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Cryptocurrency Pump-and-Dump Schemes

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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 dramatic increases in prices, volume, and volatility, followed by quick reversals. The evidence we document, including price run-ups before P&Ds start, suggests 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.

I. Introduction

This article 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

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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 article, 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 2 parties: a "manipulator" who coordinates P&Ds, and investors who are invited to participate as members of the channel. To attract investors, manipulators may 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 1 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 document in this article, a typical cryptocurrency P&D seems to last only several minutes, leaving little time for nonmembers to participate.

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

[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.

[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 article are not associated with company information releases or other actions and, therefore, cannot be explained by information- or action-based manipulation theory.

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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 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 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.

[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.

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Using a sample of 500 hand-collected P&Ds that were carried out on 3 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 10 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% of the total volume within a window of −100 days to +100 days around P&Ds.

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 realized large returns, ranging from 18% on the CEXs to 152% on PancakeSwap, and made 1 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 likely 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 a naïve reinforcement learning (Kaustia and Knupfer (2008), Chiang, Hirshleifer, Qian, and Sherman (2011), and 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 Nov. 24, 2017, Bittrex announced that it would ban P&Ds. On Oct. 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 article 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 article, however, do not involve the release of false information or derivatives trading.

[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)).

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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 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 5-minute intervals and Xu and Livshits (2019) use data at 1-hour intervals. Both of their data sets are aggregated across *all* exchanges. As we show later in this article, most P&D effects occur in seconds and concentrate on target exchanges. Data at 5-minute or 1-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, 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

[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 Supplementary Material for a discussion of academic research on cryptocurrency trading.

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

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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 article 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 7PM. Coordinated Universal Time (UTC; in this case, the UTC time was 3PM EDT)

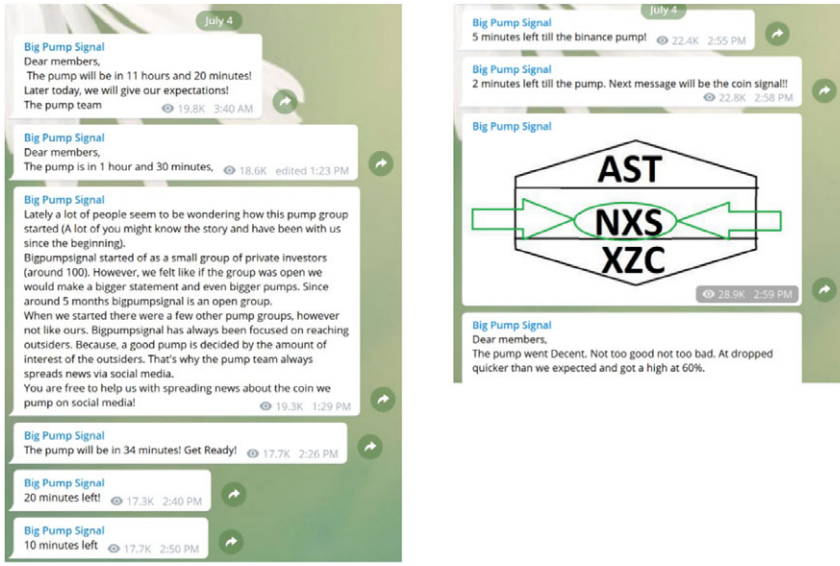
[7]See Figure 1 for an example in which the P&D operator urged the participants to "spreading news" on social media. While some P&D organizers may announce P&Ds to attract social media followers and generate income from those followers, we find no evidence that such a motive is of first-order importance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

FIGURE 1

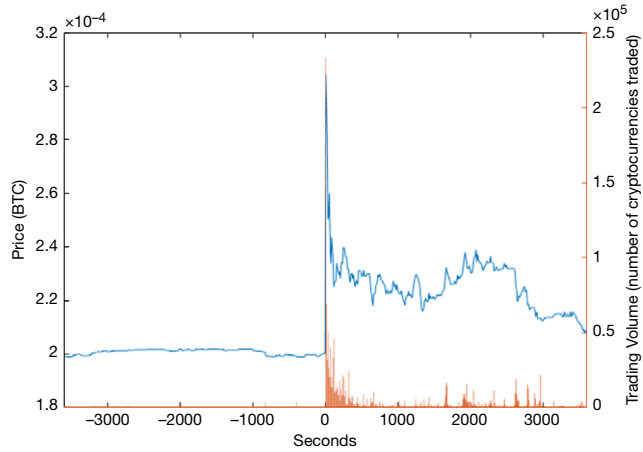
An Example of Pump-and-Dump Schemes on Telegram

Figure 1 Graph 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). Graph B plots Nexus's prices and volumes around the pump announcement ($t = 0$).

Graph A. Telegram Pump Announcements on Nexus



Graph B. Nexus's Price and Volume Around The P&D Announcement (t=0)



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 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.

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At 6:59:57PM UTC, 3 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 10 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 4 (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]

III. Data

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

A. P&D Events

We collected data manually in two separate batches: first in Sept. 2018 on CEXs and then in Jan. 2022 on DEXs. We first collected a list of pump groups from

[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 Supplementary Material.

[9]We provide details on cryptocurrency trading in Part A1 of the Supplementary Material.

[10]In Figure A2 of the Supplementary Material, 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 5 months plus 1 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 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 Supplementary Material, we discuss the details relating to matching cryptocurrencies across multiple data sets.

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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 Sept. 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 Jan. 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 article are based on the UTC scale. In cases where multiple channels target a cryptocurrency at the same scheduled time, we use the earliest announcement time for our analysis. As we document later in the article, 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 Aug. 2018. For DEXs, we identified 2,404 P&D announcements from 123 Telegram channels from Sept. 2020 through Dec. 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 Sept. 2018, they were ranked first, 36th, and 27th by trading volume, respectively, on CoinMarketCap. All the DEX P&Ds took place on PancakeSwap.

[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.

[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 Oct. 10, 2018, Yobit announced on its website and official Twitter page that it would pump cryptocurrencies listed on the exchange randomly. This is 1 of the 2 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 4 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 1 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 Jan. 2019 after suffering a hack that stole around $16 million, Cryptopia was ranked 77th among all cryptocurrencies, according to CoinMarketCap.

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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 3 exchanges is that they all listed a reasonably large number of cryptocurrencies. Based on data from CoinAPI, 147, 204, and 1261 cryptocurrencies were involved in at least 1 trade in Aug. 2018 on Binance, Bittrex, and Yobit, respectively.[15] Based on the number of listed cryptocurrencies, these 3 exchanges were all among the 10 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 a 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.

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 3 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

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

[16]In Feb. 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 Supplementary Material.

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

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 Supplementary Material, 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 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 3 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 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.

[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 7 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.

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TABLE 1

Summary Statistics

We report the characteristics of P&Ds in Panel A of Table 1 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. The *Number of channels* is the average number of channels coordinating a P&D. The *Total number of viewers* is the sum of viewers across all channels in a P&D event. The *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 7-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 7-day return* is the return during the 7-day period before a pump. *Token dummy* equals 1 if a cryptocurrency is a digital token issued by a particular project, and 0 if it is a digital equivalent of money (a coin). *Covered by CoinMarketCap* equals 1 if a cryptocurrency is covered by CoinMarketCap, and 0 otherwise. *Cryptocurrency age* is the number of years since the cryptocurrency was first listed. The *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	4010.9	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%	1371.2%	1000%

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 7-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

(continued on next page)

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TABLE 1 (continued)

Summary Statistics

Panel B. Characteristics of Cryptocurrencies (continued)

	Target Cryptocurrency	Non-Target Cryptocurrency	Difference	*t*-Stat. of Diff.
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 7-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		

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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 log trading volume, log market capitalization (in dollars), return volatility, preceding-7-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 1 if a cryptocurrency is a digital token issued by a particular project, and 0 if it is a coin. The pumped before dummy equals 1 if a cryptocurrency was pumped previously, and 0 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 7 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 a higher volume and are less volatile. The average targeted cryptocurrencies earn similar preceding-7-day returns on the CEXs but higher preceding-7-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 3 CEXs. Conditional on CoinMarketCap coverage, their market capitalization is similar to that of other covered cryptocurrencies. For covered cryptocurrencies, the average market capitalization

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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 10-second interval from 600 seconds before to 600 seconds after the announcement of a P&D. Graph A covers the CEXs, and Graph B covers PancakeSwap. The *x*-axis represents time. Time 0 indicates the 10-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 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 10-second interval. To minimize the effects of extremely large returns, we measure volatility as the absolute value of returns rather than squared returns.

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 10 minutes before announcements and hold until 1 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

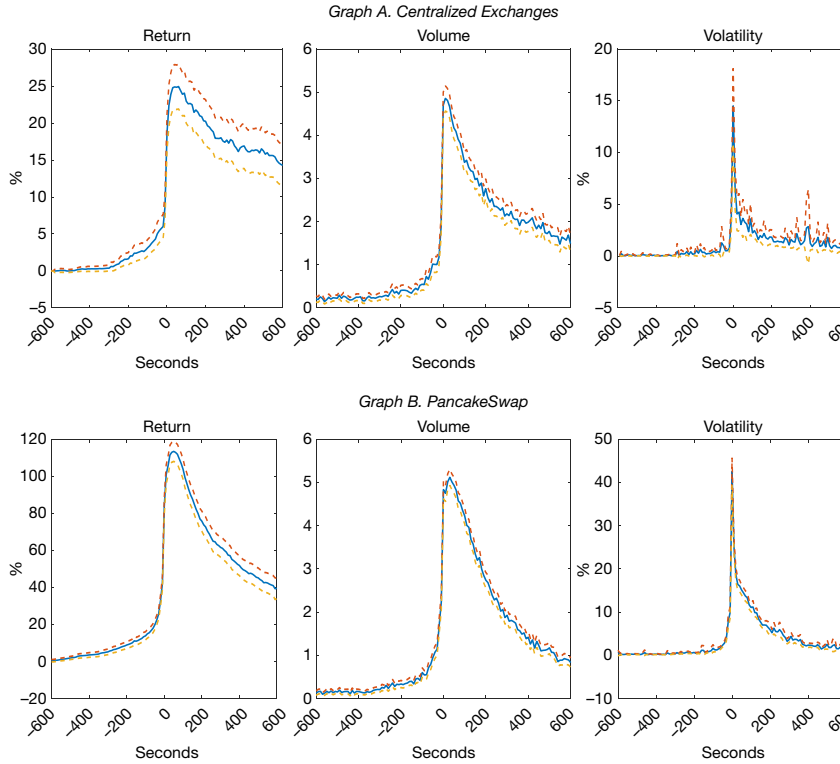
[21]Both trading volume and P&Ds concentrate from 12:00 to 22:00 UTC (daytime in the U.S.). Part A6 of the Supplementary Material presents the distribution of our sample P&Ds and trading volume by hour and exchange. Although the 3 CEXs are located on 3 continents, P&Ds and trading volume distributions by hour look remarkably similar. The distributions are also similar for PancakeSwap. In Part A7 of the Supplementary Material, we discuss issues that might arise with our data and explain how we address them.

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FIGURE 2

Return, Volume, and Volatility Around Pump and Dumps: Short-Term Analysis

Figure 2 displays cumulative returns, abnormal volume, and the volatility of pumped cryptocurrencies for a 20-minute period around pump announcements: Graph A for the 3 centralized exchanges and Graph B for PancakeSwap. The graphs depict the pattern for each 10-second interval. Time 0 indicates the 10-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 Graph A and log (1 + volume over an interval/average volume in the interval over day −37 to day −2) for Graph 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.



10-second volume is 128 and 167 times higher than the average in the baseline period for the CEXs and PancakeSwap, respectively; the average 10-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.

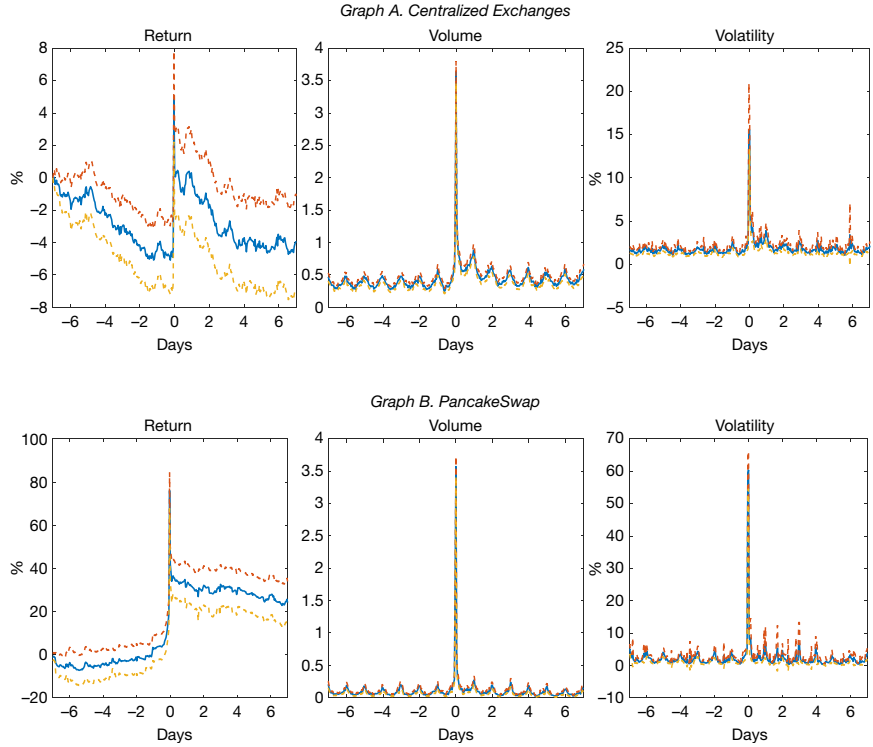
In Figure 3, we present the returns, trading volume, and volatility patterns over a longer period—from 7 days before an announcement to 7 days after. Outside of

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FIGURE 3

Return, Volume, and Volatility Around Pump and Dumps: Longer-Term Analysis

Figure 3 displays cumulative returns, abnormal volume, and the volatility of pumped cryptocurrencies for the [−7 day, +7 day] period around pump announcements: Graph A for the 3 centralized exchanges and Graph B for PancakeSwap. The graphs depict the analysis for each 1-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 7 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 Graph A and log (1 + volume over an interval/average volume in the interval over day −37 to day −2) for Graph B. Volume is measured by the number of cryptocurrencies traded. Volatility is measured as the absolute value of the return during each 1-hour interval.



the short period around a P&D, trading typically decreases sharply, preventing us from accurately calculating these variables based on 10-second data. Therefore, we calculate price, volume, and volatility over 1-hour intervals for this longer-term analysis. On average, volume and volatility return to their original levels within 1 to 2 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.

B. P&D Effects by Market Capitalization

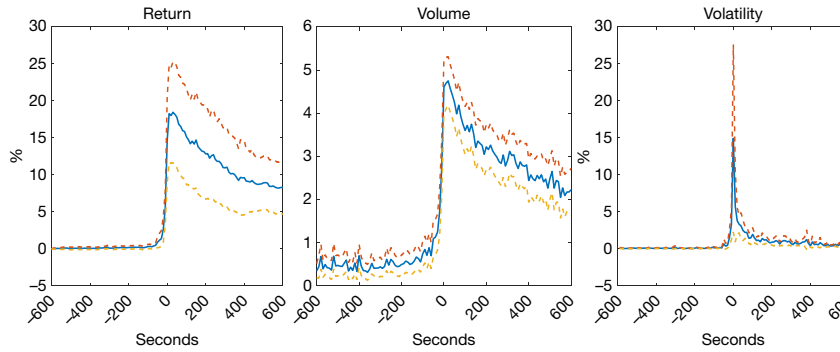
In this subsection, we examine whether the prices of big cryptocurrencies move after P&Ds. The average cryptocurrency on the CEXs is much bigger than

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FIGURE 4

Return, Volume, and Volatility of the Largest Market Capitalization Group

Figure 4 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 8 days before a P&D announcement using CoinMarketCap data. We plot cumulative returns, abnormal volume, and the volatility in each 10-second interval from 600 seconds before to 600 seconds after P&D announcements. Time 0 indicates the 10-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.



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 8 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 Supplementary Material. 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 Supplementary Material 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.

[22]In Part A9 of the Supplementary Material, 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.

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C. Spillovers to Ethereum Pairs and Other Exchanges

For P&Ds on the 3 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 2 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 3 CEXs we studied, and are highly liquid, facilitating exchange between these 2 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 1 or 2 other exchanges. Figure 5 displays the patterns for these ETH pairs and cross-listed cryptocurrencies. If a cryptocurrency is cross-listed on 2 other exchanges in addition to the target exchange, we take the average of returns, abnormal volume, and volatility across the 2 exchanges. Figure 5, Graph 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, Graph B. The results reported in Figure 5 and Figure 2, Graph A, are not directly comparable, as the sample compositions differ. In Part A10 of the Supplementary Material, we present an analysis in which we restrict our data to the same sample and find similar results.

Overall, the results reported in Figure 5 and Part A10 of the Supplementary Material 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 the weaker spillover to other exchanges, as shown in Figure 5, Graph B imply that the price increases are likely not supported by changes in cryptocurrency fundamentals.

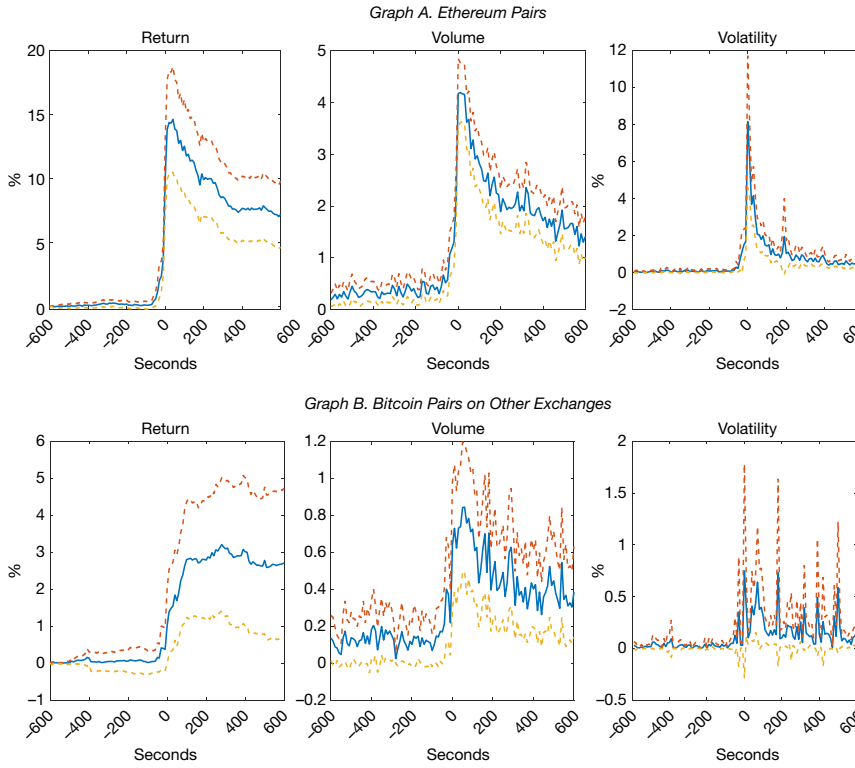
D. Performance by Purchase Time

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

FIGURE 5

Spillovers to Ethereum Trading Pairs and Other Exchanges

Figure 5 shows whether any spillover to prices and volume quoted in Ethereum occurs during P&Ds that takes place on CEXs (Graph A) as well as prices and volumes quoted in Bitcoin on other exchanges (Graph B). In Graph A, for pumped cryptocurrencies with trading data on Ethereum pairs, we report cumulative returns, abnormal volume, and the volatility of the Ethereum pairs. In Graph 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 nontargeted exchange(s). If a cryptocurrency is cross-listed on 2 other exchanges in addition to the target exchange, we take the average of the maximum return, abnormal volume, and volatility across the 2 exchanges.



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 10 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 1 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 10-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

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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.

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 6 10-second intervals after a P&D, we also include a "Before P&D" interval, which is the 10-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

TABLE 2

Trade Performance by Purchase Time

In Table 2, we report the returns (in percentages) by purchase time. We consider 6 10-second intervals after a P&D starts and one "Before P&D" interval, which is the 10-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 10-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.

	Purchase Time, in Seconds						
Delay Time	Before P&D	10	20	30	40	50	60
Panel A. Centralized Exchanges							
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							
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)

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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 10 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 10-second interval cannot delay selling by more than 10 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., 10 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 made about 2.9 BNB (about $1,300), while for an average CEX P&D, insiders made 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 10 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.

We conduct the analyses for the CEXs and PancakeSwap separately. For the CEXs, in the 2 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 the 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 Table 3, 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

TABLE 3

Persistent Advantages for Certain Telegram Channels

In Table 3, 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-10 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

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.

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TABLE 4

Effects of the Size of Pump Groups

In Table 4, 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 10-minute period before the pump announcement. The dependent variable for columns 3 and 4 is the natural logarithm of 1 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 10 minutes after the pump announcement and the price 10 minutes before the pump. The *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 7-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

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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 10-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 10 minutes after a pump announcement to the price 10 minutes before the announcement minus 1. 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 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 shown 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

[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 Supplementary Material Part A11 for additional details.

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), and Daniel and Hirshleifer (2015)). In other words, these investors think 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), and 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]

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 6 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,

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

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TABLE 5

Investor Characteristics and P&D Participation

In Table 5, 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	First Quartile	Median	Third 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∗∗∗ (−12.39)					−0.072∗∗∗ (−17.57)
Selling probability		2.722∗∗∗ (54.32)				3.025∗∗∗ (12.63)
Log (Portfolio size)			0.254∗∗∗ (5.68)			0.277∗∗∗ (8.92)
Experience				−0.244∗∗∗ (−4.91)		−0.252∗∗∗ (−4.14)
$Return_{t-1}$					0.219∗∗∗ (2.99)	−0.011 (−0.25)
$Return_{t-2}$					0.178∗∗∗ (4.91)	0.037∗∗ (2.30)
$Return_{t-3}$					0.073∗∗∗ (2.95)	−0.042 (−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^2	0.153	0.138	0.156	0.139	0.137	0.184

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.

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

[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.

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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. Our results are qualitatively similar if we use 10 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 4651 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%).

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 Supplementary Material, 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 4 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 0. 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), and Anagol et al. (2021)).

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TABLE 6

Past P&D Performance and Future P&D Participation

In Table 6, 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^2	0.024	0.000	0.140	0.062	0.031	0.002	0.075	0.030

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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 Nov. 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* 10 days earlier that found traders were colluding in groups on Telegram to inflate the prices of cryptocurrencies (Williams-Grut (2017)). On Oct. 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 provide additional details in Part A14 of

[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 Supplementary Material presents a snapshot of Yobit's Twitter announcement.

the Supplementary Material. 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 2 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 to 31 days before the event, and preceding-7-day return based on prices 1 and 8 days before the event. We conduct our analysis based on CoinMarketCap data rather than on data from the 3 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 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 1 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 1 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.

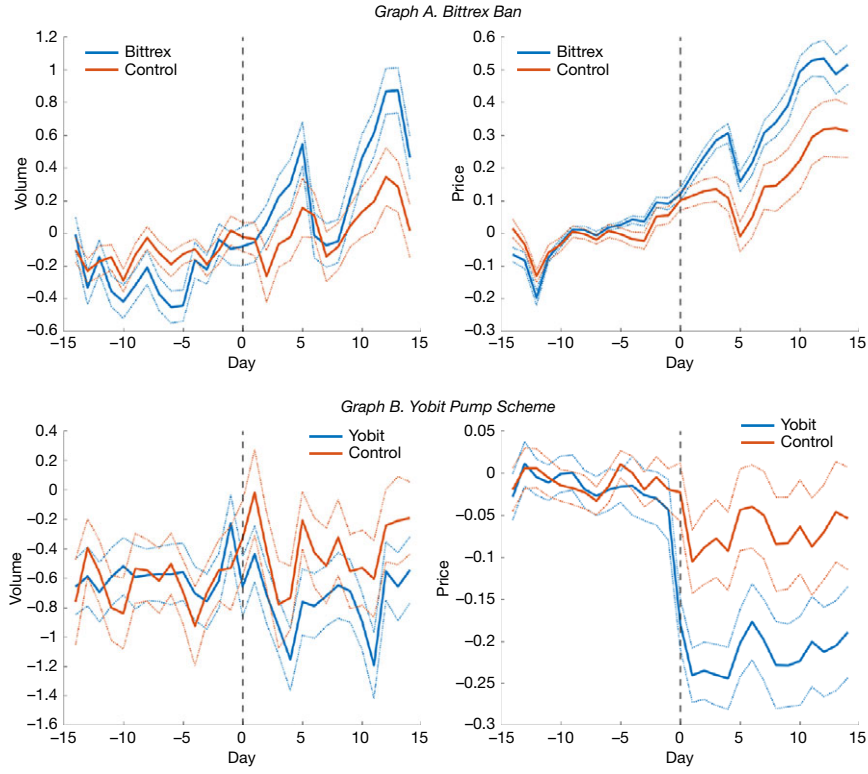
[29]Part A15 of the Supplementary Material provides additional details on the sample and variable construction.

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FIGURE 6

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

Figure 6 plots the volume (left) and prices (right) of Bittrex cryptocurrencies and their controls in Graph A and of Yobit cryptocurrencies and their controls in Graph B. See Table 7 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.



C. The Difference-in-Differences Regressions

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

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

where DV is either log 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 Nov. 24, 2017, for the Bittrex event (and after Oct. 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]

[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 Supplementary Material.

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TABLE 7

The Bittrex Ban and Yobit's Pump Scheme Events

In Table 7, we report the difference-in-differences results of the Bittrex ban (Yobit's Pump Scheme) on Nov. 24, 2017 (Oct. 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 to 31 days before the ban, market capitalization 15 days before the ban, and the past 7-day return. In the regression, there are 2 observations for each cryptocurrency: 1 for the pre-ban period and 1 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 0. 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.

	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
Panel A. Propensity Score Matching								
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^2	0.363	0.351	0.689	0.388	0.378	0.070	0.297	0.148
Panel B. Cross-Listed Cryptocurrencies								
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 × Exchange FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	704	704	704	704	668	668	668	668
Adj. R^2	0.070	0.209	0.525	0.031	0.199	0.036	0.051	0.248

Instead of running a pooled regression with observations at the cryptocurrency-day level, we aggregate all the data and produce 2 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 2 (7) days before the event and 2 (7) days after the event. For trading volume, we calculate the average for the week (or 2 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 5-day (2-week) window after the Bittrex ban and the volume increased by 22.5% (36.0%) during a 2-week (4-week) window after the ban. For the Yobit case, on average prices dropped by about

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12.1%–15.5% more, and the volume dropped by about 40% more for Yobit cryptocurrencies than non-Yobit cryptocurrencies after the announcement.[31]

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 1 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 nonevent exchange price using volumes on Bittrex (Yobit) and other exchanges.[32] Equation (1) is revised as follows:

$$DV_{i,e,t} = \beta_1 Post_t + \beta_2 Treat_{i,e} \times Post_t + \alpha_{i,e} + \varepsilon_{i,e,t}. \tag{2}$$

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 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": i) the scheme makes prices less accurate as signals for efficient resource allocation, and ii) it makes markets less liquid for risk transfer. Our results suggest that cryptocurrency P&Ds satisfy both conditions.

[31] In Part A16 of the Supplementary Material, 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.

[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.

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VI. Conclusion

This article 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), and Bordalo et al. (2012), (2013)). Our results are consistent with both mechanisms. We also find evidence 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.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109025000201.

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