903	-1.266	-1.125
	(7.93)	(7.70)	(2.83)	(-0.33)	(-2.26)	(-2.74)	(-3.05)
10	17.661	6.494	1.634	-0.610	-1.156	-1.924	-2.046
	(8.79)	(7.10)	(2.54)	(-1.07)	(-2.24)	(-3.78)	(-4.54)
20	17.612	6.542	1.262	-0.884	-1.653	-2.764	-3.156
	(8.61)	(6.62)	(1.68)	(-1.30)	(-2.82)	(-4.50)	(-5.59)
30	17.632	5.557	0.616	-1.310	-2.626	-3.758	-3.493
	(8.45)	(5.54)	(0.77)	(-1.78)	(-3.91)	(-5.40)	(-5.08)
40	17.261	4.774	-0.011	-2.254	-3.451	-3.846	-4.276
	(8.10)	(4.50)	(-0.01)	(-2.81)	(-4.60)	(-4.96)	(-5.72)
50	16.597	4.357	-0.952	-3.092	-3.693	-4.375	-4.705
	(7.81)	(3.92)	(-1.06)	(-3.64)	(-4.59)	(-5.21)	(-5.81)
60	15.642	3.519	-1.497	-3.327	-4.093	-4.870	-4.664
	(7.53)	(2.98)	(-1.56)	(-3.70)	(-4.68)	(-5.36)	(-5.69)

Panel B. PancakeSwap

	Purchase time, in seconds						
Delay time	Before P&D	10	20	30	40	50	60
N.A.	152.378	63.467	23.180	9.827	-1.422	-11.164	-15.870
	(24.30)	(17.73)	(6.94)	(3.09)	(-0.44)	(-3.71)	(-5.40)

Table 3. Persistent Advantages for Certain Telegram Channels

In this table we report the results pertaining to the persistent advantages certain Telegram channels enjoy. The analysis is carried out at the channel level. For the P&Ds on the centralized exchanges (Binance, Bittrex, and Yobit), the reported results are based on analyses using two samples: one with all the P&D channels and the other with only the channels for which trading data are available. In Panel A, we report the announcement delay times for each channel, measured in seconds. A positive number indicates that the announcement occurred *after* the scheduled time. We winsorize the variable at ±30 seconds. In Panel A, we report the average delays for each top-ten Telegram channel based on the number of P&D events initiated. In Panel B, we report the results of our regression analysis, in which the dependent variable is delay time and the independent variable is lagged delay. We include only P&Ds that are covered by more than one channel when using P&D fixed effects. In each column, we report coefficient estimates and their heteroscedasticity-robust *t*-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Delay in the announcement (seconds)

	Centralized exchanges				PancakeSwap		
	All		With trading data				
Pump group name	N	Delay	N	Delay	Pump group name	N	Delay
Alt the Way	303	9.79	62	16.21	RisingPancake$	93	16.03
Crypto Mega Pumps Yobit	244	6.90	44	13.70	Pancakeswap Pumping	93	6.85
The Pumpers	220	7.33	37	15.43	Crypto King Signals	79	9.85
Superb Pumps	180	7.05	40	11.05	ShitCoin - PancakeSwap Pump	68	11.00
YoBit Pumpers	159	4.45	31	14.74	Cryptocurrency Pump	67	6.12
Bittrex Signals	148	5.83	25	16.56	Shitcoin pump	66	6.73
World Pumps	130	6.65	7	1.86	Shitcoin Pumps	65	9.95
Crypto VIP Signals	116	4.99	23	14.61	PooCoin Moon Pumps	65	10.57
Premium Yobit Pump	107	11.29	53	10.13	Legit Pancake Pumps	64	16.72
PumpZone	89	0.73	27	0.96	Pump Pancake Pumps	64	14.78
Other channels	788	7.15	439	6.38	Other channels	1,680	10.52

Panel B. Persistent advantages

	Dependent variable: Delay time					
	Centralized exchanges				PancakeSwap	
	All		With trading data			
	1	2	3	4	5	6
Lagged delay time	0.293***	0.152***	0.341***	0.109***	0.163***	0.100**
	(15.17)	(8.62)	(9.85)	(2.99)	(6.95)	(3.03)
Constant	4.962***		6.052***		8.788***	
	(16.62)		(9.74)		(25.50)	
P&D FEs	No	Yes	No	Yes	No	Yes
Observations	2,433	1,901	746	377	2,289	1,278
Adj. R^2	0.09	0.87	0.11	0.87	0.03	0.78

Table 4. Effects of the Size of Pump Groups

In this table we report the results pertaining to the effects of pump-group size. CEXs denote centralized exchanges: Binance, Bittrex, and Yobit. The dependent variable for columns 1 and 2 is insider profit (in Bitcoin for CEXs and Binance Coin for PancakeSwap). We assume that insiders are the traders who purchase in the ten-minute period before the pump announcement. The dependent variable for columns 3 and 4 is the natural logarithm of one plus the average daily volume from day -37 to -8 (-2) for CEXs (PancakeSwap). The dependent variable for columns 5 and 6 is log(1 + volume in the 30 minutes after the announcement). Volume is measured in Bitcoin for CEXs and in Binance Coin for PancakeSwap. The dependent variable for columns 7 and 8 is P&D return, which is the logarithm of the ratio of the highest price achieved within ten minutes after the pump announcement and the price ten minutes before the pump. *Number of channel members* is the sum of members across all channels in a P&D event. All other control variables are defined in Table 1. Standard errors are clustered by channel and day. In the case of multiple channels coordinating a pump, the channel we use for clustering is defined as the biggest channel among coordinating channels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	Insider profit		Past trading volume		Trading volume 30-minute after announcement		P&D return	
	CEXs	PancakeSwap	CEXs	PancakeSwap	CEXs	PancakeSwap	CEXs	PancakeSwap
	1	2	3	4	5	6	7	8
Log (number of channel members)	0.098***	0.704***	0.258**	0.074**	0.426***	0.340***	0.034	0.147***
	(2.85)	(3.29)	(2.02)	(2.24)	(3.13)	(7.05)	(1.07)	(2.75)
Past seven-day return	0.165	-0.193*	-0.005	-0.020	0.749**	-0.001	-0.155*	-0.050*
	(1.48)	(-1.66)	(-0.02)	(-0.95)	(2.63)	(-0.05)	(-1.84)	(-1.88)
Cryptocurrency age	-0.022	4.814*	0.322***	2.191***	0.193***	-0.055	-0.099***	-2.457***
	(-0.79)	(1.97)	(3.95)	(2.74)	(3.30)	(-0.07)	(-5.45)	(-2.74)
Token dummy	0.085		1.230***		0.703***		-0.202***	
	(1.15)		(5.38)		(3.09)		(-4.85)	
Log (social media index)	0.066*		0.611***		0.433***		-0.062***	
	(1.95)		(9.50)		(5.69)		(-2.91)	
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	500	1,495	500	1,495	500	1,495	500	1,495
Adj. R^2	0.110	0.096	0.539	0.449	0.463	0.388	0.206	0.061

Table 5. Investor Characteristics and P&D Participation

In this table we report the summary statistics for investor characteristics (Panel A) and the logistic regression results for the relationship between investor characteristics and P&D participation (Panel B). The unit of analysis is the investor-month. The dependent variable is a dummy that equals 1 if an investor participates in any P&Ds in month t and 0 otherwise. The independent variables are investor characteristics measured at the end of month t-1. *Log(Price)* is the natural logarithm of the median price (in Binance Coin) across all the previous purchases. *Selling probability* is the daily probability that a held cryptocurrency is sold. *Log(Portfolio size)* is the natural logarithm of the portfolio size (in Binance Coin) at the end of month t-1. *Experience* is the number of months since an investor started to trade on PancakeSwap. $Return_{t-1}$, $Return_{t-2}$, and $Return_{t-3}$ are portfolio returns in months t-1, t-2, and t-3, respectively. We report coefficient estimates and their t-statistics. Standard errors are clustered by investor and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary statistics

	Mean	1st quartile	Median	3rd quartile	Std. Dev.
Participation (%)	0.072	0	0	0	2.676
Log (Price, in Binance Coin)	-15.087	-22.400	-18.144	-6.030	8.784
Selling probability	0.015	0.000	0.003	0.012	0.046
Log (Portfolio size, in Binance Coin)	2.738	-0.402	4.426	5.418	3.555
Experience	2.836	1.000	2.000	5.000	2.353
$Return_{t-1}$	0.001	-0.274	-0.005	0.156	0.721
$Return_{t-2}$	-0.023	-0.263	0.000	0.031	0.685
$Return_{t-3}$	-0.076	-0.229	0.000	0.000	0.533

Panel B. Regression analysis

	Dependent variable: Participation					
	1	2	3	4	5	6
Log (Price)	-0.076***					-0.072***
	(-12.39)					(-17.57)
Selling probability		2.722***				3.025***
		(54.32)				(12.63)
Log (Portfolio size)			0.254***			0.277***
			(5.68)			(8.92)
Experience				-0.244***		-0.252***
				(-4.91)		(-4.14)
$Return_{t-1}$					0.219***	-0.011
					(2.99)	(-0.25)
$Return_{t-2}$					0.178***	0.037**
					(4.91)	(2.30)
$Return_{t-3}$					0.073***	-0.042
					(2.95)	(-1.28)
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,354,535	50,354,535	50,354,535	50,354,535	50,354,535	50,354,535
Pseudo R-squared	0.153	0.138	0.156	0.139	0.137	0.184

Table 6. Past P&D Performance and Future P&D Participation

In this table we report the regression results pertaining to whether an investor's past P&D performance (Ret_t) predicts the likelihood of future P&D participation ($Participation_{t+1}$) and performance (Ret_{t+1}). Early outsiders are investors who buy in the first 20 seconds after pump announcements and the ones buying later are late outsiders. The analysis is performed at the investor-pump level. For the odd columns, the dependent variable is a dummy that equals 1 if an investor participates in the next P&D organized by his channel and 0 otherwise. In the even columns, the dependent variable is the return in the next P&D organized by his channel. If an investor does not participate in the next P&D, Ret_{t+1} is 0. Ret_t is the investor's return in the last P&D organized by his channel. $I(Ret_t>0)$ is a dummy variable that equals 1 if Ret_t is positive and 0 otherwise. In this analysis, we include the explanatory variables of Table 5 as control variables. We report coefficient estimates and their *t*-statistics. Standard errors are clustered by investor and date. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Early outsiders				Late outsiders			
Dependent variable	$Participation_{t+1}$	Ret_{t+1}	$Participation_{t+1}$	Ret_{t+1}	$Participation_{t+1}$	Ret_{t+1}	$Participation_{t+1}$	Ret_{t+1}
	1	2	3	4	5	6	7	8
$I(Ret_t>0)$	0.126***	0.002	0.113***	-0.004	0.140***	-0.022***	0.127***	-0.021***
	(6.52)	(0.14)	(5.49)	(-0.27)	(16.91)	(-3.64)	(17.33)	(-4.18)
Constant	0.142***	-0.016**			0.073***	-0.026***		
	(9.85)	(-2.11)			(18.33)	(-11.98)		
Control variables	No	No	Yes	Yes	No	No	Yes	Yes
Channel FEs	No	No	Yes	Yes	No	No	Yes	Yes
Date FEs	No	No	Yes	Yes	No	No	Yes	Yes
Observations	4,651	4,651	4,630	4,630	83,905	83,905	83,902	83,902
Adj R-squared	0.024	0.000	0.140	0.062	0.031	0.002	0.075	0.030

Table 7. The Bittrex Ban and Yobit's Pump Scheme Events

In this table we report the difference-in-differences results of the Bittrex ban (Yobit's Pump Scheme) on November 24, 2017 (October 10, 2018). In Panel A, the treatment group comprises cryptocurrencies listed on Bittrex (Yobit) as of the event, and the control group includes matched cryptocurrencies not listed on Bittrex (Yobit) at that time. In Panel B, we focus on the cross-listed cryptocurrencies and compare their volumes and prices on Bittrex (Yobit) with those on other exchanges. The control sample in Panel A is formed by matching each cryptocurrency listed on Bittrex (Yobit) to a non-Bittrex (non-Yobit) cryptocurrency with the closest propensity score, where the propensity score is estimated using trading volume over the period running from 60 days to 31 days before the ban, market capitalization 15 days before the ban, and the past seven-day return. In the regression, there are two observations for each cryptocurrency: one for the pre-ban period and one for the post-event period. Volume is the average volume in the pre- or post-period, scaled by the average in the [-14, -1] period. Price is the price at the end of the post-period or at the beginning of the pre-period, scaled by the average in the [-14, -1] period. In Panel B, we exclude observations where non-Bittrex (non-Yobit) volume is zero. In Panel A, standard errors are clustered at the treatment–control pair level, and in Panel B, standard errors are clustered at the cryptocurrency level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Propensity score matching

	The Bittrex ban				Yobit's pump scheme			
Dependent variable	Volume		Price		Volume		Price	
	[-7, +7]	[-14, +14]	[-2, +2]	[-7, +7]	[-7, +7]	[-14, +14]	[-2, +2]	[-7, +7]
	1	2	3	4	5	6	7	8
Treat × Post	0.225**	0.360***	0.063***	0.151***	-0.443***	-0.343**	-0.121***	-0.155***
	(2.21)	(3.35)	(2.73)	(3.12)	(-3.06)	(-2.14)	(-2.74)	(-3.09)
Post	0.155**	0.246***	0.077***	0.162***	0.145	0.140	-0.085***	-0.017
	(2.39)	(3.39)	(4.21)	(3.81)	(1.42)	(1.04)	(-2.91)	(-0.45)
Cryptocurrency FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	760	760	760	760	696	696	696	696
Adj. R-squared	0.363	0.351	0.689	0.388	0.378	0.070	0.297	0.148

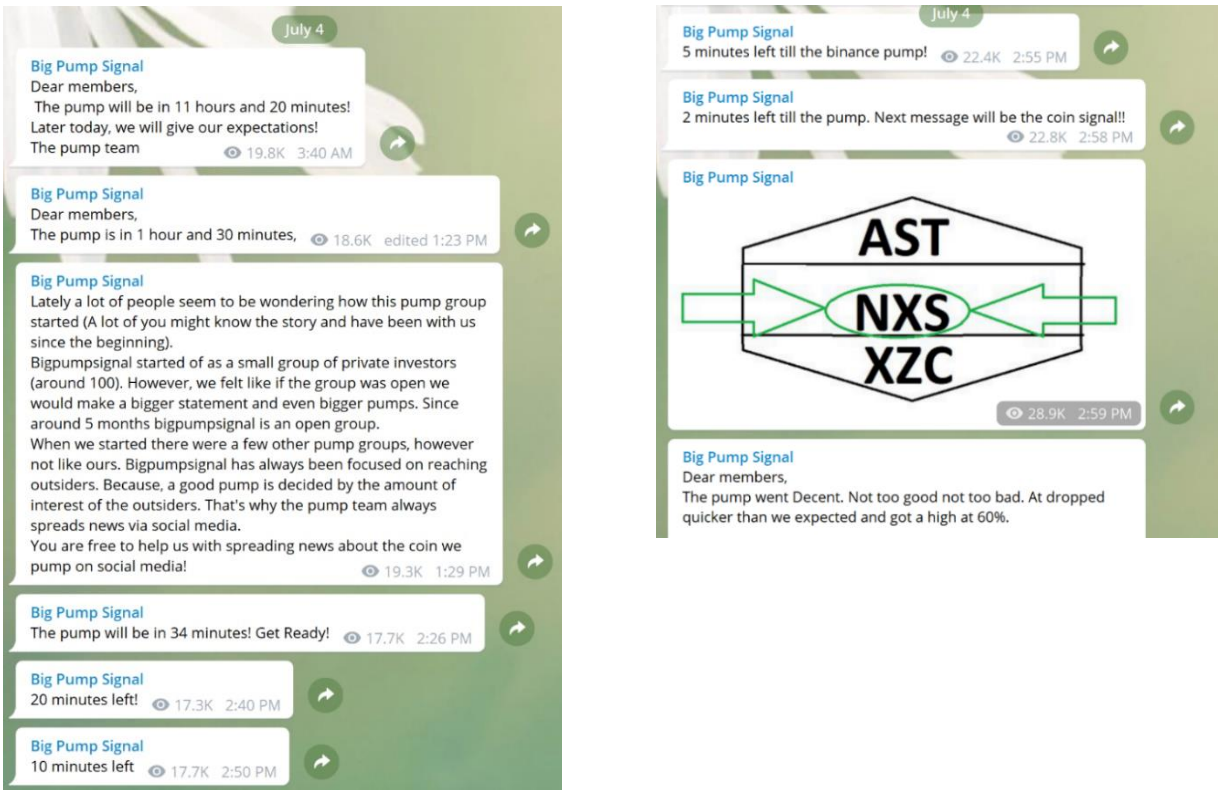
Panel B. Cross-listed cryptocurrencies

	The Bittrex ban				Yobit's pump scheme			
Dependent variable	Volume		Price		Volume		Price	
	[-7, +7]	[-14, +14]	[-2, +2]	[-7, +7]	[-7, +7]	[-14, +14]	[-2, +2]	[-7, +7]
	1	2	3	4	5	6	7	8
Treat × Post	0.081***	0.094***	0.004	-0.007	-0.283**	-0.232**	0.010	-0.025
	(5.37)	(6.34)	(0.86)	(-0.99)	(-2.60)	(-2.32)	(0.17)	(-0.54)
Post	0.326***	0.581***	0.011	-0.017	-0.452***	-0.284***	-0.144**	-0.151***
	(4.78)	(9.07)	(0.77)	(-0.76)	(-4.38)	(-2.74)	(-2.35)	(-3.13)
Cryptocurrency x Exchange FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	704	704	704	704	668	668	668	668
Adj. R-squared	0.070	0.209	0.525	0.031	0.199	0.036	0.051	0.248

Figure 1: An Example of Pump-and-Dump Schemes on Telegram

Panel A displays a series of Telegram announcements by Big Pump Signal, one of the biggest pump groups, regarding their July 4, 2018 pump targeting Nexus (NXS). Panel B plots Nexus's prices and volumes around the pump announcement (t =0).

Panel A: Telegram pump announcements on Nexus



Panel B: Nexus's price and volume around the P&D announcement (t=0)

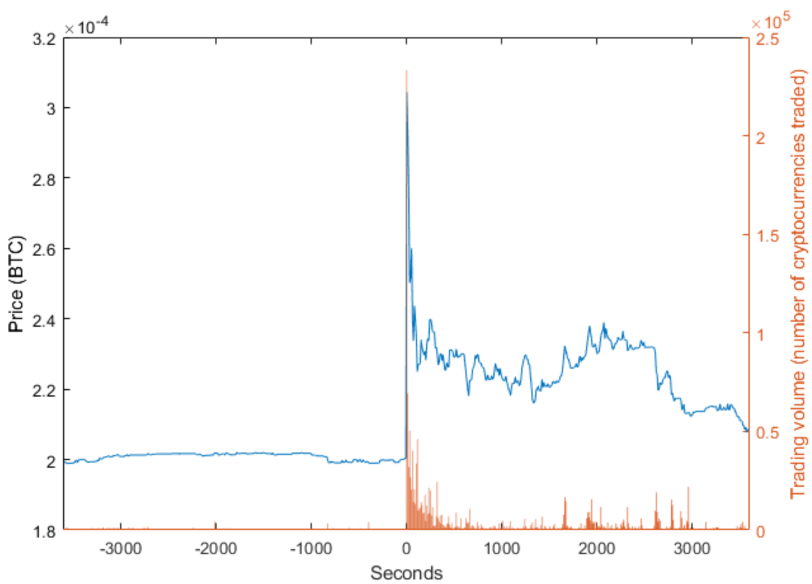
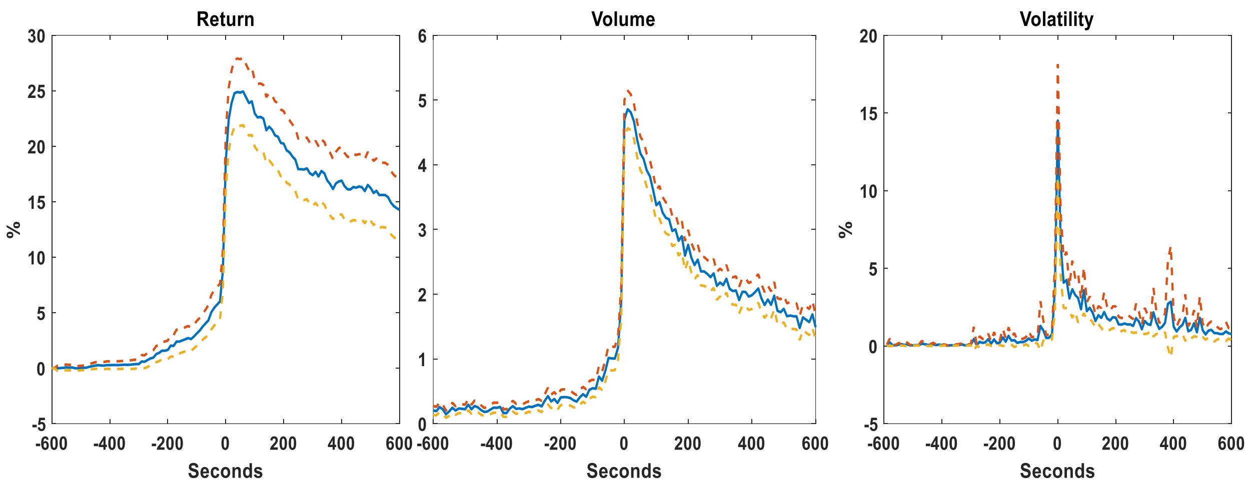


Figure 2: Return, Volume, and Volatility around Pump and Dumps – Short-term analysis

This figure displays cumulative returns, abnormal volume, and the volatility of pumped cryptocurrencies for a 20-minute period around pump announcements: Panel A for the three centralized exchanges and Panel B for PancakeSwap. The graphs depict the pattern for each ten-second interval. Time 0 indicates the ten-second interval between 0 and 10, in which 0 is the announcement time. The solid lines represent the averages across all target cryptocurrencies and the dashed lines show the 95% confidence intervals. Cumulative returns are calculated as the logarithm of price changes from 600 seconds before an announcement. Abnormal volume equals log (1 + volume over an interval/average volume in the interval over day -37 to day -8) for Panel A and log (1 + volume over an interval/average volume in the interval over day -37 to day -2) for Panel B. Volume is measured by the number of cryptocurrencies traded. Volatility is measured as the absolute value of the return during each 10-second interval.

Panel A. Centralized exchanges



Panel B. PancakeSwap

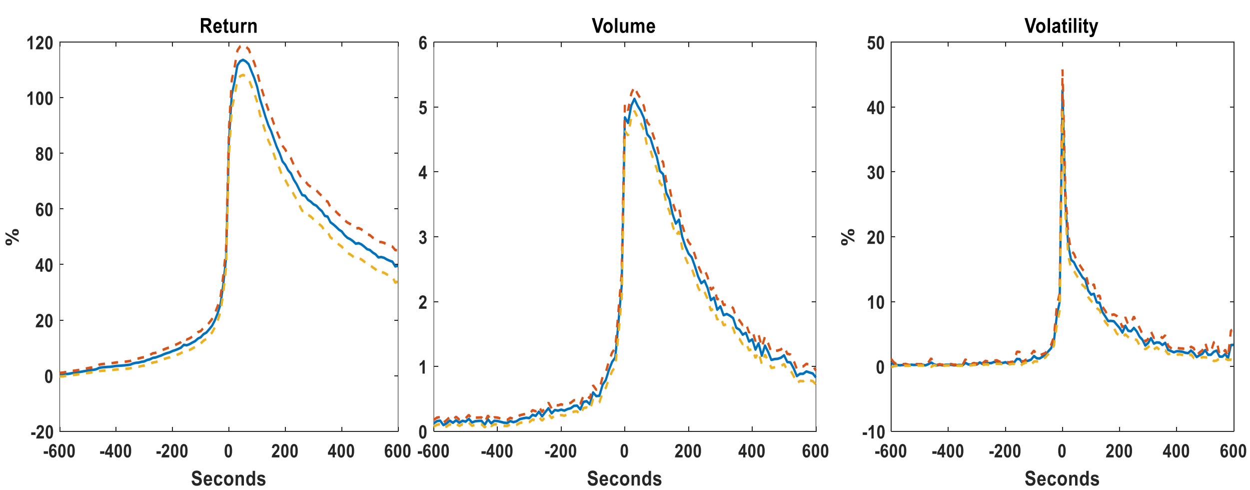
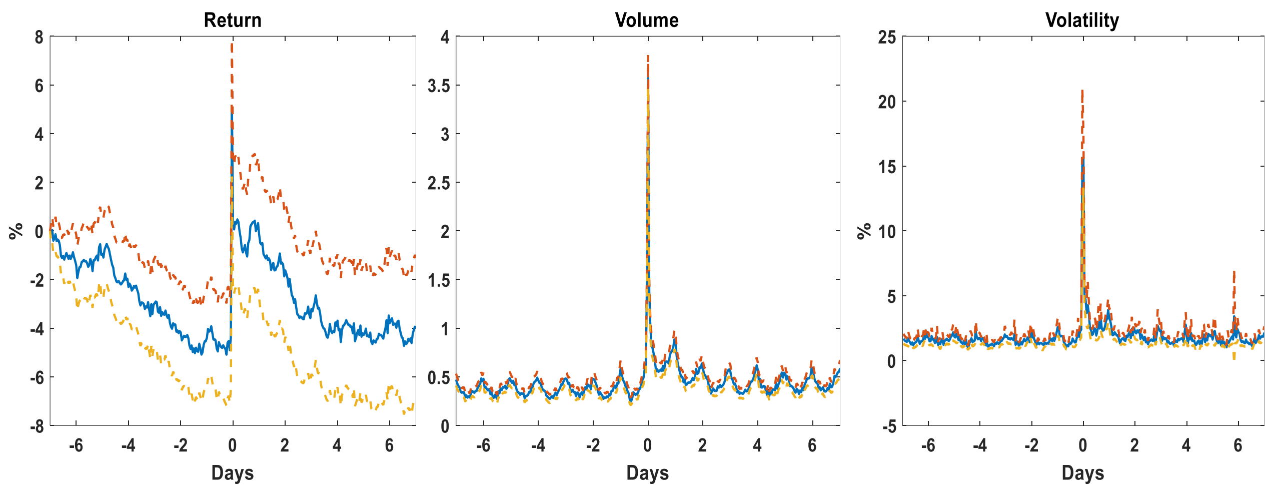


Figure 3: Return, Volume, and Volatility around Pump and Dumps – Longer-term analysis

This figure displays cumulative returns, abnormal volume, and the volatility of pumped cryptocurrencies for the [-7 day, +7 day] period around pump announcements: Panel A for the three centralized exchanges and Panel B for PancakeSwap. The graphs depict the analysis for each one-hour interval. The x-axis indicates time. The solid lines represent the averages across all target cryptocurrencies and the dashed lines show the 95% confidence intervals. Cumulative returns are calculated as the logarithm of price changes from seven days before an announcement. Abnormal volume equals log (1 + volume over an interval/average volume in the interval over day -37 to day -8) for Panel A and log (1 + volume over an interval/average volume in the interval over day -37 to day -2) for Panel B. Volume is measured by the number of cryptocurrencies traded. Volatility is measured as the absolute value of the return during each one-hour interval.

Panel A. Centralized exchange



Panel B. PancakeSwap

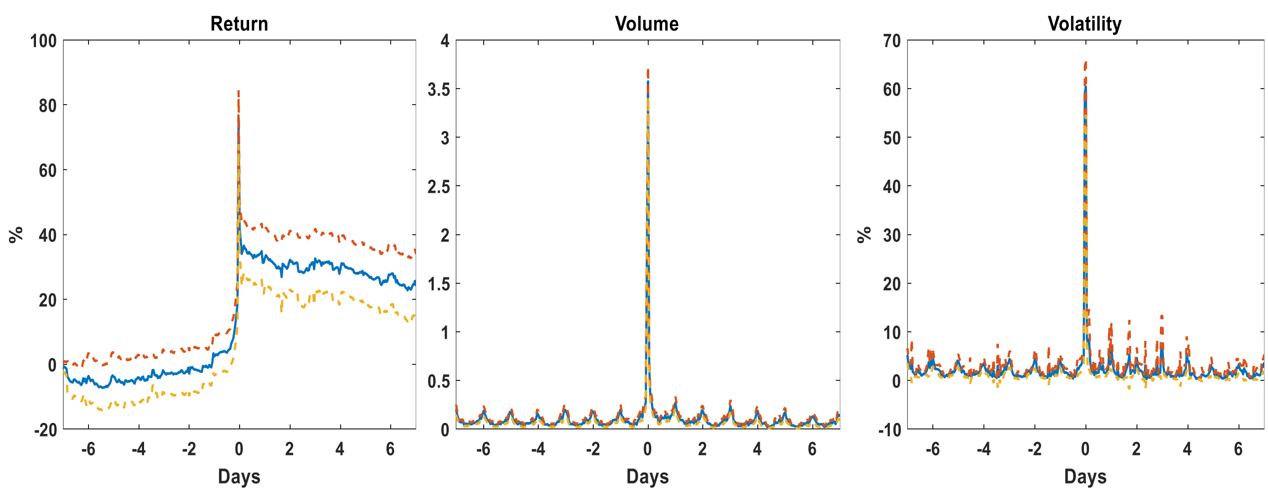


Figure 4: Return, Volume, and Volatility of the Largest Market Capitalization Group

This figure displays short-term cumulative returns, abnormal volume, and the volatility of the largest pumped cryptocurrencies on centralized exchanges. We divide P&Ds into five groups based on the market capitalization of pumped cryptocurrencies. Market capitalization is measured eight days before a P&D announcement using CoinMarketCap data. We plot cumulative returns, abnormal volume, and the volatility in each ten-second interval from 600 seconds before to 600 seconds after P&D announcements. Time 0 indicates the ten-second interval between 0 and 10, in which 0 is the announcement time. The x-axis indicates time. The solid lines represent the averages across all target cryptocurrencies and the dashed lines show the 95% confidence intervals. Cumulative returns are calculated as the logarithm of price changes from 600 seconds before an announcement. Abnormal volume equals log (1 + volume over an interval/average volume in the interval over day -37 to day -8). Volume is measured by the number of cryptocurrencies traded. Volatility is measured as the absolute value of return in each interval.

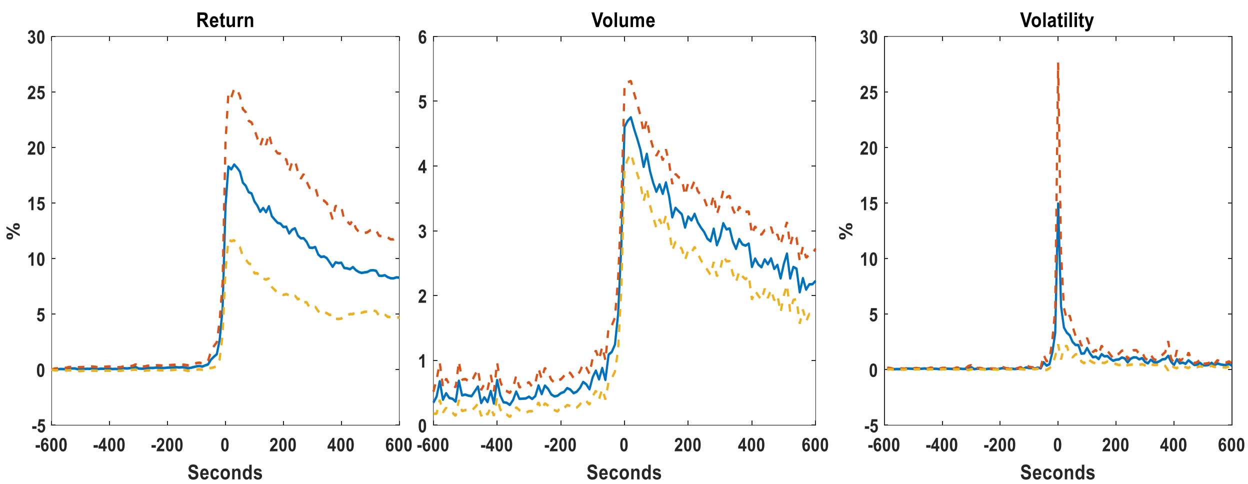
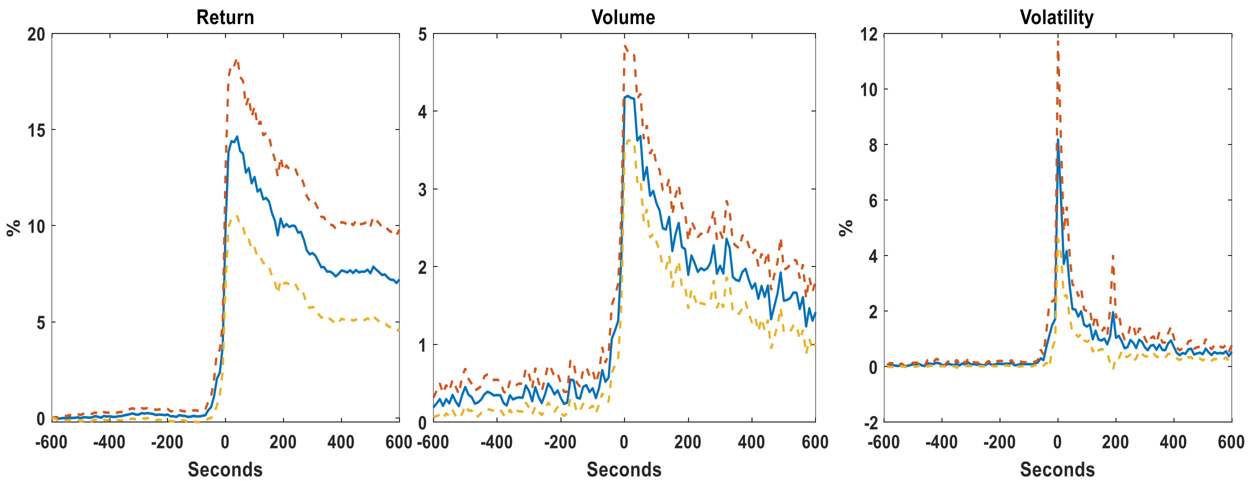


Figure 5: Spillovers to Ethereum Trading Pairs and Other Exchanges

This figure shows whether any spillover to prices and volume quoted in Ethereum occurs during P&Ds that takes place on CEXs (Panel A) as well as prices and volumes quoted in Bitcoin on other exchanges (Panel B). In Panel A, for pumped cryptocurrencies with trading data on Ethereum pairs, we report cumulative returns, abnormal volume, and the volatility of the Ethereum pairs. In Panel B, for pumped cryptocurrencies with trading data from other exchange(s), we report cumulative returns, abnormal volume, and the volatility of these cross-listed cryptocurrencies on the non-targeted exchange(s). If a cryptocurrency is cross-listed on two other exchanges in addition to the target exchange, we take the average of maximum return, abnormal volume, and volatility across the two exchanges.

Panel A. Ethereum pairs



Panel B. Bitcoin pairs on other exchanges

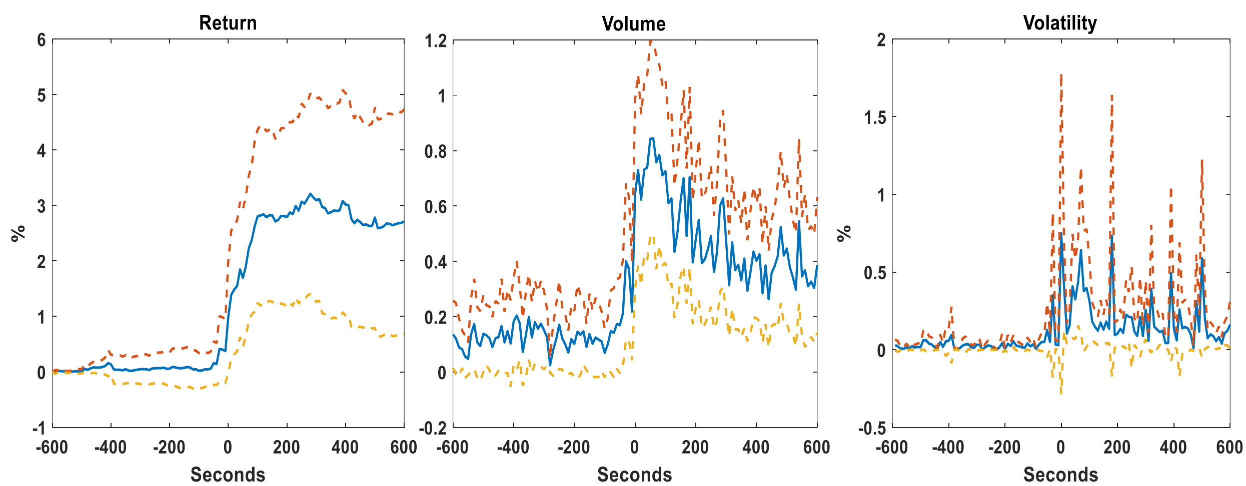
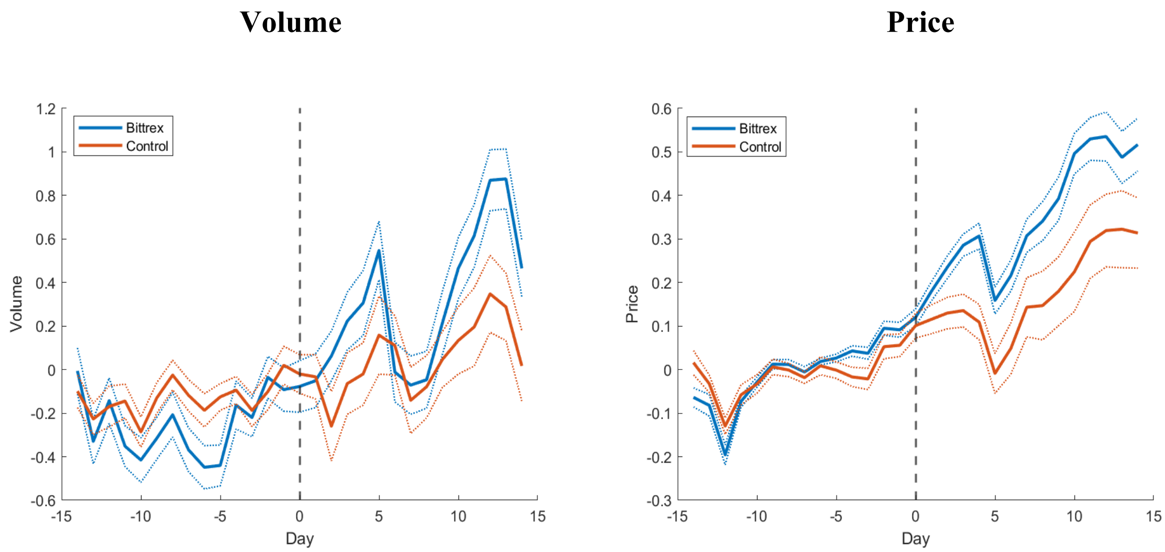


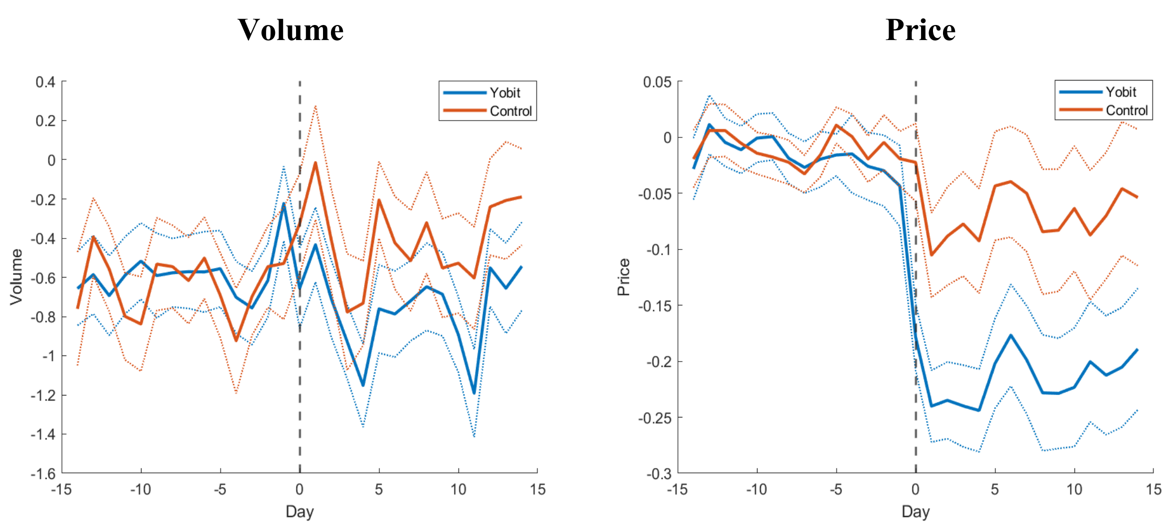
Figure 6: The Effects of the Bittrex Ban and Yobit's Pump Scheme on Price and Volume

This figure plots the volume (left) and prices (right) of Bittrex cryptocurrencies and their controls in Panel A and of Yobit cryptocurrencies and their controls in Panel B. See Tables 7 and 8 for the construction of the samples. Volume is measured as the natural logarithm of the ratio between the volume on day *t* and the average over the [-14, -1] period. Price is measured as the natural logarithm of the ratio between the price on day *t* and the average over the [-14, -1] period. The black dashed vertical line indicates the event date. The solid lines display the average, and the dashed lines display the 95% confidence intervals.

Panel A. Bittrex ban



Panel B. Yobit pump scheme



Internet Appendix for

"Cryptocurrency Pump-and-Dump Schemes"

Part A1: Cryptocurrency Trading

Most secondary-market trading in cryptocurrencies occurs on centralized or decentralized exchanges. Cryptocurrencies are typically listed on one or more exchanges. Exchanges operate 24 hours a day, 365 days a year. Centralized exchanges (CEXs) operate similarly to stock markets, where traders can place market or limit orders. Binance, Bittrex, and Yobit, the three CEXs we study, charged flat fees during our sample period for both market and limit orders of 0.1%, 0.2%, and 0.25%, respectively.

Cryptocurrency prices are quoted in ticker pairs that function much like exchange rates. For example, NXS/BTC is a pair that indicates that a trade is an exchange between NXS (Nexus) and BTC (Bitcoin). In this pair, Nexus is quoted in the number of Bitcoins, which is the base cryptocurrency.

An extensive literature exists on pricing and trading cryptocurrencies. Harvey (2016) discusses the mechanics and applications of crypto finance. Cong, Li, and Wang (2021) study cryptocurrency prices using a theoretical framework. They show that, in contrast to traditional assets, cryptocurrencies' value is determined by transactional user demand and is affected by network externality. Liu and Tsyvinski (2021) find that cryptocurrencies have no exposure to the most common stock market and macroeconomic factors or returns on fiat currencies and commodities. Liu, Tsyvinski, and Wu (2022) study cross-sectional expected cryptocurrency returns. Hu, Parlour, and Rajan (2019) present stylized facts about cryptocurrency returns. Makarov and Schoar (2020) study cryptocurrency mispricing and arbitrages across exchanges. Chan, Ding, Lin, and Rossi (2020) study the behavior of cryptocurrency investors. Shams (2020) studies the structure of cryptocurrency returns.

Wash trading is prevalent on some CEXs (Fusaro and Hougan(2019), Aloosh and Li (2024), Cong, Li, Tang, and Yang (2023), Amiram, Lyandres, and Rabetti (2021)). Binance and Bittrex are considered free of the wash-trading problem. For example, Fusaro and Hougan (2019), in their Bitwise report presented to the SEC, indicate that both Binance and Bittrex have reported genuine trading volume. Cong, Li, Tang, and Yang (2023) also find that wash trading is less of an issue for Binance and Bittrex. Although we cannot find studies designed to investigate whether Yobit reports false volumes, our consistent findings across all three CEXs in our sample and PancakeSwap suggest that wash trading is unlikely to affect our conclusions.

Since mid-2020, cryptocurrency trades have taken place increasingly on leading decentralized exchanges (DEXs), such as Uniswap and PancakeSwap. Traders execute transactions against a liquidity pool run by smart contracts, often called automated market makers (AMMs).

To illustrate the mechanisms of an automated market maker (AMM), such as PancakeSwap, here we provide an example regarding the ETH-BNB pair.[1] We assume that a sole liquidity provider provides 100 ETH and 1,000 BNB tokens to a PancakeSwap liquidity pool (assuming the fair exchange rate is 1:10) and that she receives 1,000 liquidity tokens. Thus the constant product k = 100 × 1,000 = 100,000. Assume that a trader swaps 100 BNB for ETH. Given that PancakeSwap charges a fee of 0.25%, the effective amount of BNB that is traded is 99.75. The total number of BNB before the fee revenue is added to the pool increases to 1,099.75. According to the bonding curve, the new balance of ETH in the pool equals 90.9298 (100,000/1,099.75). Therefore, the trader receives 9.0702 ETH. The effective exchange rate for the trader is 9.0702/100 = 0.91:10. The swap transaction increases the relative price of ETH.

[1] More precisely, the pair involves wrapped ETH and wrapped BNB. PancakeSwap is deployed on Binance Smart Chain (BSC), which supports tokens using the BEP-20 standard. Because ETH and BNB do not conform to the BEP-20 standard, they need to be "wrapped" before being used in BSC. In this paper, we use ETH (BNB) and wrapped ETH (wrapped BNB) interchangeably.

As PancakeSwap specifies, liquidity token holders receive a fee of 0.17%, with the remaining 0.08% being kept in the PancakeSwap Treasury to maintain the platform. Therefore, the total BNB balance in the pool post-trade equals (1,099.75 + 0.17) = 1,099.92. The new constant product becomes 100,015.50 (90.9298 × 1,099.92), which will be applied to the next trade.

For a more detailed discussion of the mechanics of AMM, the reader is referred to Lehar and Parlour (2021).

Part A2: An Example of a PancakeSwap pump-and-dump (P&D) scheme

Figure A1 presents the example. Panel A displays a series of Telegram announcements by Pump HypeCoin, one of the biggest pump groups active on PancakeSwap, regarding their December 8, 2021, pump targeting Drosix (DRX). Panel B plots Drosix's prices and volume before and after the pump announcement (*t* =0).

Part A3: Matching Cryptocurrencies Across Datasets

Both our exchange data and the CoinMarketCap data use tickers to identify unique cryptocurrencies. In most P&Ds, the Telegram channels provide cryptocurrency tickers and often names as well. In most cases, a cryptocurrency has the same ticker on the exchange (or exchanges if it is cross-listed) and on CoinMarketCap. In some cases, however, a cryptocurrency can have a different ticker on the exchanges than on CoinMarketCap. It is also possible that two cryptocurrencies have the same ticker on different exchanges. We manually matched these cryptocurrencies.

CoinMarketCap provides both cryptocurrency tickers and names. However, the exchange data include only cryptocurrency tickers but not their names. We search for cryptocurrency names using their tickers on the websites of the exchanges. For delisted cryptocurrencies, we rely on Binance's Announcements page (https://support.binance.com/hc/en-us/categories/115000056351-Announcements), Bittrex's Coin Removals page (https://support.bittrex.com/hc/en-us/sections/200560334-Coin-Removals), and Yobit's press releases to identify their names.

Part A4: PancakeSwap vs. Uniswap

PancakeSwap and Uniswap are deployed on Binance Smart Chain (BSC) and Ethereum, respectively. We collect average gas fees associated with transactions on BSC and Ethereum from Ycharts and plot them in Panel A of Figure A3. The fee is measured based on all transactions, including lending, borrowing, and token swaps, and therefore, it is considered the average fee that investors pay for any on-chain activities on BSC or Ethereum. Panel A shows that, on average, investors pay higher gas fees on Ethereum than on BSC. In 2021, the average gas fees on BSC and Ethereum were $0.36 and $9.99, respectively. We also note that the average gas fee on Ethereum fluctuates significantly over time.

The data used in Panel A are averaged across all types of transactions. Different platforms charge different gas fees depending on the complexity of computations executed by smart contracts and market conditions. Gas fees associated with token swaps bear greater relevance to our study. To collect information on the average gas fees that PancakeSwap and Uniswap investors pay to trade tokens, we collect all transactions executed by PancakeSwap v1 and v2 and Uniswap v2. PancakeSwap is a fork of Uniswap, and therefore, they share several functions in their smart contracts, which allows us to compare the gas fees on both DEXs directly. We choose six common token swap-related functions on PancakeSwap and Uniswap and calculate the average gas fees for the transactions executed by calling those functions. Panel B shows that for both PancakeSwap and Uniswap, the average token swap-related gas fee changes over time, and it is generally higher in Uniswap than in PancakeSwap. In 2021, the average token swap-related gas fee on Uniswap was $38.93, whereas it was only $0.53 on PancakeSwap.

Regarding trading fees, PancakeSwap v2 (v1) charges a fee of 0.25% (0.2%) of the trading volume, while Uniswap v2 charges a 0.3% fee on the total trading volume.

Part A5: Blockchain Data

We begin by downloading all DEX trades executed on BSC during our sample period. Our sample comprises the entire history of token transfers between wallets from September 2020 to December 2021, the end of our sample period.

Among all DEX trades, those whose associated exchange names contain “Pancake” are classified as trades taking place on PancakeSwap v1 or v2. Among these PancakeSwap trades, we select trades that swapped a token for Binance Coin (BNB) as BNB is the main numeraire on BSC.

The majority of BSC token transfer transactions involve a swap between two tokens (i.e., using token A to buy token B). However, some transactions are transfers involving more than two tokens (e.g., using token A to buy tokens B and C) or activities other than token swaps (e.g., using flash loans for an arbitrage trade targeting two DEXs). We focus on the transactions involving a swap between two tokens because it is harder to calculate the exchange rate between two tokens in other types of transactions.

In this dataset, each trade contains information such as the exchange name, the name and amount of sold tokens, the name and amount of bought tokens, the associated smart contract, and the transaction hash (i.e., the unique key for each transaction). Each wallet address includes a list of hashes associated with all trades the wallet has executed. We use the transaction hash to identify the wallet addresses involved in a trade. The resulting dataset is similar to the NYSE TAQ data for U.S. stocks, augmented with the identity of investors executing each trade.

We use this trade dataset to compare cryptocurrency-level characteristics of targeted and non-targeted tokens, describe patterns of the price, volume, and volatility of targeted tokens around P&Ds, construct pump-level characteristics such as maximum returns, and study investor behavior around P&Ds.

Part A6: Distribution of P&Ds and Trading Volume by Hour

Figure A4 presents the distribution of P&D events (Panel A) and trading volume (Panel B) by hour and exchange. Both trading volume and P&Ds concentrate from 12:00 to 22:00 UTC (daytime in the U.S.).

Part A7: Mitigating Potential Issues of the Data

Selection bias might occur in one of three ways, which we illustrate by using data for the CEXs (the first two also apply to the PancakeSwap data). First, 81 of our 210 initially identified Telegram pump channels are closed. Telegram closes channels to save disk space. When closing a channel, Telegram will delete all messages, contacts, and data stored in the Telegram cloud. This explains why, in those circumstances, we can no longer access the messages. The most prominent cause of channel closures is that operators do not log onto their channels within a six-month period. Many channels in our sample had been inactive for months (but for fewer than six months) but were not closed. We assess the importance of this source of bias in Figure A5. Figure A5 presents the results for P&Ds in the six-month window before late August 2018. This figure displays cumulative returns, abnormal volume, and volatility for the P&Ds that occurred in the six-month period from February 27, 2018, to August 26, 2018. The last P&D event in our sample took place on August 26, 2018. This sample includes 146 P&D events. The results are similar to the full sample results.

Second, our sample Telegram channels may over-represent the channels that actively advertise on Reddit and BitcoinTalk or are more successful. After reading many social media posts, however, we conclude that most Telegram channels are active on Reddit and BitcoinTalk, and our list of Telegram pump groups is comprehensive. Of the 129 pump groups that were still open as of September 2018, 49 did not initiate any pumps, and 37 initiated ten or fewer P&Ds. This suggests that our sample covers a wide range of pump groups, including unsuccessful ones.

The third problem is that the trading data from Bittrex and Yobit do not cover all the listed cryptocurrencies. This is because our data provider occasionally experienced technical issues when querying the two exchanges. We believe this is unlikely to cause any bias in our results. Nevertheless, to address any such concern, we replicate our main results by focusing only on P&Ds that target Binance. We download trading data from Binance directly and can collect data on all of their cryptocurrencies. Figure A6 displays cumulative returns, abnormal volume, and volatility for the P&Ds that occurred on Binance. This sample includes 76 P&D events. The results are similar to the full sample results. P&Ds on PancakeSwap do not have this problem because trades are all recorded on the blockchain.

Part A8: P&D Schemes by Market Capitalization

Figure A7 displays short-term cumulative returns, abnormal volume, and the volatility of pumped cryptocurrencies sorted by market capitalization. We divide P&Ds into five groups based on the market capitalization of pumped cryptocurrencies. Each panel reports the results for a market capitalization group.

Part A9: Prices Change in Most P&Ds

Figure 3 shows that, on average, prices and trading volume change in P&Ds. In this section, we examine the cross-sectional distribution of the price effects and measure how long it takes for the price to reach its peak.

Figure A8 displays the distribution of maximum returns (Panel A) and time to maximum returns (Panel B) across P&D events. A P&D's maximum return is defined as the natural logarithm of the ratio of the highest price achieved within ten minutes after the pump announcement to the price ten minutes before the announcement minus one. The time to maximum return is defined as the number of seconds it takes from the announcement to reach the maximum price. There are a few extreme returns. For ease of illustration, we cap maximum returns at 600% for the results displayed in Figure A8, Panel A. In all other analyses, returns are not capped. A maximum return can be negative if the maximum price of a pumped cryptocurrency during the ten minutes after the announcement is lower than its price ten minutes before the announcement. This can happen if the scheme is unsuccessful and the price drops.

In Figure A8, Panel A we show that, in most P&Ds cryptocurrency prices increase. The increases are generally larger for PancakeSwap P&Ds than CEX P&Ds. In Figure A8, Panel B, we show that, on average, it takes 2.3 minutes and 2.0 minutes for prices to reach the maximum level for P&Ds on the CEXs and PancakeSwap, respectively. This short window indicates that one needs to trade quickly to make profits from P&Ds.

Part A10: Spillovers to Ethereum Pairs and Other CEXs

In Table A2 we report results pertaining to potential spillovers. In Panel A we report the results for the Ethereum pairs on the same exchange. Panel B reports the results for the Bitcoin pairs on other exchanges. In Panel A for pumped cryptocurrencies with trading data on Ethereum pairs, we report maximum returns, abnormal volume, and the volatility of the Ethereum pairs. In Panel B for pumped cryptocurrencies with trading data from other exchange(s), we report maximum returns, abnormal volume, and the volatility of these cross-listed cryptocurrencies on the non-targeted exchange(s). If a cryptocurrency is cross-listed on two other exchanges in addition to the target exchange, we take the average of maximum returns, abnormal volume, and volatility across the two exchanges. The *t*-values and the Wilcoxon *p*-values are calculated based on the paired sample.

Part A11: Discussion of the Hierarchical Structure of P&Ds

In this section, we highlight the importance of a hierarchical structure of P&Ds and discuss how it can contribute to large-scale P&Ds on the CEXs. We focus on the CEXs for two reasons: (1) as shown in Table 1, P&Ds targeting the CEXs are larger on average than those on PancakeSwap, based on trading volume, and (2) market capitalization information for PancakeSwap tokens is often unavailable from reputable data sources, such as CoinMarketCap.

First, we emphasize that a hierarchical structure exists and takes various forms in the P&D setting. We find that there is a significant information gap between insiders and outsiders. Such an information gap also exists between different types of outsiders, which is evident in the existence of VIP premium members who often receive pump signals earlier than other outsiders. Section

IV.E highlights the coordination between multiple P&D channels, another type of hierarchical structure.

Second, the hierarchical structure has economic consequences. In Section IV.D, we document that the wealth transfer from outsiders to insiders is economically significant: For an average PancakeSwap P&D, the insiders make about 2.9 BNB (about $1,300), and for an average CEX P&D, the insiders make 1 Bitcoin (about $10,000). Moreover, Section IV.E reveals that members of some P&D channels in coordinated P&Ds are persistently discriminated against.

Third, we find some evidence that a hierarchical structure may enable large-scale P&Ds. Table 4 provides evidence that a large number of participating channels' aggregate members can generate large-scale P&Ds. In addition, column 1 of Table A3 reports that the number of channels is positively correlated with the number of aggregate channel members, suggesting that collaboration between channel members can at least partly contribute to large-scale P&Ds. However, the number of channels does not fully explain the entire variation in the aggregate number of channel members (adj. R^2 is about 0.1 with month-fixed effects), indicating that collaboration by multiple channels is not a sufficient condition for large-scale P&Ds. We proceed to investigate the composition of collaborating Telegram channels in P&Ds. As shown in column 2 of Table A3, the number of members of the largest channel, which likely plays a leading role in the pump, is positively correlated with the average number of members of the other collaborating channels, suggesting that channels targeting the same P&D have similar numbers of members.

Furthermore, we measure the similarity in the size of collaborating channels in each P&D by computing the standard deviation of channel members. The standard deviation of the number of channel members for coordinated P&Ds is 7,194 on average. In contrast, the standard deviation of the number of channel members for all channels is 20,073. Therefore, collaborating channels tend to be similar in size. In other words, (large) channels tend to work with other channels of a similar size, which appears to contribute to large-scale P&Ds. While it is challenging to explain why specific hierarchical structures prevail due to data limitations, the collective evidence suggests that a hierarchical structure may enable large-scale P&Ds.

Part A12: Individual Investor-Level Variables Using Blockchain Data

In Tables 5 and 6, we use monthly individual wallet-level variables to study the determinants of participation in P&Ds. We provide more details on how these variables are constructed.

Our proxy for gambling preference, *Log(Price)*, is the median price of all the cryptocurrencies an investor has bought. *Experience* is the time since an investor started trading on PancakeSwap. To calculate the other variables, we follow the steps below.

First, for each wallet, we compute the end-of-day holdings based on token flows. The balance could be slightly negative if there are small numerical errors. If the balance is between -10^{-6} and 0, we treat the balance as 0. If the balance of a trader-token is below -10^{-6} on any day during our sample period, we drop the trader-token pair from our sample. Our results are very similar if we choose a different cutoff, such as -10^{-7} or -10^{-5}. We flag a token-day when the balance reduces (increases) as a sale (purchase). Based on this daily holdings dataset, we calculate *Selling Probability* as the number of token-days with a sale divided by the total token-days with tokens available for sale (Ben-David and Hirshleifer (2012)).

Second, we create a daily cryptocurrency dataset. We use the last trade price of a day as the close price and the total volume over a day as the daily volume.

Third, the above two daily datasets (investor-token-day holdings and daily token prices) allow us to calculate daily token returns, investor *Portfolio Size*, and daily investor portfolio returns. Daily investor portfolio returns also allow us to calculate past monthly portfolio returns: $Return_{t-1}$, $Return_{t-2}$, and $Return_{t-3}$. However, PancakeSwap lists many new and low-cap tokens, so their prices may be extremely volatile and inaccurate.[2] This issue, without proper treatment, will lead to many outliers. Now, we discuss how we treat them.

Specifically, we choose the top 500 tokens based on the average daily trading volume (in BNB), fraction of days with positive volume, and maximum/minimum price ratio. Specifically, we require the fraction of positive volume days to be greater than 80% to exclude illiquid tokens and the maximum/minimum price ratio to be less than 10^{10} % to exclude extremely volatile tokens. After applying these two filters, we choose the top 500 tokens based on the average daily trading volume. Then, we compute the 0.1 and 99.9 percentiles of those 500 tokens' daily returns and use them to winsorize the daily returns of all tokens in our sample.

For these 500 tokens, we calculate the value of each investor's holding. Then, we compute the 99.9 percentile of the postion values. For all tokens in our sample, if the value of any holding exceeds this value, we set it to equal this value.

Fourth, we compute the end-of-month *Portfolio Size* by aggregating each individual wallet's holdings. To compute an individual wallet's return for a given month, we first compute daily portfolio returns by taking the weighted average of daily returns using the previous day's token balances as weights. Then, we take the sum of the log daily gross portfolio returns for each month to calculate an investor's log monthly return.

[2] The PancakeSwap information page (https://pancakeswap.finance/info), which highlights general PancakeSwap market level information, warns that "The markets for some of the newer and low-cap tokens displayed on the (PancakeSwap) v2 info page are highly volatile, and as a result, token information may not be accurate."

Our PancakeSwap P&D sample starts in March 2021 and ends in December 2021. Given that we predict traders' participation in P&Ds occurring next month, we could use the explanatory variables between February 2021 and November 2021. However, we find that there was only one P&D in March 2021 (on March 31, 2021), and P&Ds became active since April 2021. Since it is likely that most traders did not even recognize any P&Ds were happening in March 2021, we create our explanatory variables from March 2021.[3]

Part A13: Reinforcement Learning

In Table A4 we report the results indicating whether past P&D performance is associated with future P&D participation and performance. Table A4 repeats Table 6 in the paper, except that the independent variable is Ret_t instead of $I(Ret_t>0)$, as in Table 6.

Part A14: A Sharp Decrease in P&Ds on Bittrex after the Ban

In this section, we provide evidence that P&Ds on Bittrex decreased sharply after the Bittrex ban. For example, one prominent pump channel, "Trading signals for crypto," canceled its P&D event on November 26, 2017 (see Figure A10, Panel A). Some message groups solicited feedback from group members regarding whether to switch to other exchanges. Many message groups eventually ceased to pump cryptocurrencies traded on Bittrex.[4]

In Figure A10, Panel B, we plot the number of P&Ds on Bittrex and the other two exchanges over the period running from five months before to eight months after the ban.[5] This

[3] In an untabulated analysis, however, we find that our results reported in Table 5 remain quite similar even after including February 2021 in the regressions.
[4] Some pump groups tried to switch to other exchanges. However, we found that none was successful.
[5] We are not able to conduct the same analysis for the Yobit pump scheme. The Yobit pump scheme occurred after the first version of this paper was completed and we did not begin looking into it until late 2021. It is difficult to collect P&Ds that are more than three years old because many Telegram pump channels have been closed.

period spans our sample period for the CEXs. Although the ban was unable to eliminate P&Ds, there was a sharp decrease in the frequency of P&Ds on Bittrex.[6] Before the ban, the monthly average number of P&Ds targeting Bittrex in our sample is 44. We have 225 cryptocurrencies listed on Bittrex with trading data, implying a significant hazard of being targeted before the ban. This suggests that Bittrex was able to adhere to its announced policy and worked to reduce the occurrence of P&Ds on its exchange.

Part A15: Data Construction for Difference-in-Differences (DiD) Analyses

This research uses two experimental settings, Bittrex's P&D ban and Yobit's P&D scheme, to estimate the causal impact of pump-and-dumps on cryptocurrency markets.

For the Bittrex event analyzed in Table 7, Panel A, we use cryptocurrency market-level daily prices, volumes, and market capitalizations obtained from CoinMarketCap in September 2018. In this analysis, cryptocurrencies traded against BTC on Bittrex from day -60 to the event date constitute the treatment group, while the control group includes all non-Bittrex cryptocurrencies featured on CoinMarketCap. We drop stablecoins from both the treatment and control samples. We then conduct a propensity score matching exercise using three characteristics constructed from CoinMarketCap data: past 7-day return based on prices one and eight days before the event, trading volume measured in USD between day -60 and day -31, and market capitalization measured on day -31. The matching exercise yields 190 treatment cryptocurrencies and 190 control cryptocurrencies.

[6] Hamrick et al. (2019) report that they identify 400 "P&Ds" on Bittrex from January to June 2018. However, only 28 are real P&Ds, which is consistent with our number of P&Ds on Bittrex in 2018. The majority, which they call "obscure pumps," are not P&Ds but rather Telegram users' predictions/forecasts of a cryptocurreny's future price. We find that such predictions/forecasts do not have any significant price or volume effect on the cryptocurrencies being predicted. Hamrick et al. (2019) report a significant price impact of these obscure pumps, which we believe reflects the potential for bias caused by their inference of the pumped timing.

Two variables are used to construct the dependent variables. The first variable is the logarithm of daily trading volume normalized by the average daily trading volume from day -14 through day -1. The second variable is the logarithm of daily price, normalized by the average daily price from day -14 through day -1. If the price is missing on a particular date, we use the most recent price up to five days before the focal date.

For Table 7, Panel B, we do not conduct a matching exercise because, in this analysis, we focus on the same cryptocurrencies traded on both Bittrex and non-Bittrex exchanges. For a Bittrex cryptocurrency, we measure its daily trading volume as the number of cryptocurrencies traded and measure daily price using BTC as the numeraire. For the identical cryptocurrency traded on non-Bittrex exchanges, we measure non-Bittrex trading volume as the CoinMarketCap trading volume minus the Bittrex trading volume, assuming that CoinMarketCap aggregates trading volumes from all major exchanges. For certain cryptocurrencies, the resulting non-Bittrex trading volumes are negative, likely because CoinMarketCap fails to include the Bittrex volume when computing the aggregate volume. For these cryptocurrencies, we use the CoinMarketCap trading volume as the non-Bittrex volume. To compute non-Bittrex prices, we take a similar approach. If a cryptocurrency's CoinMarketCap volume is smaller than its Bittrex volume, we use its CoinMarketCap price (in BTC) as a non-Bittrex price. Otherwise, we use the following equation to back out the non-Bittrex price: *CoinMarketCap price = Fraction of Bittrex volume × Bittrex price + Fraction of non-Bittrex volume × non-Bittrex price.* If the price is missing on a particular date, we use the most recent price up to five days before the focal date. We drop from our sample cryptocurrencies that miss prices.

For the Yobit event, we follow the same procedure discussed above. Cryptocurrency market-level daily prices, volumes, and market capitalizations were obtained from CoinMarketCap in June 2021.

Part A16: Controlling for Pre-Trends in the DiD Test

Our main DiD tests do not allow us to control for pre-trends because each cryptocurrency has only two observations, one for the pre-event period and the other for the post-event period. This is the preferred DiD method advocated by Bertrand, Duflo, and Mullainathan (2004).

In robustness analysis, however, we use a multiple-period DiD, which enables us to include exchange-specific parametric time trends (exchange-day trends). By controlling for exchange-specific time trends, we acknowledge that trading behavior, as reflected in price and volume, may have been differentially trending across multiple exchanges. If the results remain qualitatively similar, the pre-trends should not affect our causal interpretation.

Specifically, we follow the methodology developed by Rambachan and Roth (2023) and impose a smoothness restriction that the counterfactual difference in trends is linear. Given the above restriction, Rambachan and Roth (2023) provide a method for creating robust confidence intervals that are guaranteed to include the true parameter at least 95% (or 99%) of the time when the imposed restrictions are satisfied. These confidence intervals account for the fact that there are estimation errors in both the estimates of treatment effects and our estimates of the pre-trends.

Following the above procedure, in Table A5, we report the 95% and 99% robust confidence intervals for both events (Bittrex and Yobit) and both outcome variables (volume and price). For comparison, we also report the confidence intervals in the DiD estimation under the assumption of no pre-trends.[7] As shown, controlling for pre-trends has only a tiny effect on the results.

[7] We note that these original estimates are not identical to those in Table 7. To address the issues raised by Bertrand, Duflo, and Mullainathan (2004), in Table 7, we aggregate all the data and produce two observations for each cryptocurrency, one for the pre-period and the other for the post-period. We use cryptocurrency-day level observations to conduct pre-trend analysis.

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Table A1. P&D Volume and Total Volume for Targeted Cryptocurrencies

In this table, we present information on P&D-related volume relative to total trading volume. We report the average ratio of P&D volume to total trading volume for each quintile sorted by total trading volume, as well as the full-sample average ratio. P&D-related trading volume is defined as the volume during a (-12 hours, +12 hours) window around P&D announcements, and the total trading volume is the aggregate trading volume during a window of -100 days to +100 days around P&D announcements. All volumes are measured in the number of BTCs (BNBs) for the CEXs (PancakeSwap).

Quintiles based on total volume	Average of P&D volume divided by total trading volume	
	CEXs	PancakeSwap
First quintile	0.133	0.907
Second quintile	0.084	0.645
Third quintile	0.045	0.377
Fourth quintile	0.017	0.312
Fifth quintile	0.025	0.251
Full sample	0.061	0.498

Table A2. Spillovers to Ethereum Trading Pairs and Other Exchanges

In this table, we report results pertaining to potential spillovers from P&Ds taking place on centralized exchanges (Binance, Bittrex, and Yobit). In Panel A we report the results for the Ethereum pairs on the same exchange. In Panel B, we report the results for the Bitcoin pairs on other exchanges. In Panel A, for pumped cryptocurrencies with trading data on Ethereum pairs, we report maximum returns, abnormal volume, and the volatility of the Ethereum pairs. In Panel B, for pumped cryptocurrencies with trading data from other exchange(s), we report maximum returns, abnormal volume, and the volatility of these cross-listed cryptocurrencies on the non-targeted exchange(s). If a cryptocurrency is cross-listed on two other exchanges besides the target exchange, we take the average of maximum returns, abnormal volume, and volatility across the two exchanges. The *t*-values and the Wilcoxon *p*-values are calculated based on the paired sample.

Panel A. Spillovers to Ethereum pairs

	Bitcoin pair	Ethereum pair	Difference	*t*-value	Wilcoxon *p*-value
Maximum return	22.79	23.07	-0.28	-0.14	0.86
Abnormal volume	1.92	1.32	0.61	9.58	<0.01
Volatility	0.66	0.69	-0.03	-1.06	0.66
Number of P&Ds	92	92			

Panel B. Spillovers to other exchanges

	Targeted exchange	Other exchange(s)	Difference	*t*-value	Wilcoxon *p*-value
Maximum return	26.84	5.15	21.69	6.01	<0.01
Abnormal volume	1.62	0.31	1.31	12.59	<0.01
Volatility	0.79	0.12	0.67	5.60	<0.01
Number of P&Ds	89	89			

Table A3. The Hierarchical Structure of P&Ds

In this table, we explore the hierarchical structure of P&Ds. *Log(number of channel members)* is the logarithm of the sum of members across all channels in a P&D event. *No. of channels* is the number of channels participating in a P&D. *Log(number of members of the largest channel)* is the logarithm of the number of members of the largest channel participating in a P&D. *Log(avg. number of members of the other channels)* is the logarithm of the average number of members of the other channels participating in a P&D.

Dependent variable	Log(number of channel members)	Log(avg. no. of members of the other channels)
	Unconditional Regression	Conditional Regression (conditional on collaboration)
	1	2
No. of channels	0.229***	
	(2.93)	
Log(no. of members of the largest channel)		0.602***
		(6.31)
Month FEs	Yes	Yes
Observations	500	111
Adj. R^2	0.108	0.675

Table A4. Past P&D Performance and Future P&D Participation

In this table, we report regression results indicating whether an investor's past P&D performance (*Ret_t*) predicts the likelihood of future P&D participation (*$Participation_{t+1}$*) and performance (*Ret_{t+1}*). The analysis is performed at the investor-pump level. In the odd columns, the dependent variable is a dummy that equals 1 if an investor participates in the next P&D organized by his channel and 0 otherwise. For the even columns, the dependent variable is the return in the next P&D organized by his channel. If an investor does not participate in the next P&D, *Ret_{t+1}* is 0. *Ret_t* is the investor's return in the last P&D organized by his channel. We report coefficient estimates and their *t*-statistics. Standard errors are clustered by investor and date. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Early outsiders				Disadvantaged outsiders			
Dependent variable	$Participation_{t+1}$	Ret_{t+1}	$Participation_{t+1}$	Ret_{t+1}	$Participation_{t+1}$	Ret_{t+1}	$Participation_{t+1}$	Ret_{t+1}
	1	2	3	4	5	6	7	8
Ret_t	0.118***	0.008	0.122***	0.004	0.105***	-0.015***	0.101***	-0.017***
	(6.21)	(0.52)	(6.08)	(0.19)	(14.10)	(-2.80)	(13.67)	(-3.56)
Inc. control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Channel FEs	No	No	Yes	Yes	No	No	Yes	Yes
Date FEs	No	No	Yes	Yes	No	No	Yes	Yes
Observations	4,651	4,651	4,630	4,630	83,905	83,905	83,902	83,902
Adj R-squared	0.039	0.002	0.149	0.062	0.030	0.002	0.075	0.030

Table A5. Controlling for Pre-Trends in the Difference-in-Differences Test

In this table, we report the results of the difference-in-differences (DiD) estimation of the Bittrex ban and Yobit's pump scheme following a recent methodology developed by Rambachan and Roth (2023). For Panel A (Panel B), the treatment group comprises cryptocurrencies listed on Bittrex on November 24, 2017 (Yobit on October 10, 2018), and the control group includes matched cryptocurrencies not listed on Bittrex (Yobit) at that time. The control samples and variable definitions are identical to those used in Table 7. For the volume (price) regressions, we choose the daily sample between [-14, 14] ([-7, 7]) days around the event dates to be consistent with the empirical setting of Table 7. In odd columns, we provide confident sets without controlling for pre-trend. In even columns, we control for the pre-trend by assuming that the trend is linear. Standard errors for the baseline DiD regressions are clustered at the treatment–control pair level.

Table A. The Bittrex Ban

Dependent variable	Bittrex Volume [-14,+14]		Bittrex Price [-7,+7]	
	Original 1	Linear trend 2	Original 3	Linear trend 4
95% robust confidence interval	(0.177, 0.541)	(0.182, 0.577)	(0.064, 0.124)	(0.026, 0.101)
99% robust confidence interval	(0.120, 0.598)	(0.120, 0.639)	(0.054, 0.134)	(0.014, 0.113)

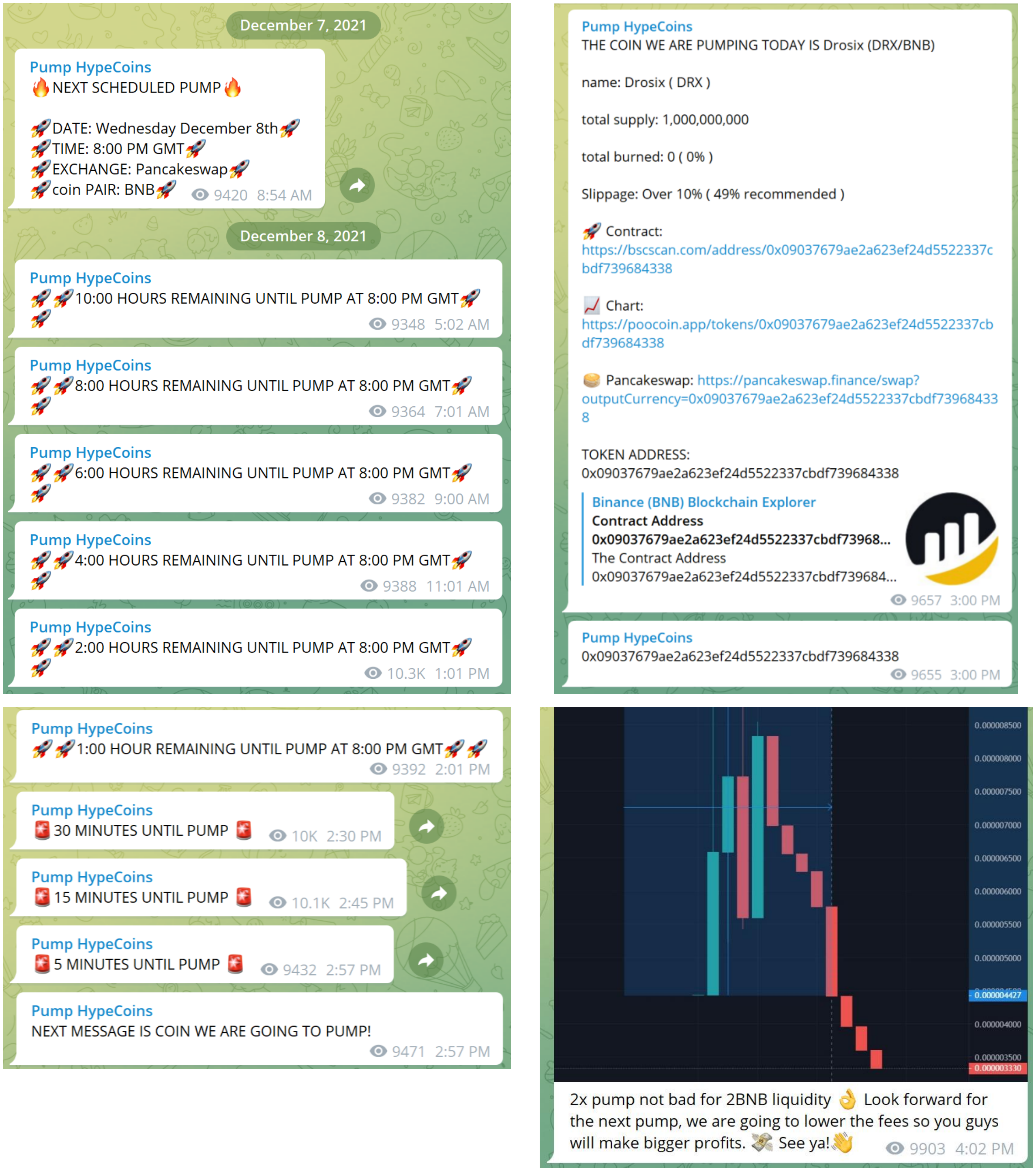
Table B. Yobit's Pump Scheme

Dependent variable	Yobit Volume [-14,+14]		Yobit Price [-7,+7]	
	Original 1	Linear trend 2	Original 3	Linear trend 4
95% robust confidence interval	(-0.923, -0.351)	(-0.832, -0.165)	(-0.174, -0.077)	(-0.172, -0.027)
99% robust confidence interval	(-1.013, -0.262)	(-0.937, -0.060)	(-0.189, -0.062)	(-0.195, -0.005)

Figure A1: An Example of a PancakeSwap Pump-and-Dump Scheme on Telegram

Panel A displays a series of Telegram announcements by Pump HypeCoin, one of the biggest pump groups active on PancakeSwap, regarding their December 8, 2021 pump targeting Drosix (DRX). Panel B plots Drosix's prices and volumes before and after the pump announcement (t =0).

Panel A: Telegram pump announcements on Drosix



Panel B: Drosix's price and volume around the P&D announcement (*t* =0)

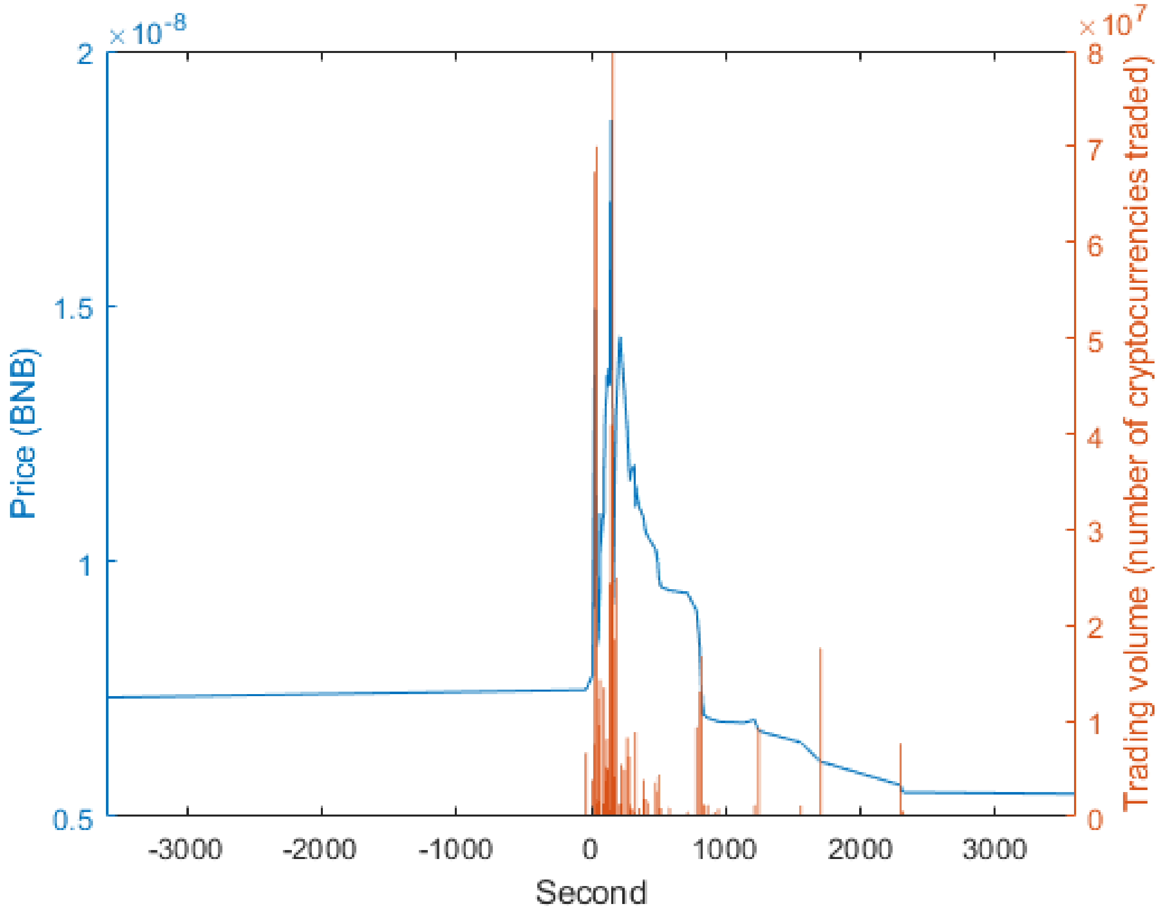
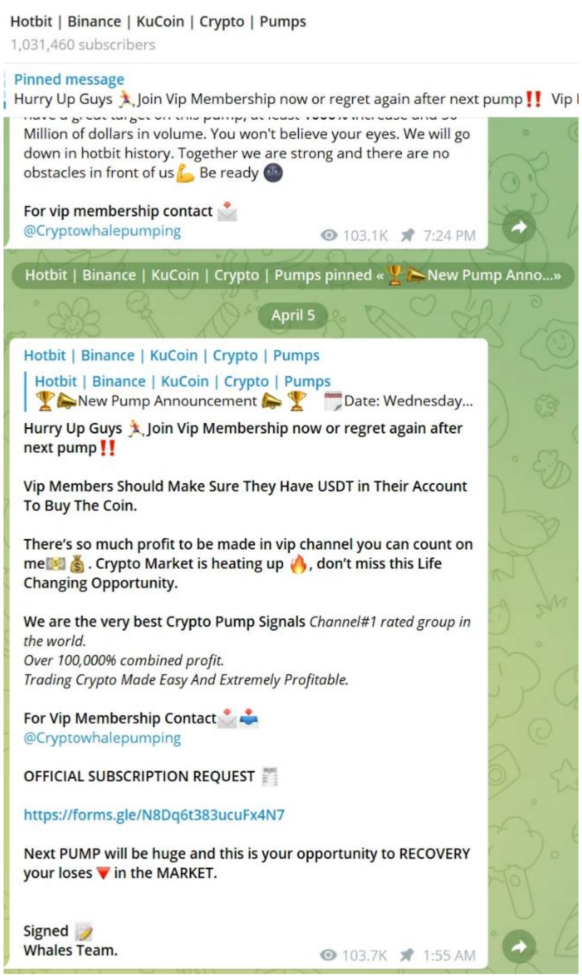


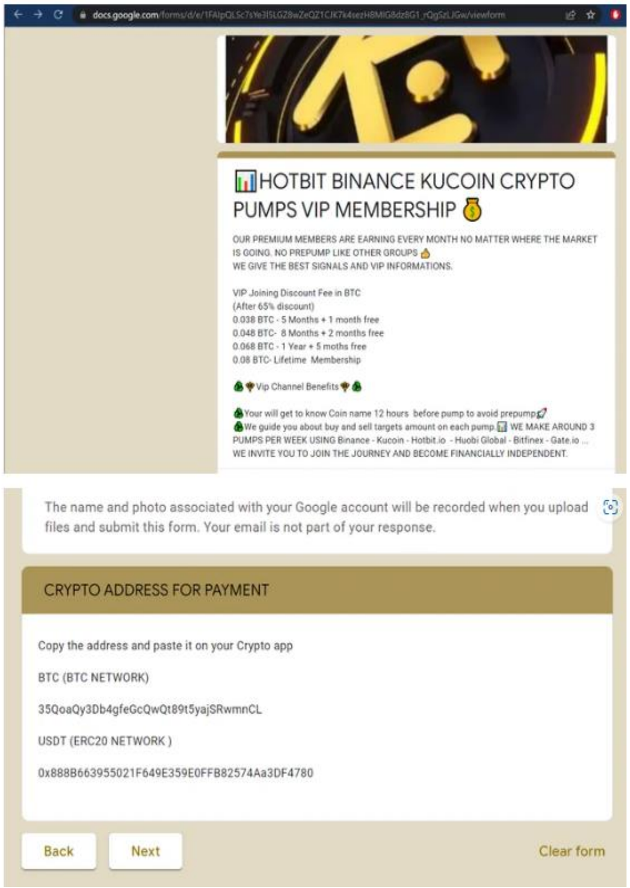
Figure A2: Evidence of the Disadvantageous Status of Outsiders in P&D Schemes

In Panel A, we provide a snapshot of a Reddit post that demonstrates the existence of VIP membership within P&D channels. Panel B presents two additional Reddit posts that highlight complaints from outsiders regarding their perceived disadvantage in comparison to P&D organizers and paid insiders, such as VIP members. For each post, we include a corresponding link to the original source.

Panel A: Existence of VIP membership

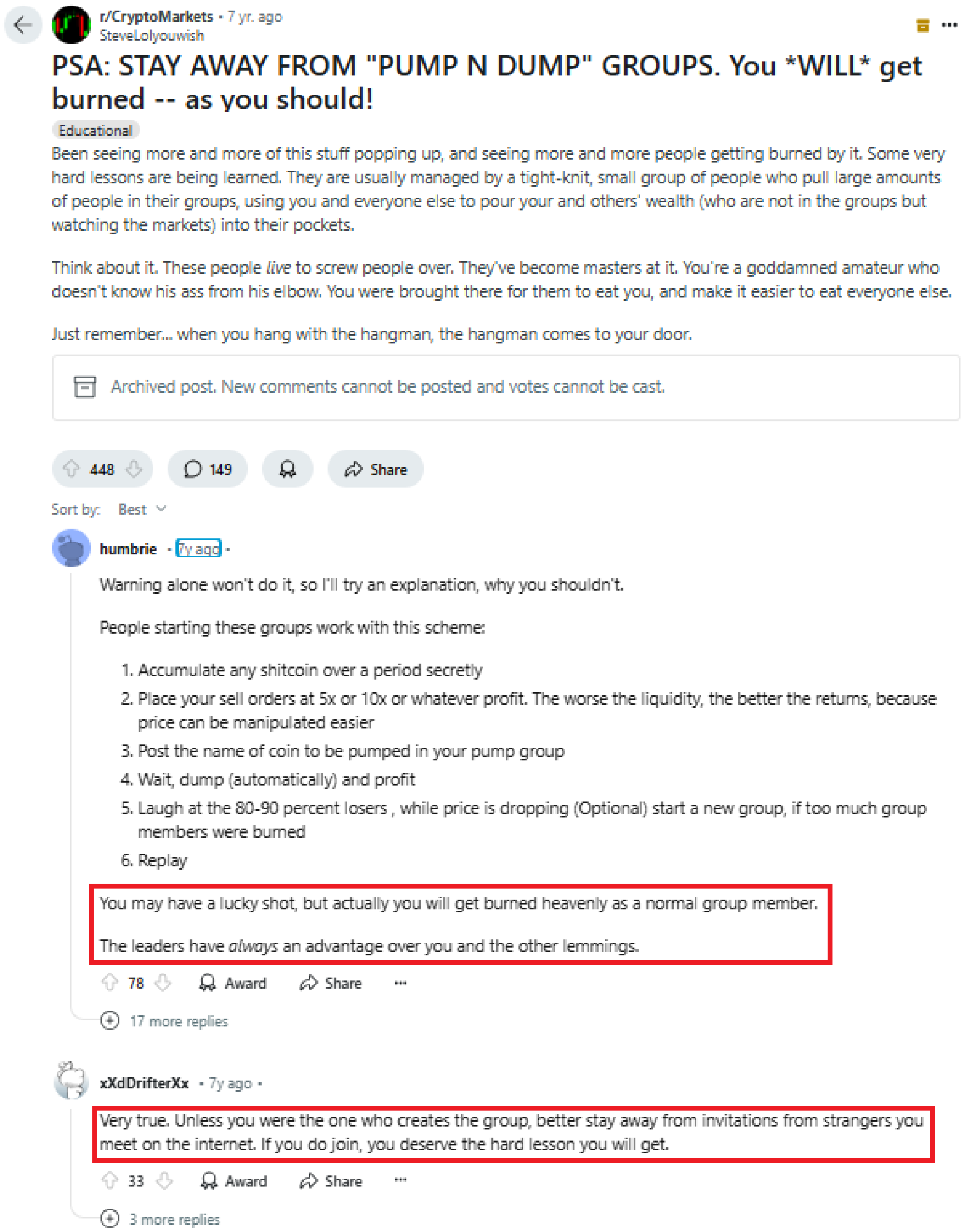
Source: https://www.reddit.com/r/CryptoScamReport/comments/twyyb8/are_the_kucoin_crypto_pump_groups_legit_vip/?rdt=44157





Panel B: Complaints regarding P&D organizers and paid insiders (VIP members)

Source: https://www.reddit.com/r/CryptoMarkets/comments/7pdnqh/psa_stay_away_from_pump_n_dump_groups_you_will/



r/CryptoMarkets • 7 yr. ago
SteveLolyouwish

PSA: STAY AWAY FROM "PUMP N DUMP" GROUPS. You *WILL* get burned -- as you should!

Educational

Been seeing more and more of this stuff popping up, and seeing more and more people getting burned by it. Some very hard lessons are being learned. They are usually managed by a tight-knit, small group of people who pull large amounts of people in their groups, using you and everyone else to pour your and others' wealth (who are not in the groups but watching the markets) into their pockets.

Think about it. These people *live* to screw people over. They've become masters at it. You're a goddamned amateur who doesn't know his ass from his elbow. You were brought there for them to eat you, and make it easier to eat everyone else.

Just remember... when you hang with the hangman, the hangman comes to your door.

Archived post. New comments cannot be posted and votes cannot be cast.

448 149 Share

Sort by: Best

humbrie • 7y ago •

Warning alone won't do it, so I'll try an explanation, why you shouldn't.

People starting these groups work with this scheme:

1. Accumulate any shitcoin over a period secretly
2. Place your sell orders at 5x or 10x or whatever profit. The worse the liquidity, the better the returns, because price can be manipulated easier
3. Post the name of coin to be pumped in your pump group
4. Wait, dump (automatically) and profit
5. Laugh at the 80-90 percent losers , while price is dropping (Optional) start a new group, if too much group members were burned
6. Replay

You may have a lucky shot, but actually you will get burned heavenly as a normal group member.

The leaders have *always* an advantage over you and the other lemmings.

78 Award Share ···

17 more replies

xXdDrifterXx • 7y ago •

Very true. Unless you were the one who creates the group, better stay away from invitations from strangers you meet on the internet. If you do join, you deserve the hard lesson you will get.

33 Award Share ···

3 more replies

Source: **https://www.reddit.com/r/CryptoCurrency/comments/n9snpj/i_get_invited_to_a_pump_and_dump_group_and/**

r/CryptoCurrency • 4 yr. ago
SkyDefender

I get invited to a pump and dump group and observe them for you

TRADING

It was around april 20, i got invited that group via discord. There were thousands of people, you could ask any question to one admin but that was all. You couldn't talk with other members. They gave the date for the coin's announcement. April 25 midnight. Also they created telegram group with thousands of people aswell.

Coin announced exactly at midnight, it was rdn/btc. But 10 seconds later it was already too late, it hit ath and dropped to ground again.

So who won? Admin and his friends/family who bought earlier and their sell order was ready.

So who lost? Thousands of small investors who bought at high prices.

What happened to the groups? Discord deleted immediatly, telegram sold to random one.

Tl;dr: please stay away from those kind of shenaningans. Don't get fooled.

Archived post. New comments cannot be posted and votes cannot be cast.

1.3K 330 Share

…

TNGSystems • 4y ago •

I made a huge post about this. It was on the front page, top, with thousands of upvotes and over 100 awards. The structure of every PnD is the same:

Accrue a lot of members.
Decide a project secretly amongst admins & paid insiders.
buy huge bags of the coin, slowly so as not to spike the price.
Bags loaded.
Announce the trading pair & exchange.
By this point, the admins & insiders have already set their SL orders at, you know, maybe current price + 150%
The noobs flood in, doing huge market buys or limit buys, spiking the price and volume dramatically.
The admin & insiders orders are filled and they walk away with huge profits.

99% of users get fucking completely rekt, and assume they were just too slow. Reality is, the odds were against them from the start.

The admins & insiders the repeat the process.

Nobody can tell anyone or warn anyone because any dissent is immediately banned and as you said, you can't talk to other users unless you message them privately.

A giant scam.

Binance etc could stop this very easily.

Look at projects with low volume that have received huge pumps and dumps over the last 4 months
Look at accounts that have been buying a steady supply of that project from the date before the pump - 2 weeks.

Find accounts that are regularly buying coins and then setting the sell orders

Fucking ban them.

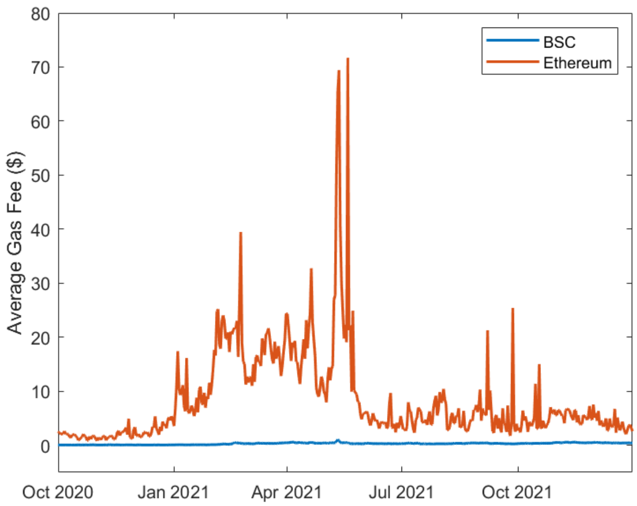
47 Award Share …

7 more replies

Figure A3: Gas Fees

In Panel A, we present average gas fees on Binance Smart Chain (BSC) and Ethereum. The blue (red) line plots the average gas fee in BSC (Ethereum). In Panel B, we present average gas fees that are directly related to token-swap transactions on PancakeSwap and Uniswap. The blue (red) line plots the average gas fee paid for the execution of six token swap-related functions in PancakeSwap v1 and v2 (Uniswap v2). BSC and PancakeSwap were launched in September 2020, and therefore we choose the October 2020–December 2021 sample period for Panels A and B.

Panel A: Average gas fee on Binance Smart Chain and Ethereum



Panel B: Average gas fee in PancakeSwap and Uniswap

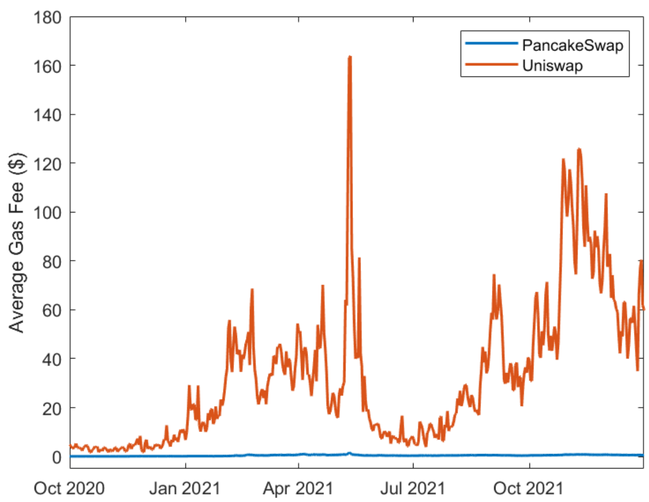
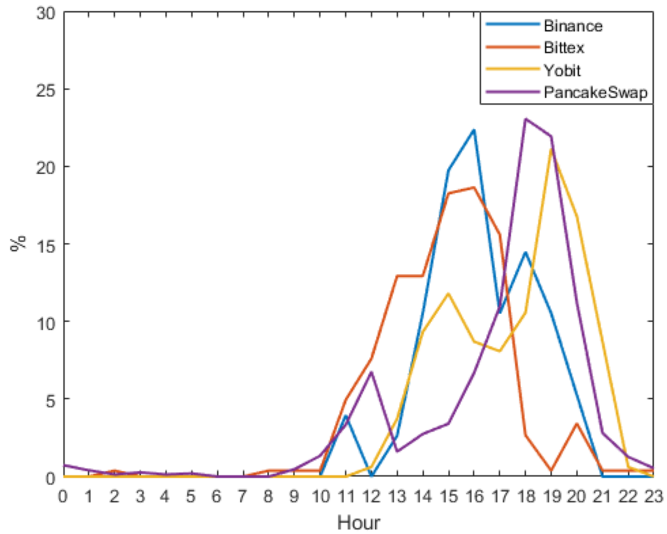


Figure A4: Distribution of Pump and Dumps and Trading Volume by Hour

We present the distribution of P&D events by scheduled hour and exchange in Panel A and the distribution of trading volume by hour and exchange in Panel B. For each exchange, we first calculate the fraction of the trading volume (in Bitcoin for centralized exchanges Binance, Bittrex, and Yobit) occurring in each hourly interval and then compute the average volume across days. For centralized exchanges, the sample period runs from May 15, 2017 to August 26, 2018. For PancakeSwap, the sample period runs from September 20, 2020 to December 17, 2021. The x-axis represents the hour, where 0 indicates the interval between 00:00:00 and 00:59:59 (Coordinated Universal Time or UTC). Other hourly intervals are similarly defined.

Panel A. Distribution of P&Ds by the hour and exchange



Panel B. Distribution of trading volume by the hour and exchange

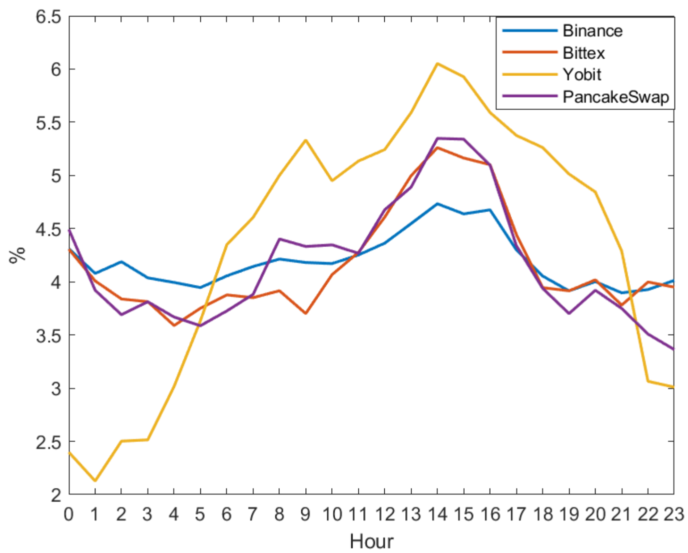


Figure A5: Pump-and-Dump Schemes in the Past Six Months

This figure displays cumulative returns, abnormal volume, and volatility for the P&Ds that occurred in the half-year period running from February 27, 2018 to August 26, 2018. The last P&D event in our sample took place on August 26, 2018. This sample includes 146 P&D events.

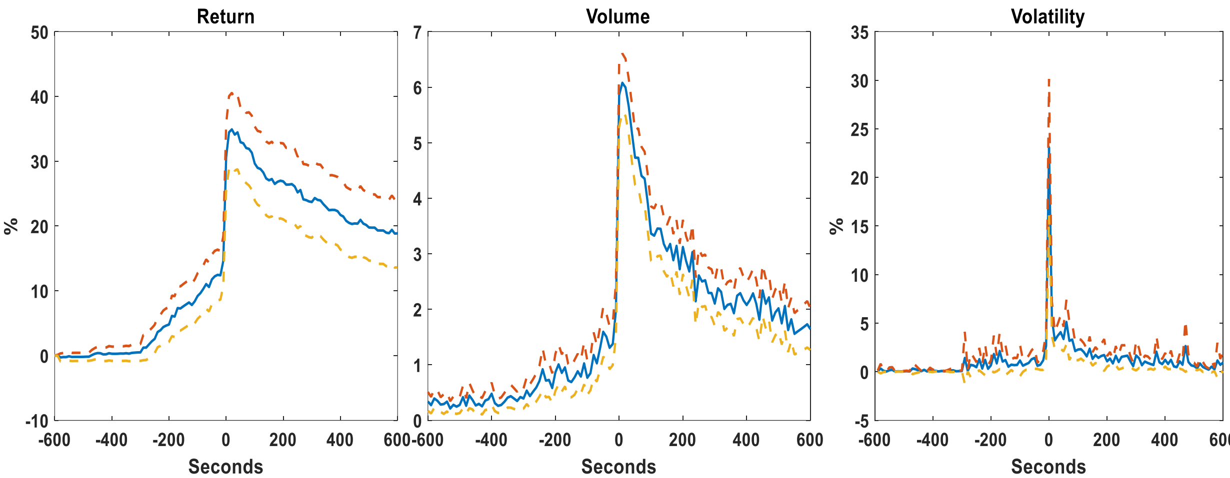


Figure A6: Pump and Dumps on Binance

This figure presents abnormal returns, abnormal volume, and volatility for the P&Ds that targeted Binance. In total, we observe 76 P&D events.

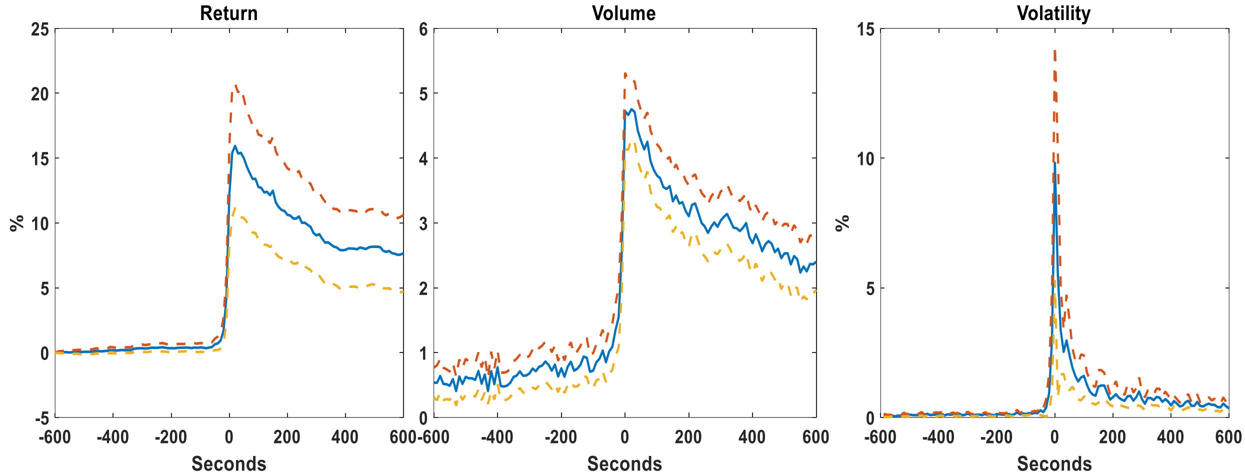
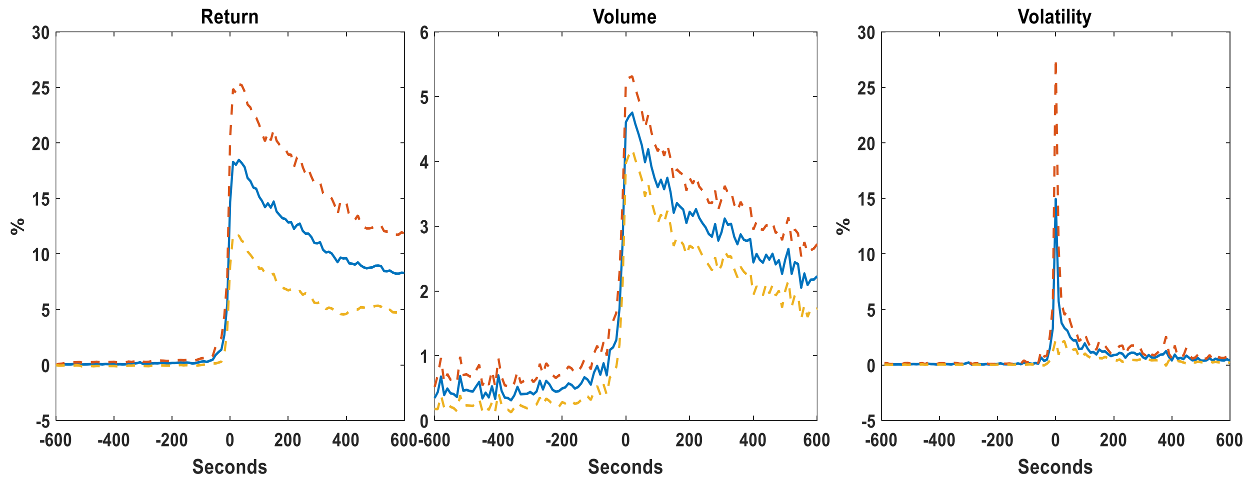


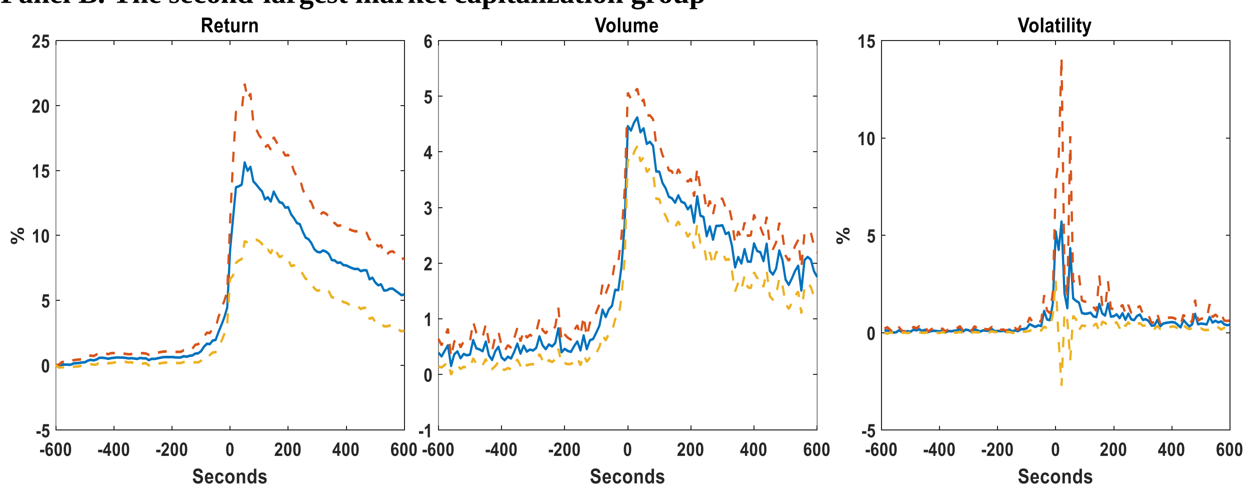
Figure A7: Return, Volume, and Volatility, by Market Capitalization

This figure displays short-term cumulative returns, abnormal volume, and the volatility of pumped cryptocurrencies sorted by market capitalization. We divide P&Ds into five groups based on the market capitalization of pumped cryptocurrencies. Market capitalization is measured eight days before a P&D announcement using CoinMarketCap data. We plot cumulative returns, abnormal volume, and the volatility for each ten-second interval from 600 seconds before to 600 seconds after P&D announcements. Time 0 indicates the ten-second interval between 0 and 10, in which 0 is the announcement time. The x-axis indicates time. The solid lines represent the averages across all target cryptocurrencies and the dashed lines show the 95% confidence intervals. Cumulative returns are calculated as the logarithm of price changes from 600 seconds before an announcement. Abnormal volume equals log (1 + volume over an interval/average volume in the interval over day -37 to day -8). Volume is measured by the number of cryptocurrencies traded. Volatility is measured as the absolute value of return in each interval.

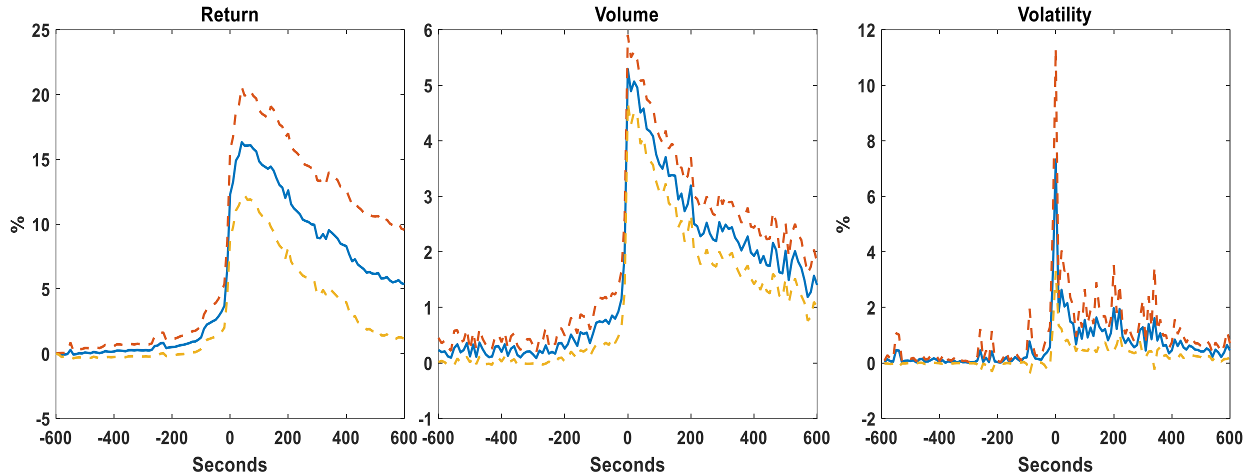
Panel A. The largest market capitalization group



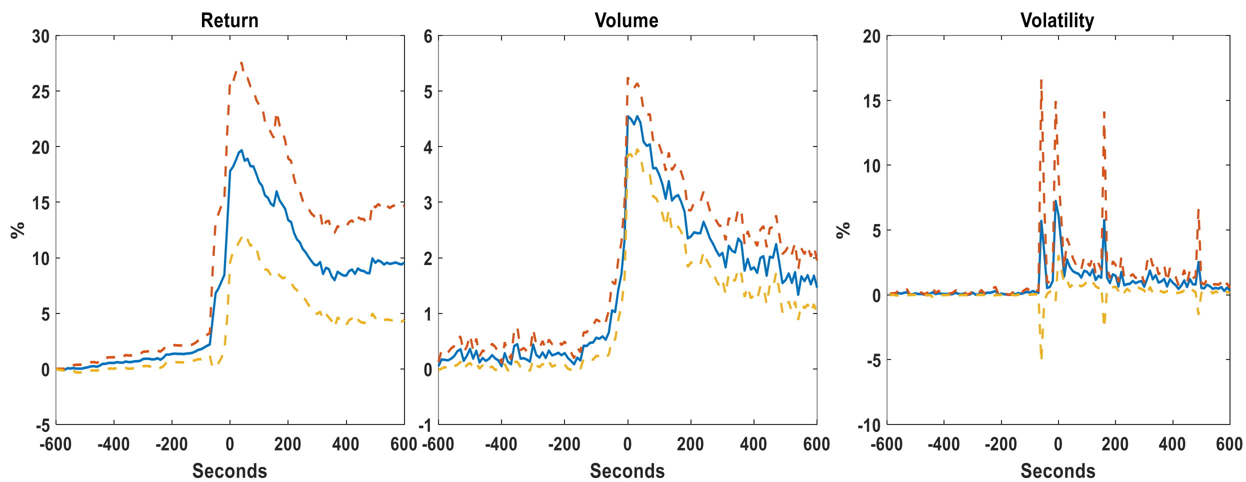
Panel B. The second-largest market capitalization group



Panel C. The median market capitalization group



Panel D. The fourth-largest market capitalization group



Panel E. The smallest market capitalization group

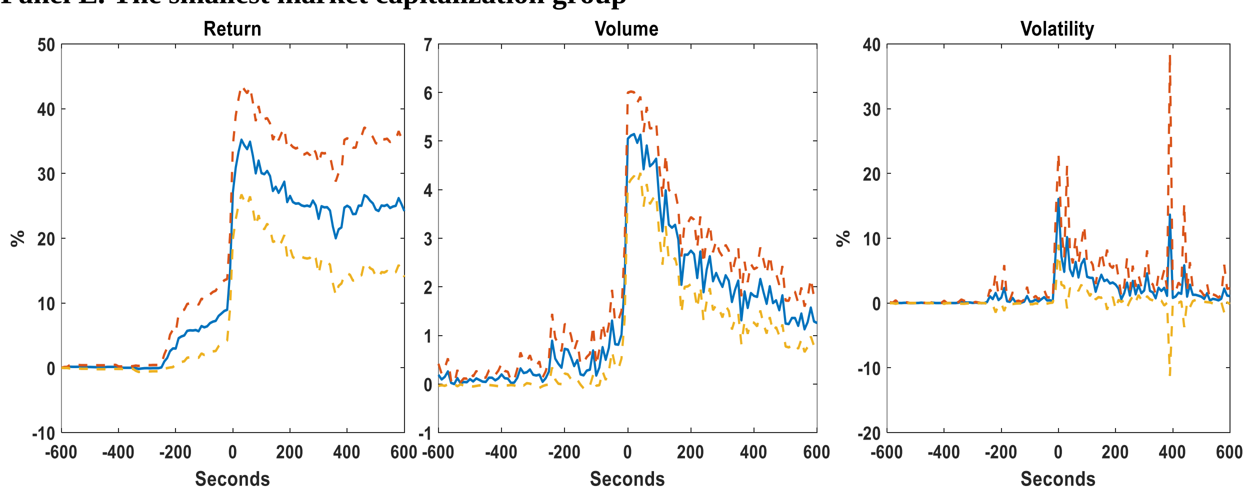
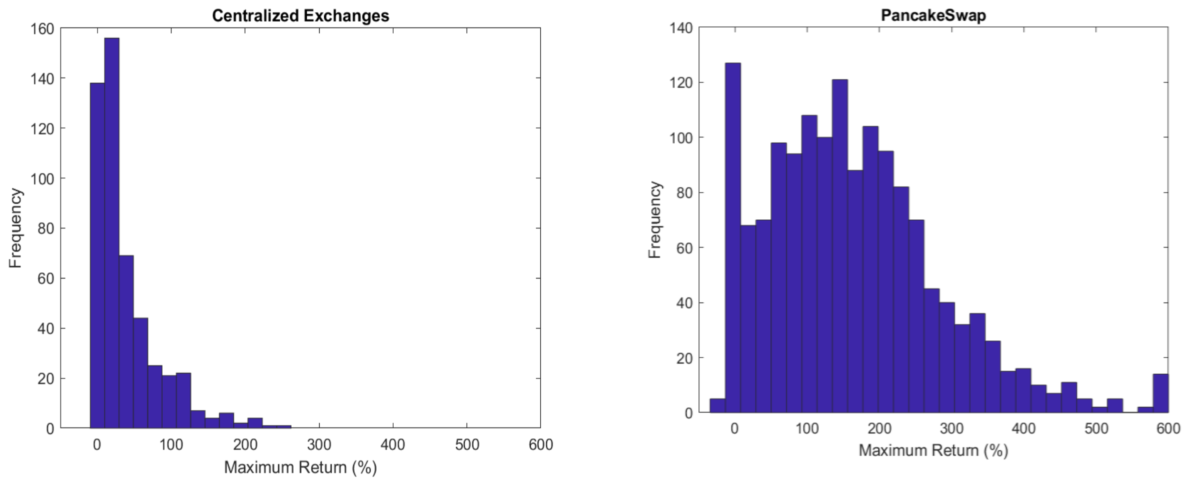


Figure A8: Distribution of Maximum Returns and Time to Maximum Returns

Panel A displays the distribution of P&D maximum returns and Panel B plots the distribution of the number of seconds it takes to reach a maximum return for our sample of P&Ds. A P&D's maximum return is defined as the natural logarithm of the ratio of the highest price achieved within ten minutes after the pump announcement and the price ten minutes before the announcement. The time to a maximum return is defined as the number of seconds it takes from the announcement to reach the maximum return. For ease of illustration, maximum returns are capped at 600% for Panel A. Centralized exchanges include Binance, Bittrex, and Yobit.

Panel A. Distribution of P&D maximum returns



Panel B. Distribution of time to maximum returns

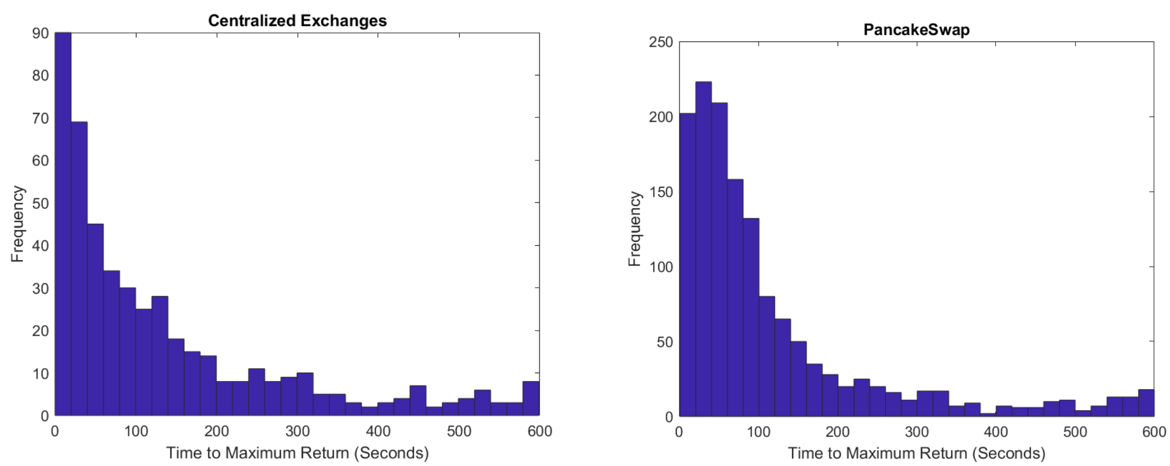
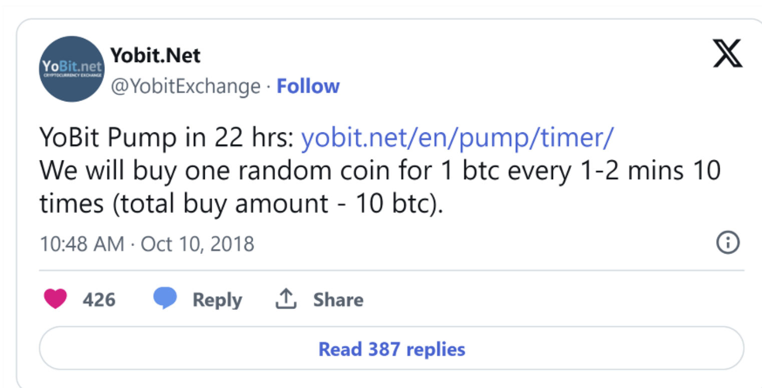


Figure A9: Evidence for P&Ds Organized by Yobit

This figure presents evidence for P&Ds organized by Yobit. Panel A is a screenshot of Yobit's announcement on X (formerly Twitter) on October 10, 2018 that it would pump cryptocurrencies listed on the exchange. Panel B shows Yobit's pump countdown timer that we captured through the Wayback Machine. Panel C presents additional evidence for continued P&D attempts by Yobit since October 10, 2018. Yobit has pumped far more than 10 times. It tweeted twice about pending pumps in 2018, on October 12 and 16. Then in 2020, it tweeted 13 times that one of the 10 cryptocurrencies would be randomly pumped for 5 BTC: April 4, 14, 15, 21, 29; May 1, 5, 8, 12, 19; June 15; July 15; and September 2. The last tweet about pumps was sent on January 12, 2021. In Panel C, we provide one screenshot for each year.

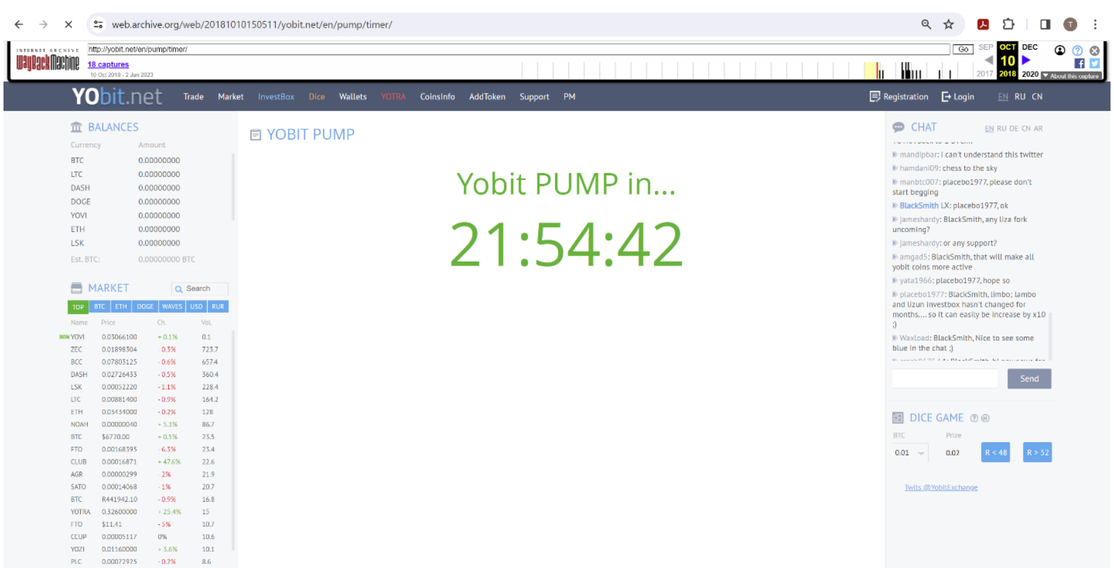
Panel A: Yobit's announcement to pump coins on October 10, 2018

Source: https://x.com/YobitExchange/status/1050035464609124352



Panel B: Yobit's pump timer on October 10, 2018

Source: https://web.archive.org/web/20181010150511/https://yobit.net/en/pump/timer/



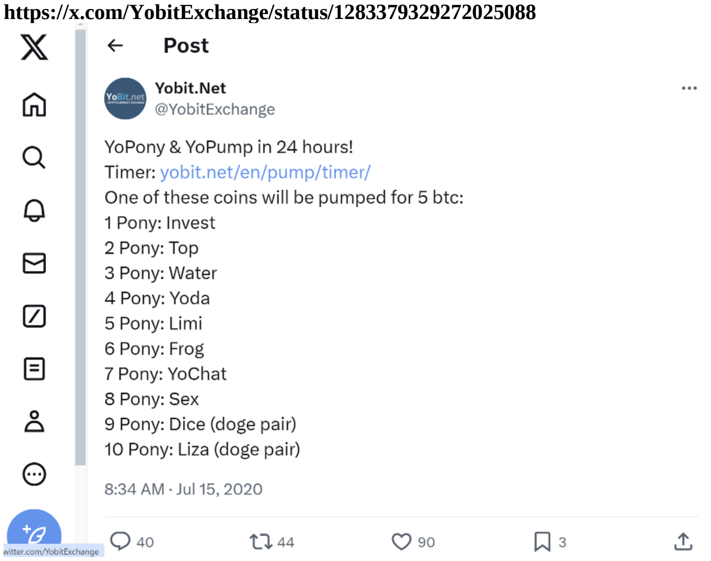
Panel C: Screenshots of Yobit's continued P&D attempts since October 10, 2018.

Source: Yobit's official Twitter page.

https://x.com/YobitExchange/status/1052226344887640064

https://x.com/YobitExchange/status/1050777225505705984

https://x.com/YobitExchange/status/1283379329272025088



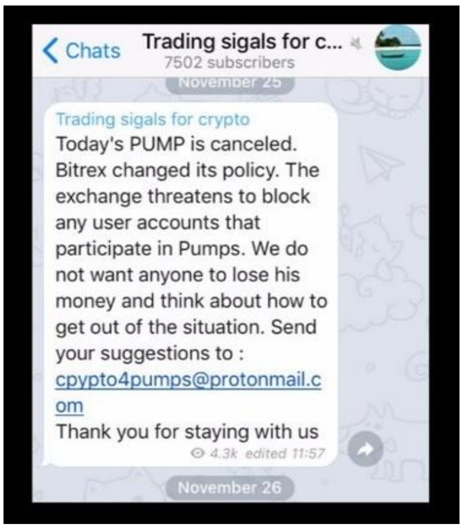
https://x.com/YobitExchange/status/1348973558505086977

Figure A10: A Sharp Decrease in P&Ds on Bittrex after the Ban

Panel A displays a screenshot of the pump cancelation after Bittrex's ban of P&Ds. Panel B displays the frequency of P&Ds before and after the Bittrex ban. The x-axis shows the months relative to the ban that occurred on November 24, 2017. Our sample period runs from five months before to eight months after the ban, corresponding to the sample period for P&Ds.

Panel A. An example of pump cancelation

Source: Business Insider. https://www.businessinsider.com/bittrex-warning-cryptocurrency-pump-and-dump-scams-market-manipulation-2017-11



Panel B. Frequency of P&Ds around the ban