Cryptocurrency Pump-and-Dump Schemes*

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Abstract

Pump-and-dump schemes (P&Ds) are pervasive in the cryptocurrency market. We find that P&Ds lead to short-term bubbles featuring dramatic increases in prices, volume, and volatility. Prices peak within minutes and quick reversals follow. The evidence we document, including price run-ups before P&Ds start, implies significant wealth transfers between insiders and outsiders. Bittrex, a cryptocurrency exchange, banned P&Ds on November 24, 2017. Using a difference-in-differences approach, we provide causal evidence that P&Ds are detrimental to the liquidity and price of cryptocurrencies. We discuss potential mechanisms why outsiders are willing to participate and describe how our findings shed light on manipulation theories.

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1 Introduction

Initial coin offerings (ICOs) have recently emerged as a popular method of financing blockchain-related startups. In an ICO, a startup creates and distributes its digital "tokens," typically in exchange for Bitcoin, Ethereum, or fiat currencies (e.g., U.S. dollars) to raise capital to fund their operations. A token gives its owner the right to use the firm's products or services once they are developed, and can be traded on the secondary market. ICOs raised nearly \$11.4 billion across over 2,000 blockchain startup deals in 2018, exceeding traditional venture capital investments in funding blockchain-related innovative projects (Pozzi, 2019). The startling growth of this market, coupled with rampant speculation and volatility, has both generated excitement and raised concern about potential exploitation or fraud.

This paper studies "pump-and-dump" schemes (P&Ds) in the cryptocurrency market. P&D is a form of price manipulation that involves artificially inflating an asset price before selling the cheaply purchased assets at a higher price. Once the assets are "dumped," the price falls and investors lose money. Such schemes are most common with microcap stocks and have recently become popular in the cryptocurrency market (Shifflett and Vigna, 2018). The U.S. Securities and Exchange Commission (SEC) deems P&Ds illegal in the stock market, but the regulation of P&Ds in the cryptocurrency market is weak or nonexistent. Many tokens are difficult to justify either as investment or consumer products, and do not fit neatly into existing securities or consumer-protection laws (Li and Mann, 2018). The regulation of cryptocurrencies also requires more global coordination than other assets, since tokens typically are traded globally.

In the cryptocurrency market, manipulators often organize "pump groups" using encrypted messaging apps such as Telegram. They create Telegram channels and invite other investors to join. They frequently advertise on social media platforms to attract investors. A Telegram channel operator can post messages for other members to read. For a planned pump, the operator announces the target date, time, and exchange, usually at least one day in advance. However, they do not disclose the identity of the target token until the scheduled time. Members also receive multiple reminder messages before the announcement of the token symbol. As we show in this paper, a typical cryptocurrency P&D lasts for only several minutes, leaving little time for non-members to participate. Therefore, it is reasonable to believe that Telegram channel members are dominant participants in P&Ds.

Relative to the stock market, on which most existing studies have focused, our setting provides several advantages for investigating P&Ds. First, in the cryptocurrency market, a typical P&D episode lasts for only minutes, while such an episode frequently lasts for months in the stock market (Aggarwal and Wu, 2006; Leuz, Meyer, Muhn, Soltes, and Hackethal, 2017). Many other factors can cloud inferences when pumps last that long. Second, there is typically no false information release or firm actions associated with P&Ds in the cryptocurrency market, reducing the occurrence of information- or action-based manipulation. In fact, most of the Telegram channels have the word "pump" in their aliases and members understand that there is no fundamental news associated with P&Ds (see Table 3, Panel A for a list of the 10 largest channels). In the stock market, however, P&Ds are often associated with the release of false information or other actions (Aggarwal and Wu, 2006; ; Putnins, 2012; Leuz, Meyer, Muhn, Soltes, and Hackethal, 2017).

Third, identifying P&Ds is much easier in the cryptocurrency market than in the stock market. The literature has focused on studying stock P&Ds that are ex post investigated by regulators (Aggarwal and Wu, 2006; Leuz, Meyer, Muhn, Soltes, and Hackethal, 2017) or the "stock pools" of the 1920s, which was perhaps the most famous case of alleged stock manipulation. The SEC anti-manipulation cases may not be representative, though, and existing studies show that "stock pools" engage in informed trading rather than manipulation (e.g., Mahoney, 1999; Jiang, Mahoney, and Mei, 2005). In the cryptocurrency market, manipulators organize pump groups, advertise on social media to attract participants, and disclose their pump plans in real time. New encryption technologies allow them to do so without revealing their identities. This feature enables us to precisely identify a sample of P&Ds, pinpoint their timing, and conduct detailed analyses.

Using 500 hand-collected cryptocurrency P&Ds, we document several stylized facts. First, P&Ds have dramatic short-term impacts on the prices and volumes of most of the pumped tokens. In the first 70 seconds after the start of a P&D, the price increases by 25% on average, trading volume increases 148 times, and the average 10-second absolute return reaches 15%. A quick reversal begins 70 seconds after the start of the P&D. After an hour, most of the initial effects disappear. The above findings hold for both liquid and illiquid tokens, although they are stronger for relatively illiquid tokens.

We also document that prices of pumped tokens begin rising five minutes before a P&D starts. The price run-up is around 5%, together with an abnormally high volume. These results are not surprising, as pump group organizers can buy the pumped tokens in advance. When we read related messages posted on social media, we find that some pump group organizers offer premium memberships to allow some investors to receive pump signals before others do. The investors who buy in advance realize great returns. We deem investors who know the identity of pumped tokens in advance as insiders and the rest as outsiders. Calculations suggest that insiders' average return can be as high as 18%, even after considering the time it may take to unwind positions. This far exceeds the round-trip trading costs that are between 20 and 50 basis points. For an average P&D, insiders make one Bitcoin (about $8,000) in profit, approximately one-third of a token's normal-period daily trading volume. The trading volume during the 10 minutes before a pump is 13% of the total volume during the 10 minutes after the pump starts. In the majority of cases, insiders are able to unwind their positions within 10 minutes. This implies that an average trade in the first 10 minutes after a pump has a 13% chance of trading against these insiders and on average the outsiders lose more than 2% (18%×13%).

The quick reversal means that an outside investor who is unaware of the P&D timing in advance needs to buy and sell very quickly to make a profit. Equally importantly, liquidity may disappear when the investor wants to sell. We conduct a performance analysis that accounts for real-time liquidity. Our analyses show that, on average, only investors who buy in the first 20 seconds after a P&D begins can make a profit, and they can do so only if they do not hold their tokens for very long. For example, if an investor buys tokens between 10 and 20 seconds after the P&D starts and begins selling one minute later, he will lose 0.72% of his investment on average. An investor who buys target tokens one minute after a P&D starts will lose more than 1% even if he sells immediately after the purchase.

The inferred performance may overestimate the real performance one can achieve. First, in the analysis we assume that when investors decide to sell they can consume all the available liquidity in the market, but that is unlikely. Second, both the token price and the volume increase before a P&D starts, suggesting trading by pump insiders. If they start unwinding their positions immediately after the P&D starts, they will consume all the liquidity between the announcement and 140 seconds later, leaving scarcely any profit available even to the fastest outsiders. Third, we find that some outsiders receive pump signals systematically later than other outsiders do. All these findings make it puzzling why outsiders, especially those who receive signals systematically later, are willing to participate.

While the cryptocurrency market enables us to conduct detailed analyses of P&Ds, our data do not enable us to pin down the exact mechanism that explains why outsiders are willing to participate.[1] The price and volume patterns around P&Ds are analogous to asset bubbles that have been studied in the literature; however, these cryptocurrency bubbles develop within much shorter time intervals.[2] We conjecture that one plausible mechanism for this is that P&Ds attract overconfident investors who believe that they can time the market more accurately than others can (Scheinkman and Xiong, 2003; Daniel and Hirshleifer, 2015). Another possible mechanism is that these investors have gambling preferences. The short-term returns on pumped tokens are very high and salient. Investors may overweight the possibility of these returns in their decision-making (Barberis and Huang, 2008; Barberis, 2013; Bordalo, Gennaioli, and Shleifer, 2012, 2013).

In trade-based price manipulation theories, where a manipulator cannot act in ways other than buying and selling assets, the manipulator needs to buy the target asset to "pump" its price first. As outside investors follow, the manipulator can sell at a higher price to make profits. Manipulators can make profits only if the price impact is greater when they buy than when they sell; otherwise this strategy is self-defeating (Friedman, 1953). Trade-based manipulation can be profitable if there is price momentum (Jarrow, 1992) or uninformed investors believe it is probable that the manipulator is informed (Allen and Gale, 1992). The price impact is abnormally high before a

[1]Tokens can also be traded off the exchanges. These trades are broadcast on a blockchain network and are viewable by the public. Blockchain trading data can potentially enable us to get investor identifier, as trading on blockchain can be linked to unique wallets. EY Research (2017) reports that 77% of cryptocurrencies issued before 2018 use the Ethereum platform and Mironov (2018) reports that this ratio increased to 95% in the first half of 2018. We therefore collect token trading data from Etherscan.io, a leading "block explorer" that allows users to view information about blocks and transactions on the Ethereum Blockchain. However, we find that virtually all P&D-related token trading occurs on the exchanges, likely due to lower trading costs and faster trading speed on exchanges.

[2]Asset bubbles have fascinated economists for centuries (Mackay, 1984; Tirole, 1985; Shiller, 2000; Scheinkman and Xiong, 2003; Fama, 2014). Many studies have documented abnormal asset price and volume behavior in bubble episodes (Hong and Stein, 2007; Xiong and Yu, 2011; Barberis, Greenwood, Jin, and Shleifer, 2018; Greenwood, Shleifer, and You, 2018).

P&D starts, which is consistent with informed insider purchases. Interestingly, at the beginning of a P&D, the large price increase is not associated with an abnormally strong price impact, consistent with the fact that the P&D announcement leads to increased participation of Telegram channel members who are typically uninformed traders. Their purchases likely cause a large price increase. These findings contrast with the existing trade-based manipulation theories that typically assume that manipulators have to buy to increase the asset price.

P&Ds, or other forms of price manipulation, are generally considered undesirable and should be regulated. Besides illegitimate wealth transfers, are there any other detrimental consequences of P&Ds? We investigate this question using a natural experiment. On November 24, 2017, Bittrex, a U.S.-based cryptocurrency exchange, announced that it would ban P&Ds. Although it was not able to eliminate P&Ds altogether, it reduced the frequency of P&Ds on its exchange. This ban affected only the tokens traded on Bittrex, not tokens on other exchanges. We employ a difference-in-differences approach and find that the ban causally increased token prices and liquidity.

Our paper contributes to the price manipulation literature. 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), derivative markets including the equity and index options markets (Griffin and Sham, 2018a), futures markets (Merrick, Naik, and Yadav, 2005), and the LIBOR market (Mollenkamp, 2008; Snider and Youle, 2010). These assets are manipulated often because their prices are used for contract settlements. If manipulators have large positions in derivative contracts, they can make profits even if they lose in the underlying market. 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, 2018). Gandal, Hamrick, Moore, and Oberman (2018) document evidence of Bitcoin price manipulation in 2013 and Griffin and Sham (2018b) document suspicious Bitcoin activities in 2017. Diverging from all these papers, we study cryptocurrency P&Ds. Special features of this market enable us to conduct detailed and clean empirical investigations.

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 by trading. Cryptocurrency P&Ds are not associated with company information releases or other actions, and therefore cannot be explained by information- or action-based manipulation theory.

There is also a theoretical debate over the profitability of trade-based manipulation. Friedman (1953) concludes that arbitrage would make such a strategy self-defeating. More recent studies argue 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).[3] The price impact behavior associated with cryptocurrency P&Ds is inconsistent with the implications of the existing trade-based manipulation theories. Instead, our results suggest that overconfident or gambling investors can "coordinate" to create short-term asset bubbles, followed by quick reversals, implying the presence of a new type of manipulation besides that considered by Allen and Gale (1992).

Our findings also contribute to the burgeoning literature on the application of blockchain technology in finance. These studies have examined how blockchain technology may reshape transaction costs and economic exchange (Biais, Bisiere, Bouvard, and Casamatta, 2019; Catalini and Gans, 2016; Malinova and Park, 2017; Cong and He, 2019; Yermack, 2017); ICOs (Catalini and Gans, 2018; Chen, Wu, and Yang, 2018; Cong, Li, and Wang, 2018; Cong and Xiao, 2018; Howell, Niessner, and Yermack, 2018; Lee, Li, and Shin, 2018; Li and Mann, 2018; Sockin and Xiong, 2018); the ecosystem of Bitcoin (Bohme, Christin, Edelman, and Moore, 2015), including mining and transaction fees (Cong, He, and Li, 2018; Easley, O'Hara, and Basu, 2017; Huberman, Leshno, and Moallemi, 2017); and Bitcoin adoption and usage, including how Bitcoin facilitates illegal activity (Athey, Parashkevov, Sarukkai, and Xia, 2016; Foley, Karlsen, and Putnins, 2019). Hu, Parlour, and Rajan (2018) document stylized facts pertaining to cryptocurrency prices. Liu and Tsyvinski (2018) study how cryptocurrency prices are related to other traditional financial assets. Makarov and Schoar (2019) study cryptocurrency mispricing and arbitrages across exchanges. Of greatest

[3] Jarrow (1992) and Huberman and Srabzl (2004) derive conditions for the nonexistence of price manipulation, and both studies show that market manipulation strategies can exist under reasonable conditions.

relevance to our study, Gandal, Hamrick, Moore, and Oberman (2018) and Griffin and Shams (2018b) provide evidence consistent with Bitcoin price manipulation. They do not, however, study P&Ds.[4]

Our study also informs the recent debate over cryptocurrency regulation. While there are many aspects of cryptocurrency regulation, our findings suggest that P&Ds should be regulated. First, the existence of price run-ups before P&Ds implies that an average outsider loses money by trading in P&Ds. Standard market forces suggest that outsiders would be unlikely to participate in P&Ds. Our evidence suggests that this market mechanism is not working. Second, our analysis based on the Bittrex ban provides causal evidence that P&Ds are detrimental to the health of the cryptocurrency market. Third, the fact that Bittrex was able to sharply reduce P&Ds on its exchange suggests that banning P&Ds is technologically feasible. An exchange may be able to distinguish itself by preventing manipulation.

2 Institutional Background

In this section, we briefly discuss what cryptocurrencies are, how they are traded, and how cryptocurrency P&D schemes are operated. We conclude with a discussion of the current regulatory environment.

2.1 Cryptocurrencies

Cryptocurrencies are digital tokens typically issued through ICOs. In an ICO, a technology startup creates and distributes its token in exchange for Bitcoin, Ethereum, or fiat currencies (e.g., U.S. dollars) to raise capital to fund their operations. A token typically 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 (Lee, Li, and Shin, 2018; Sockin and

[4] Two concurrent papers also study cryptocurrency P&Ds. Xu and Livshits (2018) study how to predict P&D events. Hamrick et al. (2018) examine which factors affect the returns of pumped tokens. Their main finding is that a token's market capitalization is the most important factor, consistent with our finding that P&Ds increase illiquid tokens' prices more than those of the liquid ones. Our token trading data are trade-by-trade from the target exchanges, while Hamrick et al. (2018) use data at five-minute intervals and Xu and Livshits (2018) use data at one-hour intervals. Both of their data sets are aggregated across *all* exchanges. The granularity of our data enables us to pin down the effects of P&Ds more accurately.

Xiong, 2018).

Most secondary market trading in cryptocurrencies occurs on online exchanges. Tokens are typically listed on one or more exchanges. Exchanges operate 24 hours a day, 365 days a year. On most cryptocurrency exchanges, traders can place market or limit orders. Limit orders provide liquidity and are rewarded by the exchanges with lower trading commissions than market orders. However, Binance, Bittrex, and Yobit, the three exchanges we study, charge flat fees for both market and limit orders of 0.1%, 0.2% and 0.25%, respectively.[5]

Token prices are quoted in ticker pairs that function in a way that is similar to exchange rates. For example, NXS/BTC is a pair that indicates that the trade is an exchange between NXS (Nexus) and BTC (Bitcoin). In this pair, Nexus is quoted in the number of Bitcoins, which is the base currency. Besides Bitcoin, other cryptocurrencies such as Ethereum, Tether, Binance Coin, and Litecoin are also commonly used as numeraires. Bitcoin is by far the most widely used base currency and all the P&Ds in our sample target trading pairs involving Bitcoin. In seven P&Ds, both Bitcoin pairs and Ethereum pairs are targeted. We therefore focus on Bitcoin pairs in our main analysis. In additional analysis, we also examine Ethereum pairs.

2.2 Pump-and-Dump Schemes

In the cryptocurrency market, operators of P&Ds often organize "pump groups" using encrypted messaging apps such as Telegram. Multiple groups also coordinate to pump cryptocurrencies together. Telegram is a cloud-based instant messaging service developed by Telegram Messenger LLP. Telegram uses end-to-end encryption, which means that nobody but the sender and recipient can read the messages. Chat messages cannot be forwarded to others outside of the conversation, and no trace is left on the servers. It is considered as one of the most heavily-encrypted messaging platforms available today. Telegram users can also use aliases. Both of these features make it difficult to track who is involved in a particular P&D scheme.

[5]In addition to trading on online exchanges, investors can also trade cryptocurrencies over the counter (OTC) or on decentralized exchanges. In the OTC market, traders typically discuss trade terms via e-mail or messaging apps such as Skype. After a trade is agreed upon, fiat money is sent to a third party who handles the settlement. On a decentralized exchange, trades occur directly between users through an automated process, without a third-party service that holds the customers' funds. Off-exchange trading is subject to the same blockchain-based mining process, which can take several minutes to several days to confirm a transaction.

Another unique feature of Telegram is that it allows operators to create Telegram channels to broadcast messages.[6] Members can join a channel free of charge and access the entire message history. Each message, timestamped to the second, has its own 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 existing participants to do the same. Some operators offer monetary incentives to members who invite new members to participate.

Figure 1 illustrates how a typical P&D works. On the morning of July 4, 2018, Big Pump Signal, one of the biggest pump groups in our sample, announced that they would pump a token at 7 p.m. Coordinated Universal Time or UTC (3 p.m. EDT) on Binance. One-and-a-half hours before the pump, the operator of the Telegram channel reminded its 70,000 followers of the event, and encouraged them to reach out to other investors: "Bigpumpsignal has always been focused on reaching outsiders. Because, a good pump is decided by the amount of interest of the outsiders ... You are free to help us with spreading news about the coin we pump on social media!" About 30 minutes before the pump, the operator urged members to get ready, and they were reminded again 20, 10, five, and two minutes before the pump. Although a target return was not set in this P&D, such a target is often announced in other pump events.

[Insert Figure 1 here.]

At 6:59:57 p.m. UTC, three seconds before the scheduled time, the ticker of the target token, NXS (Nexus), was announced. Telegram's record shows that 28,800 followers viewed the message. The price of Nexus jumped 52.0% immediately, to 0.0003045 Bitcoin ($2.01), before plummeting 24.5% from the peak after 10 minutes. During this time, 4,153 trades worth 222.68 Bitcoin ($1.5 million) were executed, compared with virtually no trading during the hour before the announcement.

Not all group members are treated equally by the operators. Tiered access to pump signals appears to be common with many groups. High-ranking members may be sent a signal several seconds earlier than others receive it. Members can pay a fee to become VIP members. The operators

[6] Users can send private messages to the operator, but are not able to leave feedback in the public domain.

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 successfully invited at least four (50) members to join.

2.3 The current regulatory environment

P&Ds in stocks are illegal in many countries and considered fraudulent by U.S. regulators. Stock exchanges that do not take adequate measures to prevent P&D schemes can also face legal penalties. The SEC regularly targets P&D scams (Mei, Wu, and Zhou, 2004). Section 9 of the Securities Exchange Act of 1934 specifically makes it unlawful to manipulate security prices. P&D groups active on cryptocurrency exchanges, however, have been operating with relative impunity because cryptocurrencies are not necessarily considered securities and the exchanges currently are unregulated markets.

In December 2017, the SEC issued a statement on cryptocurrencies and ICOs, warning investors to beware of scams and criminal activities in the sector. The statement explains that "excessive touting in thinly traded and volatile markets can be an indicator of 'scalping,' 'pump and dump' and other manipulations and frauds." On February 15, 2018, the U.S. Commodity Futures Trading Commission (CFTC) published a customer advisory, warning investors to avoid cryptocurrency P&D schemes. It offers eligible whistleblowers between 10% and 30% of the value of enforcement actions that involve $1 million or more in P&D investing.

Despite the regulatory scrutiny, P&D groups in the cryptocurrency market have not ceased operating. One potential reason for this is that most cryptocurrencies are traded on multiple exchanges globally, which could lead to regulatory arbitrage. Encrypted messaging apps such as Telegram can also help P&D organizers hide their identities.

3 Data

We obtain a list of P&D events, cryptocurrency trading data, and additional token-level variables from various data sources. We discuss them one by one. Separate data sources may have distinct token identifiers and we manually match them by token symbol and name.[7] We discuss potential problems with our data at the end of this section.

3.1 P&D events

There exists no central database of P&D events. We therefore manually construct a sample. We first collect a list of pump groups from Reddit and BitcoinTalk, two popular cryptocurrency message boards. Pump groups typically advertise on these boards to attract participants. For completeness, we also conduct an Internet search for additional advertisements posted by such groups. We initially identify 210 Telegram groups that engage in P&Ds, 129 of which were still accessible as of September 2018. Forty-nine of the 129 groups did not initiate any pumps.[8] All these Telegram groups are publicly accessible.

We read all messages posted in these Telegram channels. For each P&D event, we collect the target token (name and symbol), target exchange, announcement time, initially scheduled time (timestamped to the second), number of viewers of the announcement, and target price or return if available. All timestamps in this paper are based on the UTC scale. In cases where a token is targeted by multiple channels at the same scheduled time, we use the earliest announcement time for our analysis. As we document later in the paper, the sharp changes in token price and trading volume occur exactly at the announcement, providing justification that our data on P&D announcement times are accurate.

We identify 3,412 P&D announcements from 80 active Telegram channels in the period between May 15, 2017 and August 26, 2018. Many P&Ds are coordinated by more than one channel. The total number of unique P&Ds is 1,747. These P&Ds target tokens traded on Binance, Bittrex, Yobit, Cryptopia, HitBTC, Poloniex, and CoinExchange. We restrict our attention to the 1,040 P&Ds targeting tokens on Binance, Bittrex, and Yobit. This choice is motivated by the small number of P&Ds on HitBTC, Poloniex, and CoinExchange, and the unavailability of trading data from

[7] We discuss the details of matching tokens across multiple data sets in Part A1 of the Appendix.

[8] We also identify a small number of Discord pump groups. We cannot access them, however, because an invitation is needed to join a Discord group. Discord groups are much smaller and less popular than Telegram groups (with up to 100,000 members) as Discord imposes a limit cap of 5,000 concurrent online users for each group. Groups reaching 5,000 simultaneous online members need to apply for hardware supporting larger servers. At that moment, members start getting "Server Unavailable" errors. In fact, the Big Pump Signal group switched to Telegram on December 28, 2017 due to "reaching maximum amount of users online on discord!"

Cryptopia.[9] Binance, Bittrex, and Yobit are among the largest cryptocurrency exchanges in the world, and are ranked first, 36th, and 27th by trading volume, respectively, on CoinMarketCap.com, a popular data provider.

The large number of P&D events suggests that P&Ds are pervasive in the cryptocurrency market. Binance is located in Asia, Bittrex in the U.S., and Yobit in Russia. Therefore, our sample covers major regions around the globe. Not all pumped cryptocurrencies are covered by our trading data. After merging with trading data, our sample shrinks to 507 P&Ds. We further require that a target token be traded at least once in the period from 37 days before an announcement to eight days before the announcement. Our final sample includes 500 distinct P&Ds involving 239 unique tokens.

Figure 2, Panel A displays the distribution of our sample P&Ds by scheduled hour (UTC). We report the distribution for each of the three exchanges. It is evident that although there is some difference across the three exchanges, the majority of pumps are scheduled from 12:00 to 22:00 UTC (daytime in the U.S.).

[Insert Figure 2 here.]

3.2 Exchange trading data

We obtain trade-by-trade data on tokens listed on Binance, Bittrex, and Yobit from two sources. For Binance tokens, we download data using its public application programing interface (API), a web interface for data retrieval. Binance's API enables us to retrieve the entire history of token trading data. However, APIs provided by Bittrex and Yobit allow access only to the past 24 hours' worth of data. We thus purchase these trading data from Kaiko Data, a data provider that has been collecting token trading data since 2014. Kaiko obtains the data by querying the APIs on a daily basis.

The data structure is similar to trade files of the NYSE Trade and Quote (TAQ) database. For each transaction, we have the ticker symbol pair (e.g., NXS/BTC, in which BTC is the base

[9] In our sample, only four announcements target HitBTC, while the number of announcements for Poloniex and CoinExchange are 54 and 44, respectively. We collected information on 690 P&Ds on Cryptipia. However, Cryptopia does not allow any third party to download tick-level trading data that are older than one week. To the best of our knowledge, no data provider collects its trading data either, potentially due to Cryptopia's small size. Cryptopia is currently ranked 77th among all cryptocurrencies, according to CoinMarketCap.

currency), execution price, quantity, UTC-based timestamp, and an indicator that specifies whether the trade is buyer- or seller-initiated. Therefore, we do not need to infer trading direction based on any algorithm such as the one proposed by Lee and Ready (1990). Trades are time-stamped to the millisecond on Binance and Bittrex, and to the second on Yobit. All three exchanges cover both active coins and delisted coins and therefore are not subject to survivorship bias.

Figure 2, Panel B displays the distribution of trading volume by UTC hour. Although the three exchanges are located on three continents (again, Binance in Asia, Bittrex in the U.S., and Yobit in Russia), the trading volume distributions by hour look remarkably similar. First, trading is active at almost all hours, reflecting the global nature of token trading. Second, trading volume is higher between 12:00 and 20:00, which is similar to the distribution of P&Ds shown in Figure 2, Panel A.

3.3 CoinMarketCap data

Our exchange trading data may not cover all the trading activities of a token if it is cross-listed on exchanges other than Binance, Bittrex, and Yobit. We therefore also obtain data from CoinMarketCap.com. CoinMarketCap is widely considered the top source for trading information on cryptocurrencies. CoinMarketCap aggregates pricing and volume data for nearly 2,000 tokens from hundreds of exchanges. The data CoinMarketCap provides are not trade-by-trade records but aggregated at the daily level. For each day, CoinMarketCap reports price (volume-weighted across exchanges), total volume, and market capitalization. CoinMarketCap does not cover all tokens, but tends to feature larger and more liquid ones.

3.4 Other data

We also collect token-level data for all cryptocurrencies traded on Binance, Bittrex, and Yobit. The initial listing date for each token is obtained from CoinMarketCap. In cases where CoinMarketCap does not feature a token or its initial listing date is more recent than the initial trading date on Binance, Bittrex, or Yobit, we use the latter. CryptoCompare.com compiles a social media activity index for cryptocurrencies, which aggregates the number of users on Reddit, Twitter, Facebook, and its own site. We manually search each token name on CryptoCompare and obtain its social media activity index.

3.5 Summary statistics

In Table 1, Panel A we report the characteristics of our P&D events. In the full sample, on average, 1.6 Telegram channels coordinate one P&D, suggesting that coordination is popular. The total number of viewers across all channels in a pump is 5,942, with Binance pumps attracting the most viewers, and Yobit pumps the least. Nearly 90% of the pumps are scheduled at the usual time, which is defined as the most frequently scheduled time for a given group. 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 running, for example, from 200% to 300%, or it differs across channels, we use the lower bound. The target returns are 212% on average. Target returns for Yobit tokens (233%) are much higher than those for Binance tokens (69%), likely because Yobit tokens are less liquid.

[Insert Table 1 here.]

In Table 1, Panel B we report summary statistics on the target tokens as well as on the non-target tokens listed on Binance, Bittrex, and Yobit. For each token characteristic on each day on which at least one pump occurs, we calculate the average value for target and non-target tokens. We then compute the time-series average. The differences between target and non-target tokens and their associated t-values are calculated using these time-series averages. The token characteristics we report are log trading volume (in Bitcoin), log market capitalization (in dollars), return volatility, coin age, social media index, and the frequency of being covered by CoinMarketCap. Trading volume and volatility are calculated over the period running from day -37 to day -8. Market capitalization is available only if a token is covered by CoinMarketCap. We also report the average percentile of pumped tokens among all tokens.

On average, 2.02 tokens are pumped per day in our sample, and 684 are not. The likelihood that a token will be pumped on a given day is 0.3%, which is equivalent to more than 107% a year. The characteristics of non-target tokens inform us of the average token's characteristics, as the majority of tokens are not pumped on any given day. The results presented in Table 1, Panel B show that the average log trading volume of non-target tokens over the previous 30 days is 3.345 (28.36 Bitcoin or around \$0.23 million) and the average daily return standard deviation is 14.1%, suggesting that the average token is illiquid and its price is highly volatile. CoinMarketCap covers 52.4% of tokens on the three exchanges. In unreported analysis, we find that covered tokens generally exhibit much higher trading volumes than uncovered ones, suggesting that CoinMarketCap is more likely to cover larger tokens. For covered tokens, the average log market capitalization is 16.375 (\$12.70 million). All these results show that the average token is small, illiquid, and volatile.

In Table 1, Panel B we also show that target tokens exhibit higher trading volumes, lower volatility, and higher social media indexes than non-target tokens, and they are older and more likely to be covered by CoinMarketCap. Conditional on being covered by CoinMarketCap, their market capitalization is similar to that of other covered tokens. The average market capitalization of target tokens is comparable to that of the 10th percentile of U.S. common stocks in the 10th percentile, and their volatility is comparable to that of stocks in the 99th percentile (Hou and Loh, 2016).[10]

3.6 Potential problems with the data

There are a few potential sources of selection bias in our sample. The first is that 81 of our 210 initially identified Telegram pump channels are closed. Telegram closes channels to save disk space. When closing a channel, Telegram will delete all messages, contacts and data stored in the Telegram cloud. This explains why in those circumstances we can no longer access the messages. The most prominent cause of channel closures is that operators do not log onto their channels within a six-month period. Many channels in our sample had been inactive for months (but for fewer than six months) but were not closed. We assess the importance of this potential bias in Part A2 of the Appendix and find that P&Ds that occurred within the past six months before we started this study, which are free of such bias, perform similarly to other P&Ds.

[10]In addition to using CryptoCompare's social media index, we also create an indicator variable equal to 1 if a cryptocurrency is rated by analysts from ICObench.com and ICORating.com, two popular websites that provide investment ratings of cryptocurrencies before they were listed. ICObench uses a rating scale that ranges from 1 to 5, with 5 being the highest rating. Their assessment algorithm evaluates four separate aspects: team, token sale information, product representation, and marketing and social media. ICORating provides three ratings—a hype score, a risk score, and an overall investment rating. The hype score indicates the level of interest on the part of potential investors, the risk score is aimed at assessing the risk of potentially fraudulent activities, and the investment rating "demonstrate[s] maximum openness to potential investors." See Lee, Li, and Shin (2018) for more information. We find that pumped tokens are more likely to be rated by these two websites.

The second potential problem arises from the fact that the trading data we collected from Bittrex and Yobit do not cover all the listed tokens. This is because our data provider occasionally had technical issues in querying the two exchanges for some token-days. We believe this is unlikely to cause any bias in our results. Nevertheless, to mitigate any such concern, we replicate our main results by focusing only on P&Ds that target Binance. We download trading data from Binance directly and are able to collect data on all of their tokens. In Part A3 of the Appendix, we report similar results after analyzing targeted Binance tokens only.

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

4 Empirical Results Pertaining to P&Ds

In this section, we first report the effects of P&Ds on token prices and trading patterns, using the standard event study method. We report all the results without adjusting for the effect of the market. Adjusting for the market effect has little influence on our results. At the end of the section, we discuss why P&Ds are puzzling and offer several potential interpretations.

4.1 Can P&Ds move token prices?

Figure 3 displays the distribution of maximum returns (Panel A) and time to maximum returns (Panel B) across P&D events. A P&D's maximum return is defined as the ratio of the highest price achieved within 10 minutes after the pump announcement to the price ten minutes before the announcement minus 1. The time to a maximum return is defined as the number of seconds it takes from the announcement to reach the maximum price. There are a few extreme returns. For ease of illustration, we cap maximum returns at 500% for the results displayed in Figure 3, Panel A. In all other analyses, returns are not capped. A maximum return can be negative if the maximum price of a pumped token during the ten minutes after the announcement is lower than its price ten minutes before the announcement. This can happen if the scheme is unsuccessful and the price drops.

[Insert Figure 3 here.]

In Figure 3, Panel A we show clearly that in the majority of P&Ds, token prices increase. On average, the mean (median) maximum return is 68.94% (24.39%). For the first and third quartiles the returns are 9.27% and 70.73%, respectively. There are only seven P&Ds in which the maximum return is negative, suggesting that these P&Ds are unable to pump the token prices. The token price reductions in these cases are much smaller relative to price increases in successful P&Ds. On average, it takes only 2.6 minutes for prices to reach the maximum level. This short window indicates that one needs to be fast to make profits from P&Ds. Later in this section, we conduct more detailed analyses on trading performance by time of purchase.

In Figure 4, Panel A we report cumulative returns, abnormal volume, and the volatility of the tokens targeted by P&D groups for each 10-second interval. The X-axis indicates the time from 600 seconds before to 600 seconds after the announcement of a P&D. 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 log change in price from 600 seconds before the announcement of P&Ds. 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 $t - 37$ to day $t - 8$). Volume is measured by the number of tokens traded. Volatility is measured as the absolute value of returns in each 10-second interval. We measure volatility as the absolute value of returns rather than squared returns to minimize the effects of extremely large returns, as we observe in Figure 3.

[Insert Figure 4 here.]

It is evident from the results displayed in Figure 4, Panel A that P&Ds move token prices and generate significant abnormal trading volumes. It is interesting that the changes start before announcements, suggesting potential leakages. Such leakages are likely driven by VIP members of pump groups who tend to receive signals in advance, or by pump group operators who may trade directly, or both.

We use Figure 4, Panel A to infer investor performance. An "insider," who knows the token identity and timing of the pump in advance and buys target tokens ten minutes before the announcement and holds until 70 seconds after the announcement, achieves a nearly 25% return. For an "outsider" who does not know about a P&D in advance but buys immediately after the announcement and sells 70 seconds later, his return of 15% is still eye-popping. These are the maximum returns an insider or an outsider can potentially achieve. In these analyses, we assume that the insider and the outsider are small investors and their trades do not affect the price. In reality, this assumption is unlikely to hold. In later analyses (Table 2), we examine this assumption in greater detail.

The second and third graphs on Figure 4, Panel A display the abnormal volumes and volatility, respectively. At the maximum, the change in the 10-second volume is around 148 times (the exponential of 5) higher than the average 10-second interval in the period running from 37 days to eight days before the announcement of a P&D. The volatility (measured as the absolute value of 10-second returns) is 15% in the first 10-second interval after the announcement.

The results for returns, trading volume, and volatility all demonstrate that P&Ds have a significant short-term impact on token prices and trading. Ten minutes after an announcement, the price, trading volume, and volatility are still significantly higher than their pre-announcement levels, although the reversal for volume and volatility is quicker than that for price.

In Figure 4, Panel B we present the patterns of returns, trading volume, and volatility over a longer period—running from seven days before an announcement to seven days after. Outside of the short period around a P&D, trading decreases sharply, preventing us from calculating these variables accurately based on 10-second data. Therefore, for this longer-term analysis we calculate price, volume, and volatility over one-hour intervals. We find that the effect of P&Ds on volatility disappears in less than a day, and the effects on price and volume last for two to three days. However, as trading volume quickly goes back to the normal level after minutes, there is hardly any liquidity for trading against the continual reversal.

In Figure 5, we show the results of replicating the above analysis using two groups of P&Ds

sorted by the liquidity of pumped tokens. Liquidity is defined as the total trading volume (in Bitcoin) over the period running from 37 days to eight days before the pump. The results show that the effects of P&D on price and volume are much stronger for illiquid tokens than for liquid ones.[11]

[Insert Figure 5 here.]

4.2 Spillovers to Ethereum pairs and other exchanges

In previous reported analyses, we focus only on Bitcoin pairs traded on the target exchanges. We focus on Bitcoin pairs because P&Ds specifically target these pairs. In this section, we investigate the effects of P&D spillovers to Ethereum (ETH) pairs, which are the second most commonly traded pairs. We also investigate whether there is any spillover effect on the same tokens traded on other exchanges.

We expect a spillover effect on the ETH pair because the limits to arbitrage between a BTC pair and an ETH pair are low. Investors can easily buy BTC pairs and sell them as ETH pairs and vice versa. BTC/ETH pairs are listed on all three of the exchanges we study and are very liquid, facilitating exchange between these two base currencies. We also expect that the spillover to other exchanges would be low in volume, due to stronger limits to arbitrage. Trades happen instantly within an exchange, but once a cryptocurrency must be transferred to another exchange the settling of that transaction takes much longer, partly due to the mining process. For example, it takes nearly an hour to settle a Bitcoin transaction, which makes exploiting mispricing opportunities across exchanges difficult. This is consistent with Makarov and Schoar (2019), who find that there are many recurrent arbitrage opportunities in Bitcoin and Ethereum across exchanges.

There are 92 pumped tokens that have also traded ETH pairs and 89 pumped tokens that are cross-listed on one or two other exchanges. Figure 6 displays the results pertaining to these ETH pairs and cross-listed tokens. If a token is cross-listed on two other exchanges besides the target exchange, we take the average of maximum returns, abnormal volume, and volatility across the

[11] An alternative measure of token liquidity is market capitalization. We do not use market capitalization because it is available for only approximately half of our tokens (see Table 1, Panel B). In untabulated results, we find that the correlation between log trading volume and log market capitalization is 0.74.

two exchanges. The results show that the average return, abnormal volume, and volatility of the ETH pairs are comparable to those of the BTC pairs (Figure 6, Panel A), but the average return, abnormal volume, and volatility of the pumped tokens traded on other exchanges are all much smaller than those of the tokens traded on the target exchanges (Figure 6, Panel B). The results reported Figure 6 and in Figure 4, Panel A are not directly comparable as the sample compositions are different. In Part A4 of the Appendix, we conduct an analysis by restricting our data to the same sample and find similar results.

[Insert Figure 6 here.]

Overall, the results reported in Figure 6 and Part A4 of the Appendix confirm our expectation that there is a substantial spillover to ETH prices, but the spillover to other exchanges is less significant. This is consistent with our previous discussion of the differences between the arbitrage limits on BTC prices and ETH prices, respectively, as opposed to similar limits across exchanges. The quick reversal shown in Figure 4 and weaker spillover to other exchanges shown in Figure 6, Panel B provide strong evidence that the price increases are not supported by changes in token fundamentals.

4.3 Performance by purchase and sale time

We can infer how investor performance depends on the timing of buying and selling based on the results reported in Figure 4, Panel A. This inference reflects the perspective of a small investor whose trade does not, however, move the market. In this section, we investigate this question from an average real-world investor's perspective. Specifically, we account not only for real-time returns but also for real-time liquidity. Note that the returns are calculated before exchange commissions, which range from 0.2% to 0.5% per round trade. Incorporating commissions does not materially affect our results.

In Table 2, Panel A we report the mean "achievable" returns by purchase time. Given the time of purchase, we also check whether the achievable returns vary with the time over which an investor delays before he begins selling. We can illustrate how to read the numbers presented in Table 2 with the following example. Suppose the total volume for token ABC in the first 10-second interval after the P&D announcement is N and the volume-weighted average price is P. Assume that all these investors follow the same strategy by waiting for D seconds before they start to sell. When they start to sell, we track how long it will take them to unwind all of their purchased tokens, of which we assume there are N. We also assume that when they sell, they are the only sellers on the market and can trade on the volume-weighted average price until they sell all of their purchased tokens. We then calculate their returns and gauge how long it takes to unwind their purchases. Given that it is unlikely that these investors are the only sellers when they sell, our measure of the time taken to unwind purchased tokens will underestimate the actual time required. The inferred achievable returns therefore will overestimate investor performance.

[Insert Table 2 here.]

In Panel A we report the mean achievable returns for each purchase time-delay combination across P&Ds. We highlight in bold the returns that are significantly positive at the 5% level. In Panel B we show the corresponding $t-$values, while in Panels C and D we report the mean and median times to unwind the initial purchase. In addition to the 12 10-second intervals after a P&D, we also include a "Before P&D" interval, which is the 10-minute window before the P&D announcement. We use this interval to evaluate the performance of "insiders."

Not surprisingly, returns depend critically on when an investor buys and sells. Investors who buy before a P&D realize great returns. If they start to sell immediately after the announcement, their return will be 13.93%. The median time to unwind their portfolio is 20 seconds, while the mean is 210 seconds, suggesting that some positions take some time to unwind. These investors' average return, at 18.44%, is highest if they sell after a delay of 30 seconds. On average, it takes 263 (median=30) seconds to unwind a portfolio. Returns start declining if sales are delayed further. However, even if sales are delayed by 180 seconds, the average return is still 8.21%. It will, however, take an average of 733 (median 145) seconds to unwind the position.

Other groups' returns are much lower. Investors who buy in the first 10 seconds after a P&D will realize a positive return if they do not delay selling by more than 140 seconds. However, they cannot delay selling by more than 80 seconds to make statistically significant positive returns. With optimal timing, their return is 6.53%. The next group who buy in the second 10-second interval cannot delay selling by more than 10 seconds to make statistically significant profits. Other groups, on average, cannot make money at all.

The results reported in Table 2 show that, to make positive returns from P&Ds, an outsider has to buy tokens in the first 20 seconds and make sure that he can sell before it is too late. Most others lose money. Compared with the results reported in Figure 4, Panel A, these results suggest that the performance of outsiders is much less impressive, highlighting the importance of real-time liquidity. As discussed above, these estimates are likely to overestimate investors' real performance, as we assume investors use the fastest possible method to unwind their positions.

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. The average volume in the "Before P&D" interval is 13% of that during the 10 minutes after P&Ds. If insiders time the market optimally, they can achieve a 18.44% return. This 18.44% return implies a 2.40% loss for an average outsider.

4.4 Other potential sources of unfairness

As noted above, not all pump outsiders are treated equally. 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 advantages VIP members enjoy. In this section, we investigate whether participants in some Telegram channels receive signals systematically later than others.

The results are reported in Table 3. Panel A reports delays in announcements, which are measured by the number of seconds that elapse after a scheduled pump time. A negative number indicates that the announcement time is ahead of schedule. We report the largest ten pump groups (measured by number of all P&Ds in which they participate) and an aggregate number for all other channels. The delay is capped at ±30 seconds, and the Table 2 statistics show that the marginal effect of further 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 also report the fractions of early announcements.

[Insert Table 3 here.]

We conduct the analyses for two samples. In the first four columns we report results for all P&Ds across the three exchanges. In the last four columns we report results based on P&Ds in our final sample, in which we require the availability of trading data. The results reported in the first four columns indicate that only about 20% of announcements are made ahead of schedule and most are delayed. The mean (median) delay for PumpZone is only 0.73 (0) seconds, while it is 11.29 (7) seconds for Premium Yobit Pump. The results based on our final sample are similar. This suggests the presence of significant heterogeneity in receiving pump signals across groups. In untabulated results, we analyze delays in a regression specification by including P&D fixed effects. The fixed-effect model tests whether separate Telegram channels for the same P&D receive the signal at the same time. The null hypothesis that all channels receive the signal at the same time is strongly rejected.

In Panel B, we present the results of 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 do this for both the Early dummy, which equals 1 if an announcement time occurs is before the scheduled time, and a continuous measure of delay. We use one specification without P&D fixed effects and another with fixed effects. All our results show strong persistence in the delay in receiving signals. Overall, although we cannot judge whether the heterogeneity in signal reception is necessarily an intentional outcome, the results reported in Table 3 provide strong evidence of additional unfairness besides that which occurs between insiders and outsiders.

4.5 Maximum returns, target returns, and viewership

In this section, we analyze factors that affect P&D maximum returns and target returns, and determine whether the target returns are achieved. This analysis sheds light on the extent to which pump group operators behave strategically. We also study the dynamics of Telegram viewership, focusing on whether investors learn from past experience. We study the former at the P&D level and the latter at the Telegram channel level.

At the P&D level, we examine factors that affect the maximum returns. For Figure 3, we define maximum return as the ratio of the highest price achieved within 10 minutes after a pump announcement and the price ten minutes before the announcement minus 1. Because we study the price run-up, which is mechanically related to the maximum return defined in this way, we redefine the maximum return as the ratio of the highest price achieved within 10 minutes after the pump announcement to the price at the announcement minus 1. At the channel level, it is interesting to study whether past pump performance, such as recent pump returns and abnormal volume, affects Telegram viewership, which we use as a proxy for investor participation.[12]

The results reported in column (1) of Table 4 confirm the findings displayed in Figure 5, which demonstrate that maximum returns are lower in liquid tokens than in illiquid ones. Potential leakages, proxied by price run-ups, negatively predict the maximum returns achieved. Pumps launched by multiple groups achieve a maximum return that is substantially higher than returns involving a single channel, suggesting that P&Ds rely on investor participantion. As shown in column (2), pump operators set target returns at a lower level for liquid tokens. In column (3) we further show that in 31.4% of the cases the target returns among the channels are achieved. However, liquidity does not affect whether or not target returns are reached. The finding that target returns are not achieved in most cases suggests that either the pump operators intentionally set the target returns too high to mislead participants or coordination between pump members is difficult to accomplish.

[Insert Table 4 here.]

Given that the average P&D lasts for only several minutes, it is reasonable to believe that Telegram channel members are the dominant outsiders because there is little time for non-members to react to sudden jumps in token price and volume. Does the performance of channel members affect the popularity of P&Ds? In Table 5, we report the results of examining factors that affect the dynamics of Telegram channel viewership. Our dependent variable is the change in the natural logarithm of Telegram channel viewers. The results suggest that past P&D performance does not affect Telegram channel viewership. Although viewership does not necessarily lead to participation

[12]One potential concern is that Telegram's post view count system may overestimate the number of real-time viewers, as the view count is updated over time. However, random checks several months after we collected the data indicate that few people view old posts retrospectively.

in P&Ds, our finding that viewership is not sensitive to past P&D performance provides indirect evidence that learning by investors may be limited.

[Insert Table 5 here.]

4.6 Potential mechanisms

To summarize, we have reported three main findings. First, an average P&D moves token prices and trading volume significantly. Second, investor performance depends critically on when they obtain their signals. Insiders could make abnormally high returns, but it is difficult for outsiders to achieve this. Third, some outsiders are disadvantaged and receive signals systematically later than others. All these findings make it puzzling that an outsider, especially a disadvantaged outsider, is willing to participate in a P&D.

In trade-based price manipulation theories in which a manipulator cannot act in ways other than buying and selling assets, the manipulator needs to buy the target asset to "pump" its price first. As outside investors follow, the manipulator can sell at a higher price to make profits. The manipulator can make profits only if the price impact is greater when they buy than when they sell; otherwise this strategy will be self-defeating (Friedman, 1953). Trade-based manipulation can be profitable if there is price momentum (Jarrow, 1992) or uninformed investors believe that it is likely that the manipulator is informed (Allen and Gale, 1992).

In Figure 7, we report the results pertaining to price impact. We estimate this impact for every minute instead of every ten seconds because estimating price impacts requires more data. Specifically, price impact λ_t is estimated based on the following equation,

$$\Delta p_{i,t} = \alpha_t + \lambda_t q_{i,t} + \epsilon_{i,t} \tag{1}$$

where $q_{i,t}$ and $\Delta p_{i,t}$ are order flow and return over interval t for token i, respectively. Order flow is defined as the volume of buy orders minus the volume of sell orders in Bitcoin units. $\epsilon_{i,t}$ is the error term. λ_t is our measure of price impacts. This method is similar to those adopted in Glosten and Harris (1988), Brennan and Subrahmanyam (1996), and more recently by Makarov and Schoar

(2019).[13]

[Insert Figure 7 here.]

The results show that the price impact immediately after a P&D starts is weaker than that immediately before and is similar to that in later intervals. The abnormally high price impact immediately before a P&D is consistent with insiders' purchase causing the price run-ups we report in Figure 4, Panel A. The weaker price impact after a P&D starts is consistent with the fact that the P&D announcement leads to increased participation of uninformed speculative traders. Their purchases likely cause the large price increase. Our results suggest that outside investors crowd into the market and effectively "coordinate" to create short-term price bubbles, followed by quick reversals. This contrasts with the existing trade-based manipulation theories which typically assume that the manipulators need to buy to increase the asset price.

These results do not, however, explain why outsiders are willing to participate. Since information on investor identification is not available, we cannot pin down the exact mechanism. We conjecture that one plausible mechanism is that P&Ds attract overconfident investors who believe that they can time the market better than others can (Daniel, Hirshleifer, and Subrahmanyam, 1998; Scheinkman and Xiong, 2003; Daniel and Hirshleifer, 2015). As we show in Table 2, buyers in the first 20 seconds can potentially make money, and there are significant variations in average returns across P&Ds even if one buys tokens later. Overconfidence has been found to be useful in explaining many phenomena in the stock market (Barber and Odean, 2000, 2001; Gervais and Odean, 2001; Daniel and Hirshleifer, 2015). Barber and Odean (2001) find that on average men are more overconfident than women. Survey evidence shows cryptocurrency traders are predominantly men (Leinz, 2018). It is likely that cryptocurrency investors may also be overconfident.

Another possible mechanism encouraging outsiders to participate is that these investors have gambling preferences. The short-term return on pumped tokens is very high and salient. Investors may overweight these returns in their decision-making or overestimate the skewness of the tokens, consistent with salient thinking or prospect theory (Barberis and Huang, 2008; Bordalo, Gennaioli,

[13] Using a similar model, Makarov and Schoar (2019) study the relationship between Bitcoin order flow and prices. They consider the fact that Bitcoin is listed on many exchanges. We consider only the order flow from the target exchange in light of our finding that spillover to other exchanges is small.

and Shleifer, 2012, 2013; Wang, 2018). Evidence of gambling preferences on the part of stock market investors abounds (Kumar, 2009; Barberis, Mukherjee, and Wang, 2016).

5 The Bittrex Ban

In this section, we examine the economic consequences of P&Ds. We find that P&Ds lead to short-term cryptocurrency bubbles featuring dramatic increases in prices, volume, and volatility, which suggests that P&Ds lower the informativeness of cryptocurrency prices. Evidence suggests that exposures to scandals lower investor trust, and reduce stock market participation and the use of financial intermediation services (Giannetti and Wang, 2016; Gurun, Stoffman, and Yonker, 2018). Do P&Ds play a similar role by lowering investors' willingness to invest in the cryptocurrency market? We study this question using a quasi-experiment.

5.1 The background

On November 24, 2017, Bittrex, then the world's third-largest cryptocurrency exchange by volume, 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 tokens trading on its platform. 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." Bittrex's ban followed an investigation by Business Insider ten days earlier that found traders were colluding in groups on Telegram to inflate the price of cryptocurrencies on platforms such as Bittrex and Yobit (Williams-Grut, 2017).

Messages about pump groups on Telegram show that traders involved in P&D tactics had taken notice of the warning. Many scheduled P&D events were immediately canceled. For example, one prominent pump channel, "Trading signals for crypto," canceled its P&D event on November 26, 2017 (see Figure 8, Panel A). Some message groups solicited feedback from group members regarding whether to switch to other exchanges. Many message groups eventually ceased to pump tokens traded on Bittrex and/or switched to alternative exchanges such as Yobit.

[Insert Figure 8 here.]

In Figure 8, Panel B we plot the number of P&Ds on Bittrex and the other two exchanges over the period running from five months before to eight months after the ban. This period spans our sample period. Although the ban was not able to eliminate P&Ds altogether, it is evident that there was a sharp decrease in the frequency of P&Ds on Bittrex. Before the ban, the monthly average number of P&Ds targeting Bittrex in our sample is 44. We have 225 tokens listed on Bittrex with trading data, implying a significant hazard of being targeted before the ban. This suggests that Bittrex was able to adhere to its announced policy and worked to reduce the occurrence of P&Ds on its exchange.

5.2 Consequences of the ban

We adopt a difference-in-differences approach to examine the effects of the Bittrex ban on the prices and trading volumes of tokens. All tokens listed on Bittrex comprise the treatment group, and other tokens comprise the control group. We conduct our analysis based on CoinMarketCap data. We use CoinMarketCap data rather than exchange data because the tokens on the other two exchanges differ in important ways from Bittrex tokens (see Table 1).

To control for differences between Bittrex tokens and others, we conduct a matched-sample exercise. Specifically, we match each token listed on Bittrex at the time of the ban with a token that is not listed on Bittrex. We match them based on the average trading volume (in Bitcoin) in the period running from 60 days to 31 days before the ban. We use the non-Bittrex token with the closest trading volume as the matched token. The matching is performed with replacement. We further require that the log difference in volume between a Bittrex token and the matched token not be greater than 20%.

In Figure 9, we present the average trading volumes and prices over the period running from 14 days before the ban to 30 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 60 days to 31 days before the ban. Price is calculated as the log price change from the price 30 days before the ban to the end of a given day. We conduct these transformations to mitigate the effects of cross-token heterogeneity in volume and price. Tokens with no volume in the period running from 60 days to 31 days before the ban are excluded. Our final sample includes 190 treatment tokens and 190 matched tokens. Figure 9 shows that in this period there was a sharp increase in both volume and price for both the treatment and control groups, suggesting a booming market. The results presented in Figure 9 make it evident that both the volumes and prices of the Bittrex tokens increased relative to those of the controls. The increases started almost exactly on the event day. In the pre-ban period, although the treatment and control groups do not move perfectly in tandem, their volumes and prices fluctuate mostly in the same direction, suggesting that the control group represents a reasonable counterfactual.[14]

[Insert Figure 9 here.]

We conduct formal difference-in-differences tests and report the results in Table 6. Specifically, we estimate model (2) below:

$$DV_{i,t} = \alpha + \beta_1 Bittrex_i + \beta_2 Post_t + \beta_3 Bittrex_i * Post_t + \epsilon_{i,t} \tag{2}$$

where DV is either volume or price, $Bittrex$ is a dummy equal to 1 for Bittrex tokens and 0 for control tokens, and $Post$ is a dummy equal to 1 if it is after November 24, 2017 and 0 otherwise. β_3 is the difference-in-differences estimator. Instead of running a pooled regression with observations at the token-day level, we aggregate all the data and produce two observations for each token, one for the pre-ban period and one for the post-ban period (Bertrand, Duflo, and Mullainathan, 2004). Specifically, for trading volume we calculate the average for the pre-ban and post-ban periods for each token. For price, we use the price at the beginning of the pre-ban period and the price at the end of the post-ban period.

[Insert Table 6 here.]

[14] As we discussed, the ban caused some pump groups to switch from Bittrex to other exchanges. Therefore, the ban reduced the frequency of P&Ds on Bittrex, and at the same time, it increased the frequency of P&Ds on other exchanges. The difference-in-differences estimate reflects both the effect of reduced frequency of P&Ds on Bittrex and the increased frequency of our controls. However, we think this "spillover" effect is likely weak, because the majority of control tokens in our sample are not listed on the exchanges that the pump groups switch to.

Our results are robust to variations in the lengths of the pre- and post-ban periods. To obtain the results we report in Figure 9, we define the pre-ban period as running from day -14 to day -1, and the post-ban period as running from day 1 to day 30. We exclude day 0 as it is ambiguous whether to include it in one or the other period. In Figure 9, we report the results of examining two specifications, one with token fixed effects and another without such effects. In the specification with token fixed effects, *Bittrex* is subsumed. We cluster the standard errors by treatment-control pair. The results show that in both the volume and price regressions the coefficient on the interaction term is both economically and statistically significant. The estimates suggest that the Bittrex ban increased the prices and volumes of its tokens by 40.1% and 63.9%, respectively.

Overall, the results we report in Figure 9 and Table 6 provide casual evidence that P&Ds are detrimental to the health of the cryptocurrency market. Kyle and Viswanathan (2008) propose two necessary conditions to classify a scheme as "illegal price manipulation:" (1) the scheme makes prices less accurate as signals for efficient resource allocation, and (2) it makes markets less liquid for risk transfer. Our results suggest that cryptocurrency P&Ds satisfy both conditions and should be considered illegal.

6 Conclusion

This paper studies pump-and-dump schemes (P&Ds) in the cryptocurrency market. We find that most P&Ds lead to short-term bubbles where prices, volume, and volatility increase dramatically, followed by a quick reversal. We also find evidence of significant wealth transfers from potential outsiders who do not know the identities of pumped tokens in advance to insiders. The quick reversals imply that it is difficult for any outsiders except the fastest movers to make profits. Standard trade-based price manipulation theories assume that manipulators need to buy to pump the asset price. In contrast to this, we find that pumps are mainly driven by uninformed speculative traders.

Our findings make it puzzling why these outsiders are willing to participate in P&Ds. We conjecture that one plausible mechanism is that P&Ds attract overconfident investors who believe that they can time the market more accurately than others can (Scheinkman and Xiong, 2003;

Daniel and Hirshleifer, 2015). Another possible mechanism is that these investors are affected by the salience of short-term extreme returns, and overweight the possibility that they will realize similar returns in their decision-making or overestimate the skewness of token returns (Barberis and Huang, 2008; Barberis, 2013; Bordalo, Gennaioli, and Shleifer, 2012, 2013).

We also conduct a difference-in-differences test of the Bittrex ban of P&Ds on its exchange to shed light on the equilibrium effects of P&Ds. Using tokens on Bittrex as the treatment group and a matched sample of tokens as the control group, we find strong evidence that P&Ds are detrimental to the health of the cryptocurrency market. Specifically, banning P&Ds increased the prices and volumes of tokens listed on Bittrex to a greater extent than those of other tokens.

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Table 1. Summary Statistics

In Panel A we report characteristics of P&D events between May 15, 2017 and August 26, 2018. *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. *Total number of viewers* is the sum of viewers across all channels in a P&D event. *Target return* is the pre-specified return before a P&D announcement. *Regular scheduled time* is a dummy variable equal to 1 if a channel's P&D announcement is scheduled at the regular pump time and 0 otherwise. A channel's regular pump time is the time most frequently used by its operator. Panel B displays the characteristics of pumped tokens on Binance, Bittrex and Yobit, and compares them with non-target tokens listed on the three exchanges. For each token characteristic, on each day with at least one pump we calculate the average value for target and non-target tokens. We then compute the time-series average. The characteristics we report are log market capitalization (U.S. dollar), log trading volume (Bitcoin), volatility, the frequency at which a token is covered by CoinMarketCap.com, token 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. *Token age* is the number of years since the cryptocurrency was first listed. *Social media index* is the logarithm of social media activity points computed by CryptoCompare.com. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Pump-and-dump events

	All (N=500)		Binance (N=76)		Bittrex (N=263)		Yobit (N=161)	
Event-level	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
Average delay time (seconds)	24.5	5.2	31.2	8	14.3	4.5	38.0	5.5
Average number of channels	1.58	1	1.42	1	1.08	1	2.45	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
Average number of viewers per channel	4,295.6	1,633	13,915.1	2,973	3,649.7	2,373	787.8	523.5

	All (N=788)		Binance (N=108)		Bittrex (N=285)		Yobit (N=395)	
Channel-level	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Target return	211.5%	200%	69.0%	51.2%	246.9%	100%	233.0%	200%
Regular scheduled time	89.5%	100%	86.1%	100%	84.2%	100%	94.2%	100%

Panel B. Characteristics of tokens

	Target tokens	Non-target tokens	Difference	*t*-stat. of Diff.	Percentile
ln(Market capitalization (dollar))	16.078	16.375	-0.219*	-1.72	49.63
ln(Volume (Bitcoin))	4.538	3.345	1.193***	5.96	58.00
Volatility	12.830%	14.072%	-1.242%***	-3.13	45.29
Covered by CoinMarketCap	0.590	0.524	0.066***	3.10	56.11
Token age (in years)	1.667	0.950	0.717***	11.53	60.47
Social media index	8.102	7.518	0.585***	3.62	59.56
Average number of tokens per day	2.02	684.0			

Table 2. Trade Performance by Purchase Time

In this table we report the "achievable" returns for each purchase time–delay combination. All the returns are calculated before taking into account exchange commissions. We consider 12 10-second intervals after the 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. Each row displays the results by delay time. Time 0 indicates sales immediately after the 10-second interval after purchase. For a combination of purchase time–delay, we assume that an investor buys tokens 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. In Panels A–D we report the mean returns, *t*-values of the average returns, and the average and median times to unwind the purchase, respectively. The average returns that are significantly positive at 5% are highlighted in bold.

Panel A. Average returns (%)

	Purchase time, in seconds												
Delay time	Before P&D	10	20	30	40	50	60	70	80	90	100	110	120
0	**13.926**	**5.619**	**1.309**	-0.063	-0.921	-1.272	-1.184	-1.051	-1.589	-0.015	-1.375	-0.703	0.048
10	**18.387**	**6.505**	**1.594**	-0.579	-1.516	-1.849	-1.050	-2.005	-1.959	-0.708	-1.890	-0.557	-0.186
20	**18.395**	**6.534**	1.180	-0.995	-1.494	-2.683	-2.143	-2.180	-2.736	-1.066	-1.606	-0.863	-0.917
30	**18.436**	**5.405**	0.709	-1.408	-1.837	-3.638	-2.541	-2.936	-3.030	-1.021	-1.969	-1.525	-1.411
40	**17.806**	**4.659**	0.200	-2.008	-2.643	-3.719	-2.347	-3.449	-2.931	-1.558	-2.702	-2.100	-1.783
50	**16.989**	**4.195**	-0.717	-2.931	-2.903	-4.267	-2.741	-3.339	-3.509	-2.128	-3.129	-2.346	-2.430
60	**15.883**	**4.222**	-1.258	-2.775	-3.383	-4.680	-2.704	-4.028	-3.979	-2.324	-3.437	-2.824	-2.884
70	**14.964**	**3.538**	-1.368	-3.105	-3.658	-4.751	-3.266	-4.361	-4.437	-3.267	-4.111	-3.540	-3.804
80	**13.894**	**3.516**	-1.698	-3.378	-3.683	-5.253	-3.723	-5.003	-4.598	-3.790	-4.863	-4.133	-4.035
90	**12.626**	2.876	-2.119	-3.603	-4.318	-5.786	-4.651	-5.732	-5.042	-4.470	-5.255	-4.498	-4.553
100	**11.534**	2.268	-2.453	-4.099	-4.910	-6.505	-5.824	-6.222	-5.864	-4.743	-5.530	-4.932	-4.714
110	**11.087**	1.963	-3.136	-4.612	-5.535	-5.999	-6.351	-6.941	-6.211	-4.981	-6.091	-5.108	-4.778
120	**11.077**	1.320	-3.352	-5.178	-6.388	-6.467	-7.082	-7.181	-6.437	-4.893	-6.204	-5.307	-5.346
130	**10.596**	0.887	-4.130	-6.146	-5.951	-6.838	-7.229	-6.706	-6.898	-4.711	-6.466	-5.743	-5.383
140	**10.045**	0.403	-3.511	-6.416	-6.648	-6.727	-7.471	-6.726	-6.028	-5.153	-6.304	-5.899	-5.682
150	**9.974**	-0.745	-3.935	-6.974	-7.024	-6.613	-8.021	-6.689	-6.399	-5.710	-6.588	-5.644	-5.621
160	**9.368**	-1.216	-4.492	-7.394	-7.251	-6.802	-7.930	-6.912	-6.547	-5.994	-7.055	-5.558	-5.988
170	**8.724**	-1.221	-4.363	-7.542	-7.580	-6.963	-8.238	-7.496	-7.008	-5.892	-7.023	-6.076	-6.181
180	**8.213**	-1.290	-4.615	-7.653	-7.747	-7.105	-8.753	-7.910	-7.458	-5.817	-7.463	-6.429	-6.584

Panel B. *t*-values

	Purchase time, in seconds												
Delay time	Before P&D	10	20	30	40	50	60	70	80	90	100	110	120
0	8.10	7.57	2.77	-0.11	-2.13	-2.75	-3.13	-1.72	-3.72	-0.02	-3.06	-1.39	0.11
10	8.77	7.02	2.42	-1.01	-2.71	-3.63	-0.96	-2.98	-3.58	-0.84	-3.79	-1.05	-0.36
20	8.48	6.48	1.57	-1.46	-2.26	-4.32	-1.87	-3.00	-4.43	-1.22	-2.99	-1.60	-1.70
30	8.37	5.45	0.90	-1.91	-2.04	-5.22	-2.09	-3.68	-4.52	-1.16	-3.41	-3.14	-2.57
40	8.19	4.50	0.24	-2.34	-2.76	-4.80	-1.55	-4.03	-4.13	-1.77	-4.45	-4.02	-3.22
50	7.93	3.88	-0.79	-3.23	-2.92	-5.09	-1.81	-3.92	-4.95	-2.45	-4.99	-4.45	-4.15
60	7.65	3.00	-1.30	-2.55	-3.27	-5.16	-1.80	-4.59	-5.40	-2.63	-5.37	-4.99	-4.40
70	7.16	2.43	-1.35	-2.71	-3.47	-5.08	-2.19	-4.87	-6.05	-5.22	-6.11	-5.53	-6.05
80	6.62	2.22	-1.54	-2.83	-3.51	-5.73	-2.51	-6.31	-6.18	-5.54	-6.66	-6.47	-6.11
90	6.52	1.79	-1.86	-2.99	-4.08	-6.12	-4.28	-7.59	-6.77	-6.13	-7.20	-6.82	-6.74
100	6.08	1.42	-2.13	-3.42	-4.52	-7.36	-6.64	-8.12	-7.35	-6.40	-7.36	-7.32	-6.77
110	5.80	1.24	-2.70	-3.77	-5.76	-4.64	-7.28	-8.55	-7.87	-6.58	-7.91	-7.46	-6.90
120	5.64	0.83	-2.87	-4.27	-6.71	-4.98	-8.17	-8.81	-8.04	-5.34	-7.91	-7.75	-7.70
130	5.33	0.55	-3.73	-5.86	-5.98	-5.23	-8.35	-7.90	-8.49	-4.83	-8.04	-8.15	-7.86
140	5.00	0.29	-2.35	-6.10	-6.54	-5.11	-8.76	-7.69	-6.79	-5.49	-7.58	-8.27	-8.48
150	5.03	-0.58	-2.63	-6.49	-6.95	-4.95	-9.26	-7.85	-7.30	-6.06	-8.11	-7.91	-8.18
160	4.76	-0.94	-2.97	-7.04	-7.05	-4.89	-8.79	-8.14	-7.49	-6.17	-8.73	-7.55	-8.31
170	4.56	-0.94	-2.86	-7.09	-7.42	-5.01	-9.12	-8.79	-8.11	-5.46	-8.63	-7.79	-8.57
180	4.28	-1.01	-3.05	-7.13	-7.64	-5.12	-9.74	-9.35	-8.85	-5.28	-8.94	-5.25	-8.94

Panel C. Average time taken to unwind the purchase

	Purchase time, in seconds												
Delay time	Before P&D	10	20	30	40	50	60	70	80	90	100	110	120
0	20.97	4.64	3.57	2.33	3.60	5.57	2.30	2.41	3.47	5.05	2.57	2.19	2.12
10	22.15	7.32	4.70	3.21	4.25	7.56	2.93	3.01	4.23	5.90	2.86	2.51	2.25
20	24.05	9.27	5.71	3.91	4.87	8.03	4.84	3.43	4.84	7.84	3.12	2.96	2.43
30	26.26	12.52	6.63	4.61	5.92	8.49	7.61	4.01	6.56	7.93	3.96	3.26	3.16
40	29.84	15.01	12.71	8.00	6.56	8.84	8.39	4.28	6.69	8.52	4.70	3.87	3.69
50	32.05	19.84	13.94	8.50	8.00	9.49	8.63	4.95	7.39	8.88	5.44	4.06	4.61
60	36.35	22.76	15.03	9.41	9.40	9.81	8.88	7.02	7.60	9.21	5.76	4.34	6.82
70	39.59	25.71	17.18	10.66	9.60	10.06	9.51	7.15	8.08	9.39	7.46	6.15	7.83
80	42.67	33.25	18.56	11.11	10.06	11.00	9.85	7.42	8.25	9.77	7.68	6.34	8.75
90	47.81	36.50	19.76	11.76	10.54	11.33	10.44	7.76	8.62	10.09	7.78	6.86	9.06
100	49.38	39.04	22.28	12.63	11.09	12.21	10.52	8.67	10.77	11.26	7.77	7.50	9.08
110	50.71	41.64	27.67	13.10	11.85	12.56	11.48	9.06	11.02	11.45	8.42	8.17	9.09
120	53.35	43.16	29.17	13.82	12.04	12.85	12.03	9.26	11.25	11.85	8.37	8.38	9.18
130	56.41	44.95	29.93	14.90	15.25	13.42	12.28	9.59	11.90	12.08	8.43	8.47	9.44
140	59.21	47.39	30.58	15.80	16.20	13.56	12.62	10.18	11.88	12.08	8.49	8.79	9.53
150	62.35	49.85	32.53	16.47	16.57	14.46	13.16	10.19	11.95	12.27	8.86	8.94	9.52
160	63.96	51.11	35.06	16.93	17.61	14.98	13.40	10.20	12.42	12.69	8.95	11.28	11.27
170	66.60	54.24	36.86	19.41	18.21	15.11	13.47	11.01	12.57	13.22	9.35	12.25	12.11
180	73.31	55.32	37.97	21.43	18.85	15.26	13.93	11.39	12.93	13.64	10.84	12.54	12.12

Panel D. Median time taken to unwind the purchase

	Purchase time, in seconds												
Delay time	Before P&D	10	20	30	40	50	60	70	80	90	100	110	120
0	2	1	1	1	1	1	1	1	1	1	1	1	1
10	2	1	1	1	1	1	1	1	1	1	1	1	1
20	2	2	1	1	1	1	1	1	1	1	1	1	1
30	3	2	2	1	1	1	1	1	1	1	1	1	1
40	3	2	2	2	2	2	2	1	2	1	1	1	1
50	4	3	2	2	2	2	2	2	2	1	2	1	1
60	5	4	3	3	2	2	2	2	2	2	2	2	1
70	6	4	3	3	3	2	2	2	2	2	2	2	2
80	6	5	4	3	3	3	2	2	2	2	2	2	2
90	7	5	4	4	3	3	3	2	2	2	2	2	2
100	8	5	4.5	4	4	3	3	3	3	2	2	2	2
110	8	6	5	4	4	4	3	3	3	2	3	2	2
120	9	7	6	5	4	4	3	3	3	3	3	2	2
130	10	7	6	5	4	4	4	3.5	3	3	3	2	2
140	11	8	6	5	5	4	4	4	3	3	3	3	2
150	12	8	6.5	6	5	4	4	4	3	3	3	2	2
160	13	9	7	6	5	5	4	4	3	3	3	2	2
170	14	10	7	6	6	5	4	4	4	3	3	3	3
180	14.5	10	7	7	7	5	5	4	4	3	3	3	3

Table 3. Persistent Advantages for Certain Telegram Channels

In this table we indicate the persistent advantages certain Telegram channels enjoy. The analysis is carried out at the channel level. In both panels, the reported results are based on analyses using two samples: one with all the P&D channels targeting Binance, Bittrex and Yobit, and the other with 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 and median delays for each top-ten Telegram channel based on P&D events initiated. *Early* is a dummy variable equal to 1 if the announcement time is before the scheduled time and 0 otherwise. *% Early* is the fraction of P&Ds in which the announcement occurs before the scheduled time. In Panel B we report the results of our regression analysis, in which the dependent variable is either delay time or the *Early* dummy, and the independent variable is lagged delay time or lagged *Early* dummy. 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 announcement (seconds)

	All P&D channels				P&D channels with trading data			
Pump group name	N	Average	Median	% Early	N	Average	Median	% Early
Alt the Way	303	9.79	7	12.5%	62	16.21	14	4.8%
Crypto Mega Pumps Yobit	244	6.90	5	25.0%	44	13.70	9	15.9%
The Pumpers	220	7.33	4	21.8%	37	15.43	16	8.1%
Superb Pumps	180	7.05	6	20.6%	40	11.05	12	25.0%
YoBit Pumpers	159	4.45	1	39.0%	31	14.74	30	22.6%
Bittrex Signals	148	5.83	2	38.5%	25	16.56	19	16.0%
World Pumps	130	6.65	3	16.9%	7	1.86	3	14.3%
Crypto VIP Signals	116	4.99	1	38.8%	23	14.61	25	21.7%
Premium Yobit Pump	107	11.29	9	11.2%	53	10.13	6	7.5%
PumpZone	89	0.73	0	13.5%	27	0.96	1	0.0%
Other channels	788	7.15	4	27.9%	439	6.38	4	25.1%

Panel B. Persistent advantages

	All P&D channels				P&Ds with trading data available			
Dependent variable	Delay time		Early dummy		Delay time		Early dummy	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Lagged delay time	0.293***	0.152***			0.341***	0.109***		
	(15.17)	(8.62)			(9.85)	(2.99)		
Lagged Early dummy			0.302***	0.301***			0.290***	0.348***
			(15.64)	(13.46)			(8.24)	(7.09)
Constant	4.962***		0.171***		6.052***		0.136***	
	(16.62)		(17.82)		(9.74)		(8.86)	
P&D fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2,433	1,901	2,433	1,901	746	377	746	377
Adj. R-squared	0.09	0.87	0.09	0.59	0.11	0.87	0.08	0.52

Table 4. Maximum Returns and Target Returns

In this table we report results pertaining to an analysis of factors that predict P&D returns at the event level. The dependent variable for column (1) is the ratio of the highest price achieved within 10 minutes after the pump announcement and the price at the announcement minus 1. The dependent variable for column (2) is the minimum target return among participating groups. The dependent variable for columns (3) is an indicator equal to 1 if the maximum return is greater or equal to the minimum target return among participating groups and 0 otherwise. *Pre-pump liquidity* is the logarithm of trading volume (in Bitcoin) over the period running from 37 to eight days before a pump. *Price run-up* is the token return over the period between 10 minutes before a P&D announcement and the announcement. *Multiple Telegram channels* is an indicator equal to 1 if multiple channels participate in the same event and 0 otherwise. *Delay in announcement* is the difference between an announcement and the scheduled time (winsorized at ±30 seconds). All other control variables are as defined in Table 1. 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.

	Ordinary least squares						Linear probability model		
Dependent variable	Maximum return			Minimum target return among channels			Dummy for achieving minimum target return		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)
Pre-pump liquidity	-0.114***	-0.123***	-0.107***	-0.073***	-0.073***	-0.061*	-0.025**	-0.016	-0.009
	(-7.04)	(-7.19)	(-5.61)	(-2.85)	(-2.61)	(-1.86)	(-2.27)	(-1.54)	(-0.58)
Price run-up		-0.903***	-0.767***		0.023	-0.584		0.497***	0.460**
		(-4.24)	(-3.95)		(0.05)	(-1.16)		(2.66)	(2.02)
Multiple Telegram channels			0.824***			1.038**			0.159
			(5.00)			(2.31)			(1.14)
Token age			-0.062**			-0.130			0.076***
			(-2.17)			(-1.53)			(3.09)
Social media index			0.076*			-0.018			-0.015
			(1.69)			(-0.17)			(-0.30)
Delay in announcement			0.003			0.018***			0.003
			(1.06)			(2.58)			(0.78)
Constant	1.041***	1.158***	0.358	2.370***	2.367***	1.703*	0.336***	0.269***	0.140
	(9.76)	(9.46)	(1.16)	(20.99)	(19.52)	(1.82)	(35.96)	(9.65)	(0.35)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	500	500	500	229	229	229	229	229	229
Adj. R-squared	0.19	0.22	0.30	0.45	0.45	0.47	0.23	0.27	0.31
% (Dep variable = 1)							31.4%	31.4%	31.4%

Table 5. Viewership

In this table we report results pertaining to factors that predict changes in the number of Telegram viewers at the channel level. *Average recent pump return* is average maximum returns after a channel's three most recent P&D announcements. *Average recent abnormal volume* is the average abnormal volume in the three most recent P&Ds, in which abnormal volume equals log(1 + volume over a [-10 minutes, +10 minutes]/average volume in the interval running from day -37 to day -8). All other control variables are as defined in Table 4. In each column, we report coefficient estimates and their *t*-statistics. Standard errors are clustered at the channel and month levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	ΔLog (No. of channel viewers)				
	(1)	(2)	(3)	(4)	(5)
Average recent pump return	-0.010	-0.009	-0.009	-0.009	-0.010
	(-1.05)	(-0.92)	(-0.84)	(-0.84)	(-1.04)
Average recent abnormal volume		0.011	0.011	0.011	0.013
		(0.98)	(1.00)	(1.00)	(1.11)
Pre-pump liquidity			0.002	0.002	-0.004
			(0.29)	(0.29)	(-0.32)
Price run-up				0.007	-0.012
				(0.09)	(-0.15)
Multiple Telegram channels					-0.071**
					(-2.46)
Token age					0.012
					(0.75)
Social media index					0.009
					(0.60)
Delay in announcement					0.002
					(1.36)
Constant	0.108	0.105	0.101	0.105	0.035
	(0.80)	(0.80)	(0.74)	(0.76)	(0.20)
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Channel fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	720	720	720	720	720
Adj. R-squared	0.05	0.06	0.06	0.06	0.07

Table 6. The Bittrex Ban

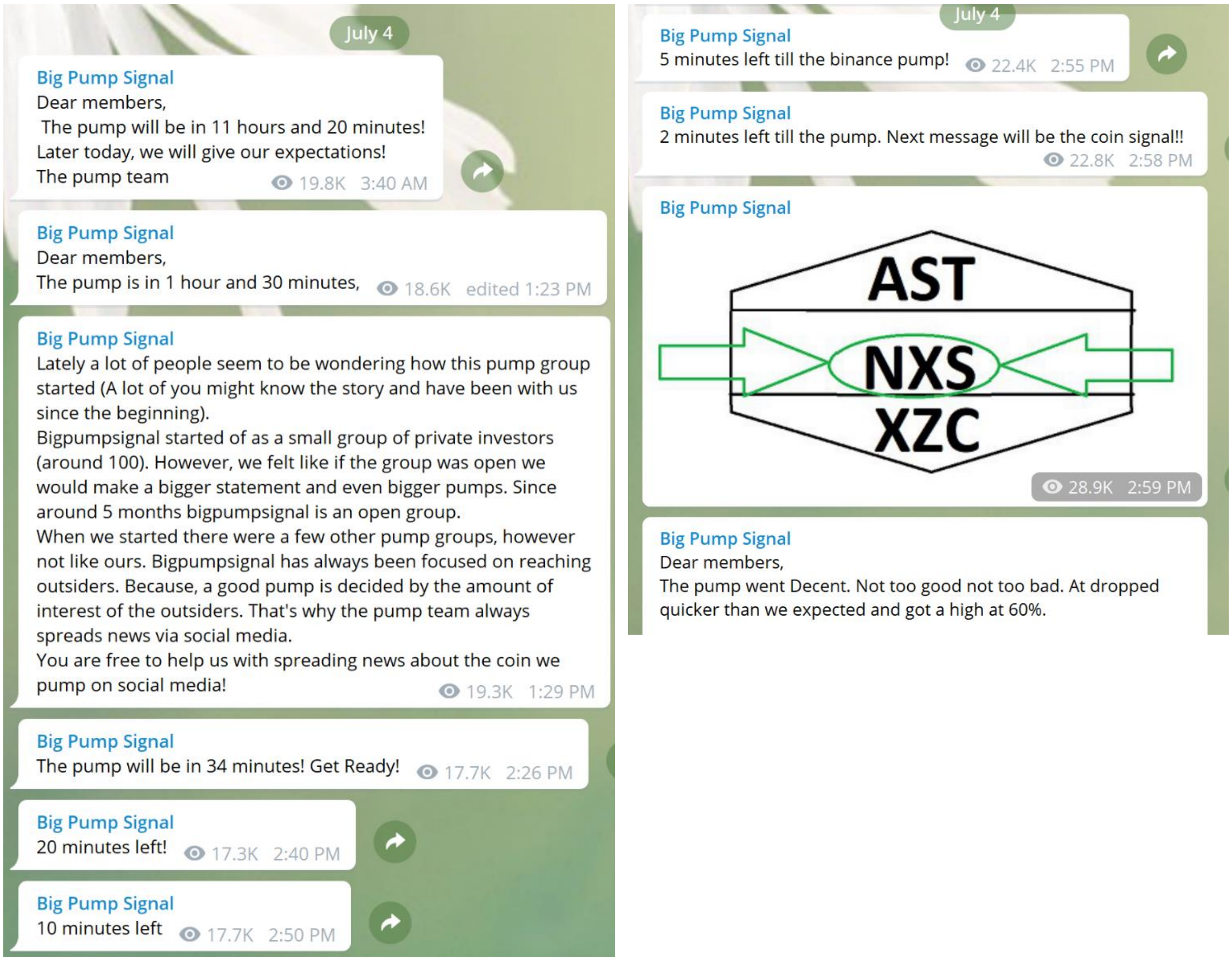
In this table we report the results of a difference-in-differences estimation of the Bittrex ban. The treatment group comprises tokens listed on Bittrex on November 24, 2017, and the control group includes matched tokens not listed on Bittrex at that time. We use the non-Bittrex token with the closest trading volume (in Bitcoin) as the matched token. Matching is based on the trading volume over the period running from 60 days to 31 days before the ban. In the regression, each token has two observations: one for the pre-ban period and one for the post-ban period. For volume, we take the average volume over the period running from day -14 to day -1 for the pre-ban period, and from day 1 to day 30 for the post-ban period. The pre-ban period price is measured at day -14, and the post-ban period price is measured at day 30. Volume is the natural logarithm of the ratio between volume on day *t* and the average volume over the period running from 60 days to 31 days before the ban. Price is defined as the natural logarithm of the ratio of the end-of-day price to the price at the end of day -31. All standard errors are clustered at the treatment–control pair level.

Dependent variable	Volume		Price	
	(1)	(2)	(3)	(4)
Bittrex × Post	0.639***	0.639***	0.401***	0.401***
	(5.25)	(5.26)	(3.88)	(3.89)
Post	0.880***	0.880***	0.734***	0.734***
	(8.34)	(8.35)	(7.65)	(7.66)
Bittrex	-0.311**		-0.033	
	(-2.15)		(-0.49)	
Constant	0.096		0.033	
	(0.93)		(0.69)	
Token Fixed Effects	No	Yes	No	Yes
Observations	754	754	750	750
Adj. R-squared	0.14	0.78	0.23	0.60

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

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

Panel A: Telegram pump announcements on Nexus



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

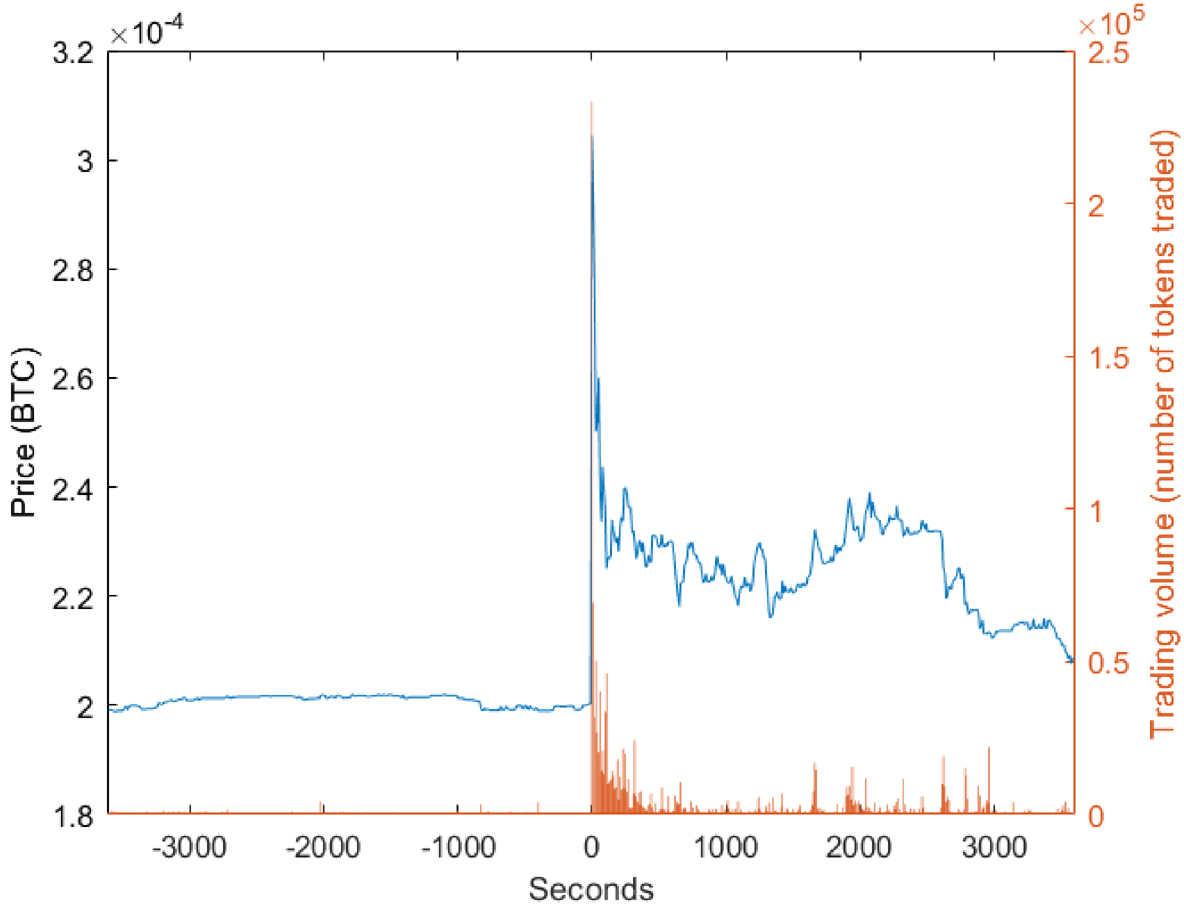
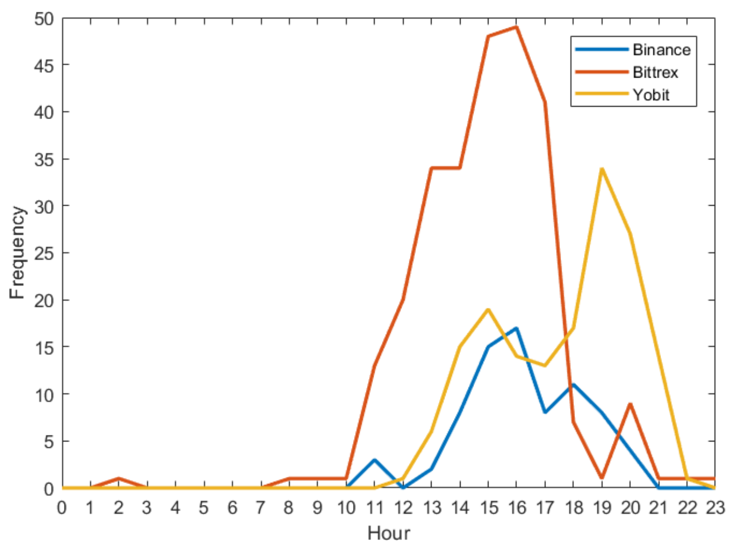


Figure 2: Distribution of Pump and Dumps and Trading Volume by Hour

In Panel A we present the distribution of P&D events by scheduled hour and exchange. Panel B displays the fraction of trading volume by hour and exchange. For each exchange, we first calculate the fraction of the trading volume (in Bitcoin) occurring in each hourly interval, and then compute the average volume across all dates running from May 15, 2017 to August 26, 2018. The X-axis represents the hour, where 0 indicates the interval between 00:00:00 and 00:59:59 (Coordinated Universal Time or UTC). Other hourly intervals are similarly defined.

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



Panel B. Distribution of trading volume by hour and exchange

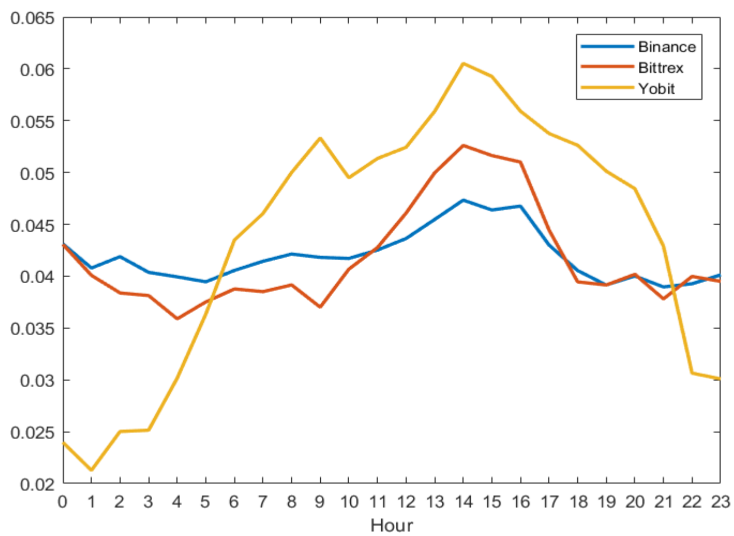
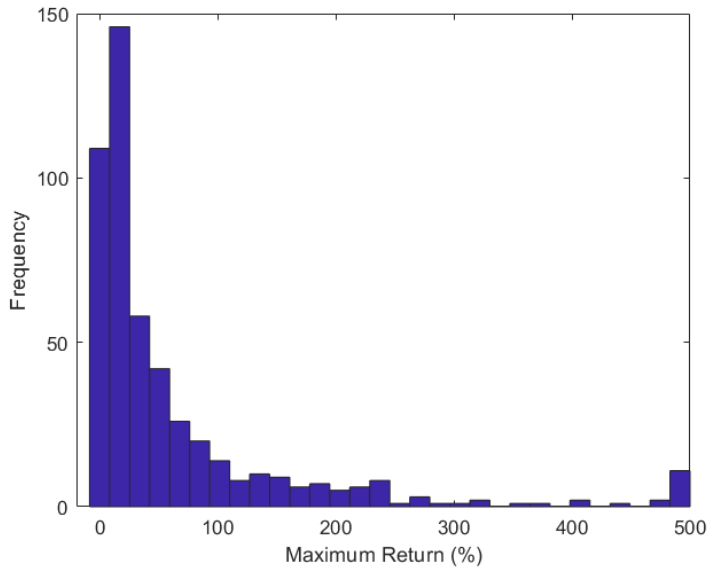


Figure 3: Distribution of Maximum Returns and Time to Maximum Returns

Panel A displays the distribution of P&D maximum returns, while Panel B plots the distribution of the number of seconds it takes to reach a maximum return for our sample of 500 P&Ds. A P&D's maximum return is defined as the ratio of the highest price achieved within 10 minutes after the pump announcement and the price ten minutes before the announcement minus 1. The time to a maximum return is defined as the number of seconds it takes from the announcement to reach the maximum return. For ease of illustration, maximum returns are capped at 500% in Panel A.

Panel A. Distribution of P&D maximum returns



Panel B. Distribution of time to maximum returns

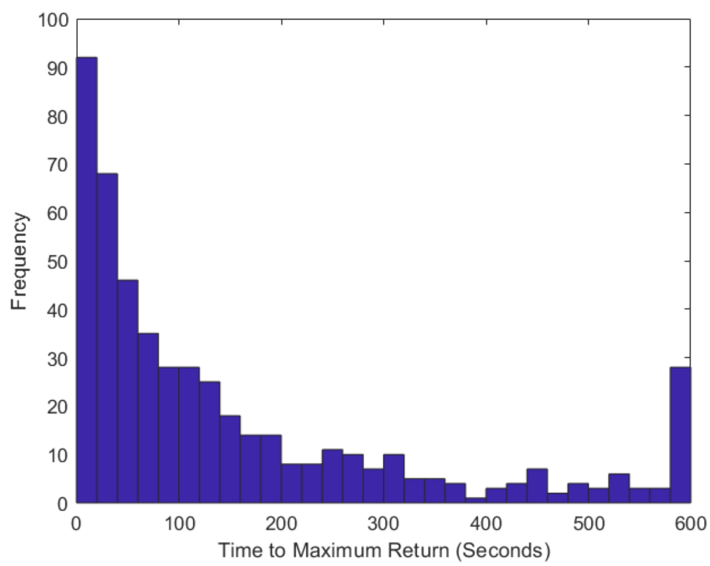
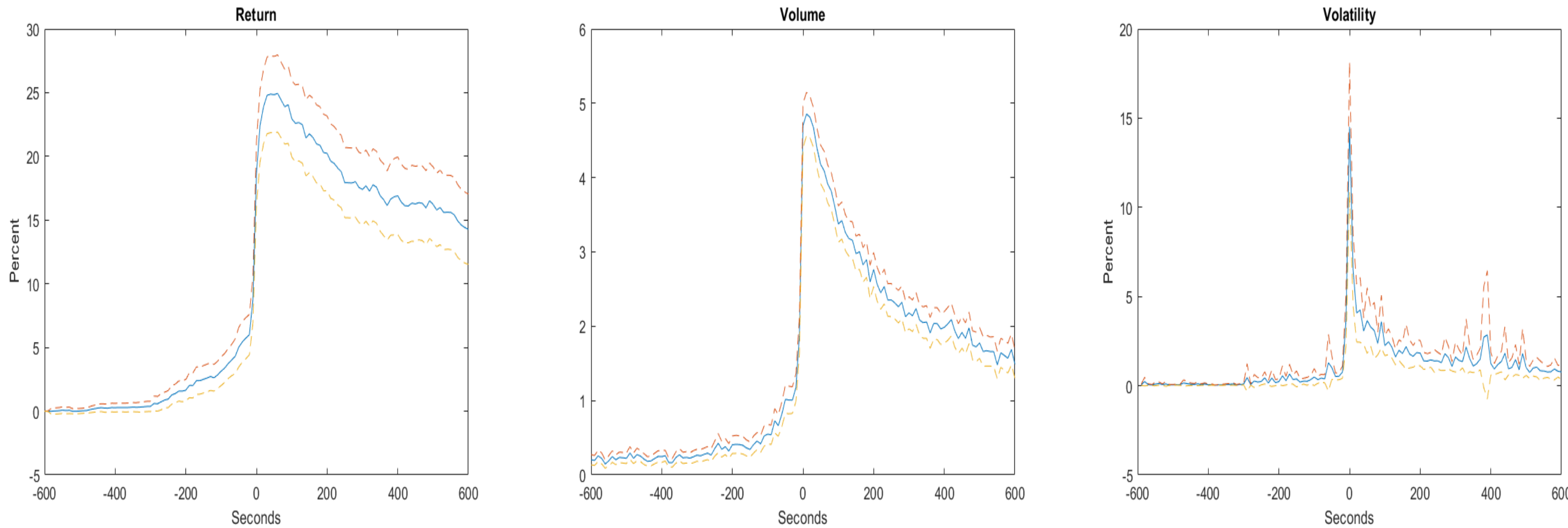


Figure 4: Return, Volume and Volatility Around Pump and Dumps

This figure displays cumulative returns, abnormal volume, and the volatility of pumped tokens. Panel A reports the pattern for 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. Panel B shows the analysis for each one-hour interval from 7 days before to 7 days after P&D announcements. The X-axis indicates time. The solid lines represent the averages across all target tokens, 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 in Panel A and from seven days before an announcement in Panel B. 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 tokens traded. Volatility is measured as the absolute value of the return during each 10-second interval in Panel A and each one-hour interval in Panel B.

Panel A. Short-term analysis



Panel B. Long-term analysis

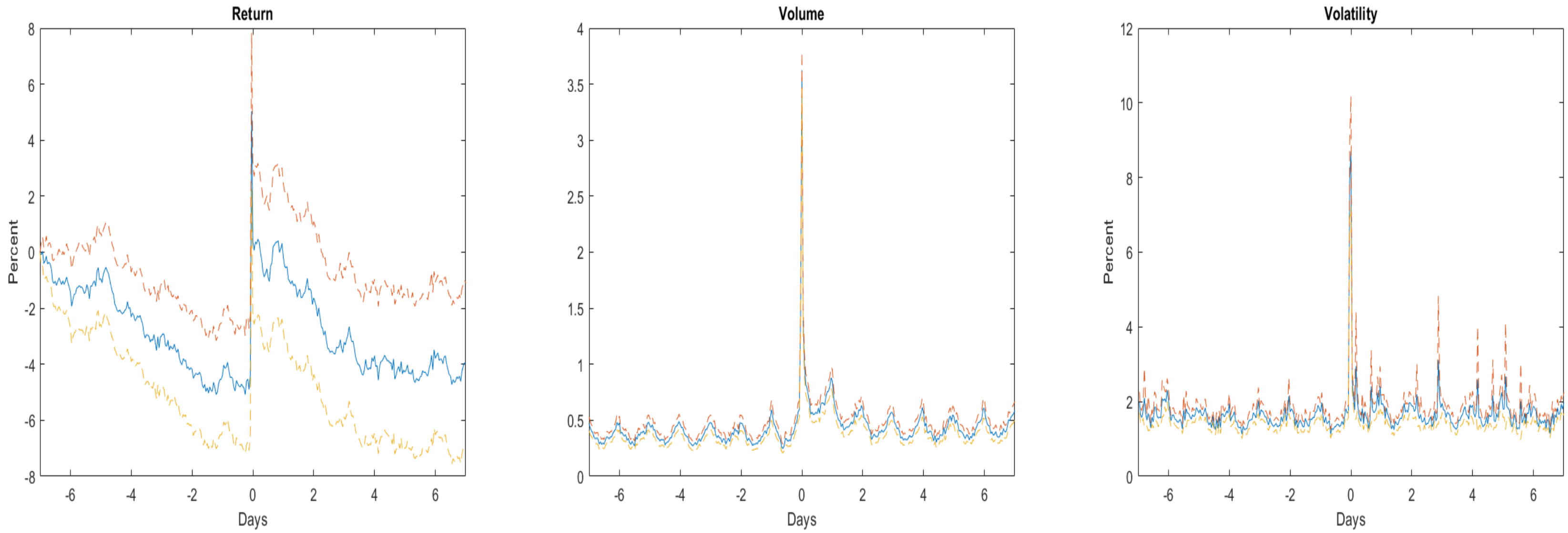
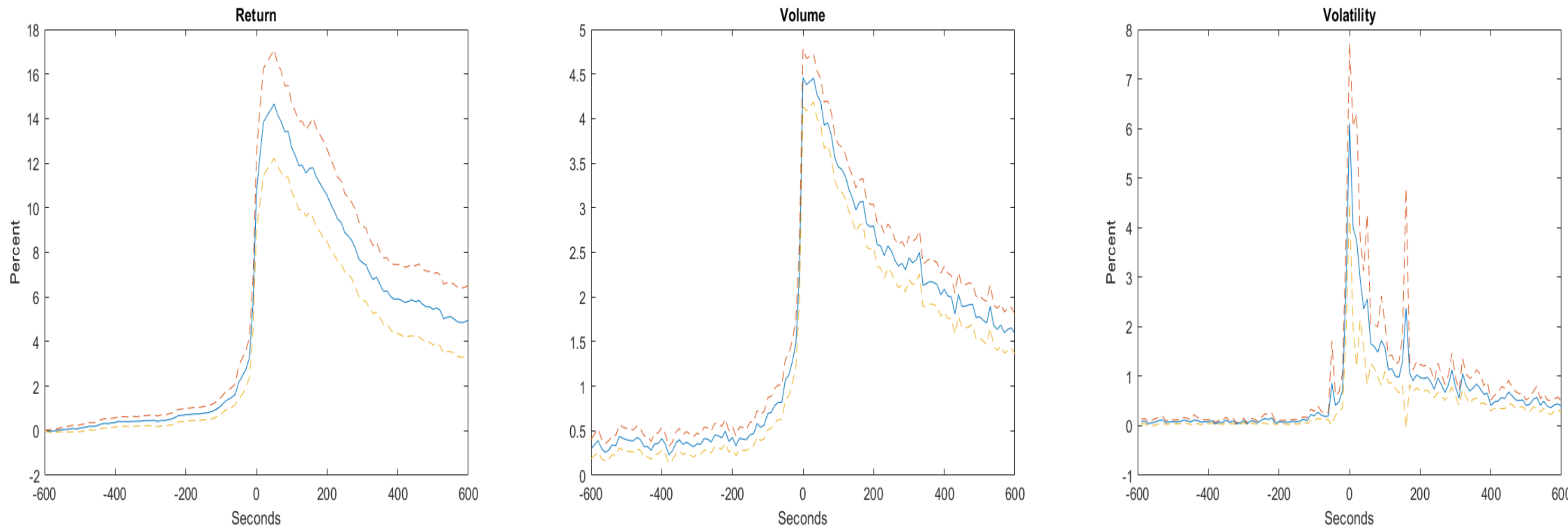


Figure 5: Return, Volume and Volatility Sorted by Liquidity

This figure displays short-term cumulative returns, abnormal volume, and the volatility of pumped tokens sorted by liquidity. Panel A features liquid tokens while Panel B shows plots for illiquid tokens. Liquidity is defined as the total trading volume (in Bitcoin) over the period running from 37 days to eight days before a P&D announcement. Liquid (illiquid) tokens are target tokens in our sample where the target's liquidity is above (below) the median value. We plot cumulative returns, abnormal volume, and the volatility for 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 tokens, 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 a 600-second interval/average volume in the interval over day -37 to day -8). Volume is measured by the number of tokens traded. Volatility is measured as the absolute value of return in each interval.

Panel A. Liquid tokens



Panel B. Illiquid tokens

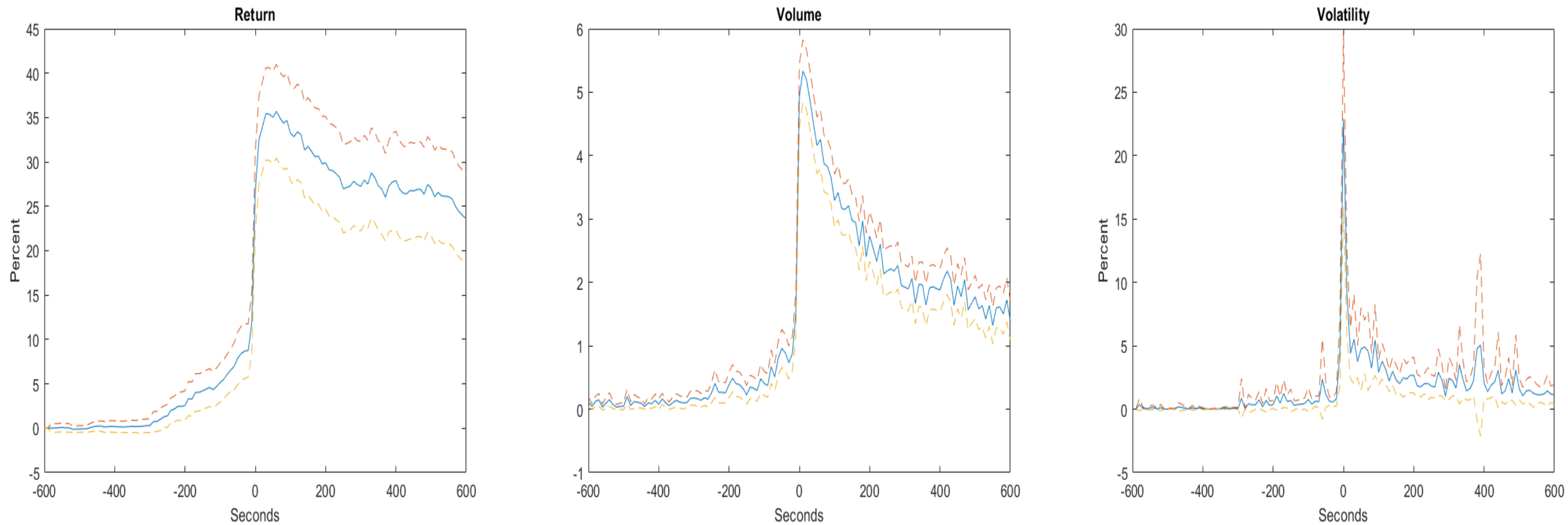
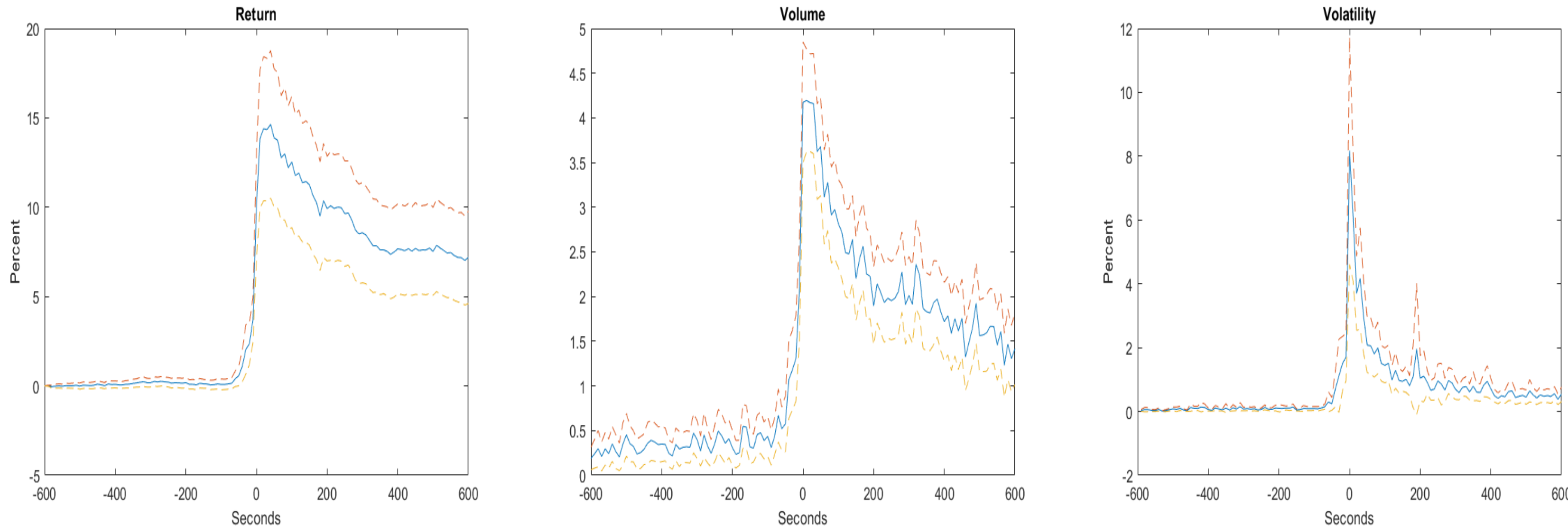


Figure 6: Spillovers to Ethereum Trading Pairs and Other Exchanges

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

Panel A. Ethereum pairs



Panel B. Bitcoin pairs on other exchanges

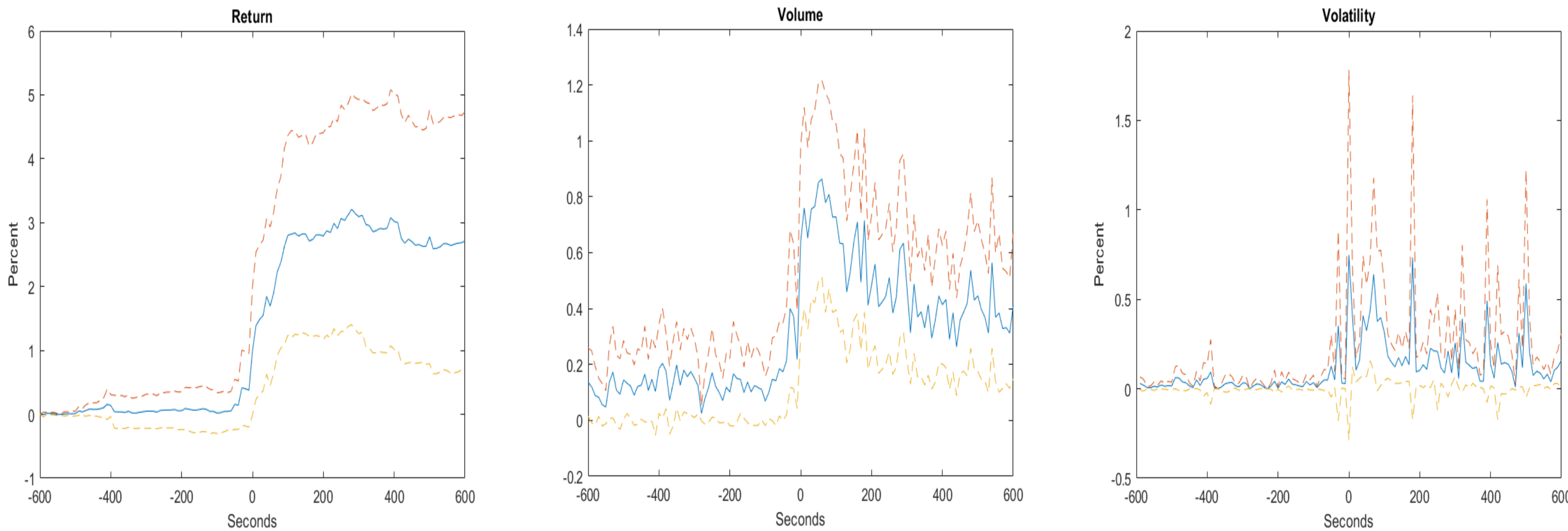


Figure 7: Price Impact

This figure displays the price impact. The price impact is estimated from the following regression for each 1-minute interval across all the P&Ds:

$$\Delta p_{i,t} = \alpha_t + \lambda_t q_{i,t} + \varepsilon_{i,t}, \quad (1),$$

in which $q_{i,t}$ and $\Delta p_{i,t}$ are order flow and return at time t for token i, respectively. Order flow is defined as the volume of buy orders minus the volume of sell orders in Bitcoin units. $\varepsilon_{i,t}$ is the error term. λ_t is our measure of price impact and α_t is an intercept.

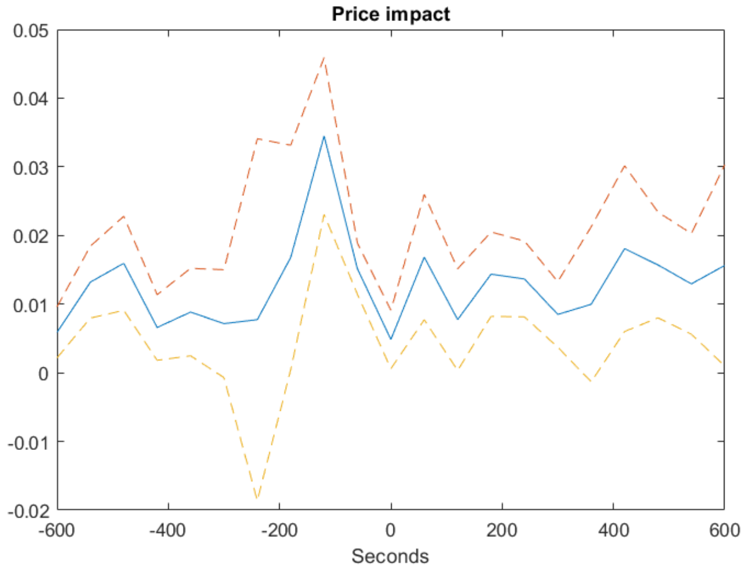
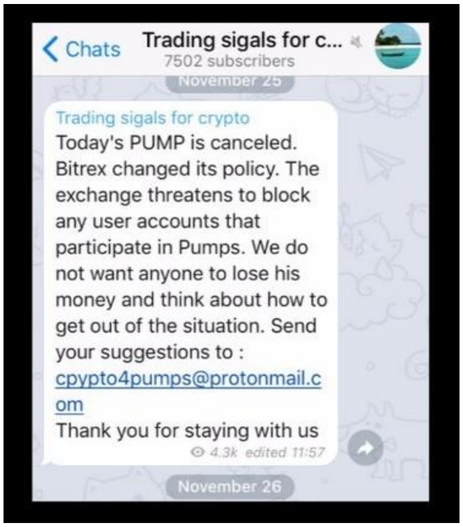


Figure 8: A Sharp Decrease in P&Ds on Bittrex after the Ban

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

Panel A. An example of pump cancelation



Panel B. Frequency of P&Ds around the ban

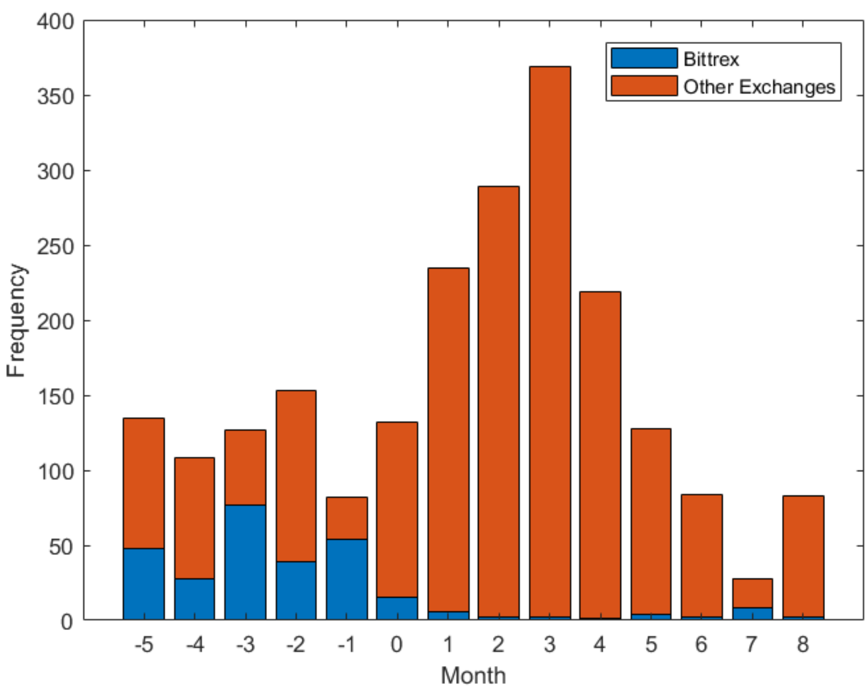
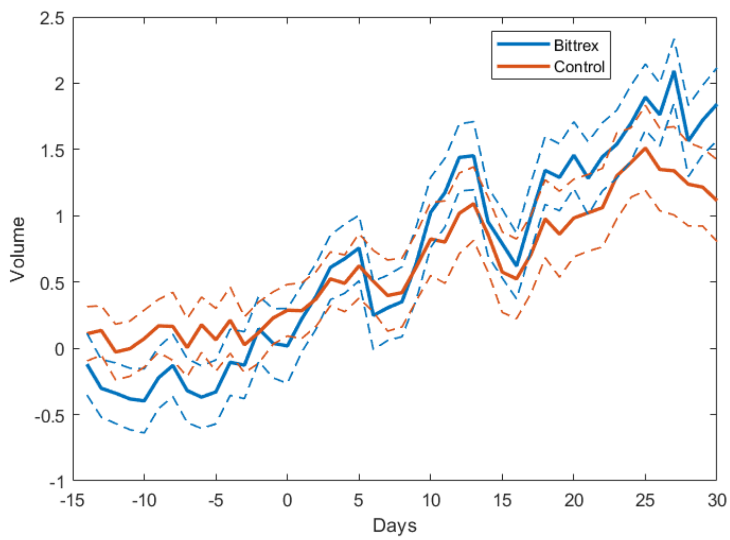


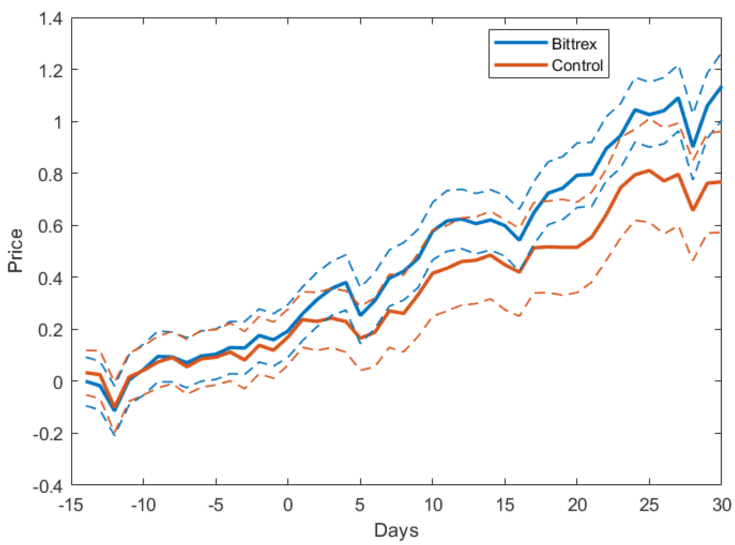
Figure 9: The Effects of the Bittrex Ban on Price and Volume

This figure displays volumes (Panel A) and prices (Panel B) of Bittrex tokens and the control tokens. The treatment group comprises tokens listed on Bittrex on November 24, 2017, and the control group includes the matched tokens not listed on Bittrex at that time. We use the non-Bittrex token with the closest trading volume (in Bitcoin) as the matched token. Matching is based on the trading volume over the period running from 60 days to 31 days before the ban. The X-axis is the day relative to November 24, 2017. Volume is measured as the natural logarithm of the ratio between volume on day *t* and the average volume over the period from 60 days to 31 days before the ban. Price is defined as the natural logarithm of the ratio between the end-of-day price and the price at the end of day -31. Each point on the solid lines is the average across either the Bittrex tokens or other control tokens. The dashed line displays the 95% confidence intervals.

Panel A. Volume



Panel B. Price



Appendix

Part A1: Matching Cryptocurrencies across Data Sets

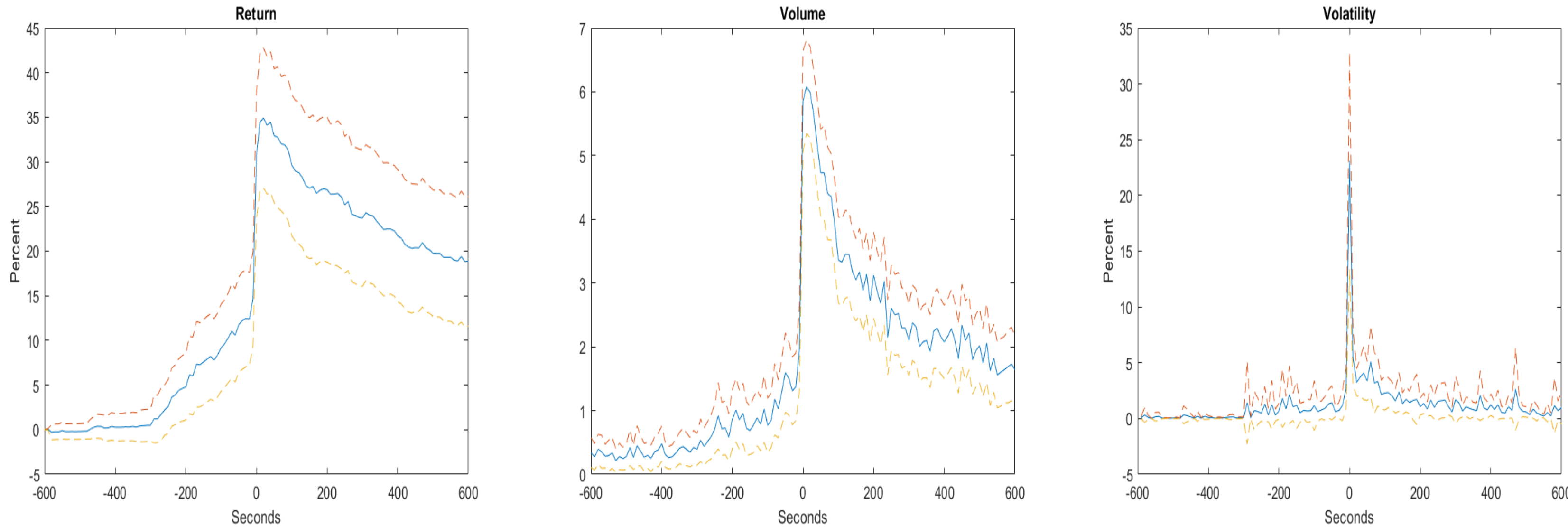
Both our exchange data and the CoinMarketCap data use token symbols to identify unique tokens. In most P&Ds, the Telegram channels provide token symbols and often token names as well. In most cases, a token has the same symbol on the exchange (or exchanges if it is cross-listed) and on CoinMarketCap.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

CoinMarketCap provides both token symbols and names. However, the exchange data include only token symbols but not their names. We search for token names using their symbols on the websites of the exchanges. Unlike the application programming interfaces (APIs) that we use to download trading data for both active and inactive tokens, the websites of the three exchanges (Binance, Bittrex, and Yobit) do not return names of delisted tokens. We therefore rely on Binance's Announcements page (https://support.binance.com/hc/en-us/categories/115000056351-Announcements), Bittrex's Coin Removals page (https://support.bittrex.com/hc/en-us/sections/200560334-Coin-Removals), and Yobit's press releases to identify such names.

Token prices are quoted in ticker pairs that function much like exchange rates. For example, NXS/BTC is a pair that indicates that the trade is an exchange between NXS (Nexus) and BTC (Bitcoin). In this pair, Nexus is quoted in the volume in Bitcoin, which is the base currency. Bitcoin is by far the dominant base currency. The second most widely used base currency is Ethereum (ETH). The symbols in our exchange data contain token tickers and base currencies. Based on this, we filter out pairs with base currencies other than BTC and ETH.

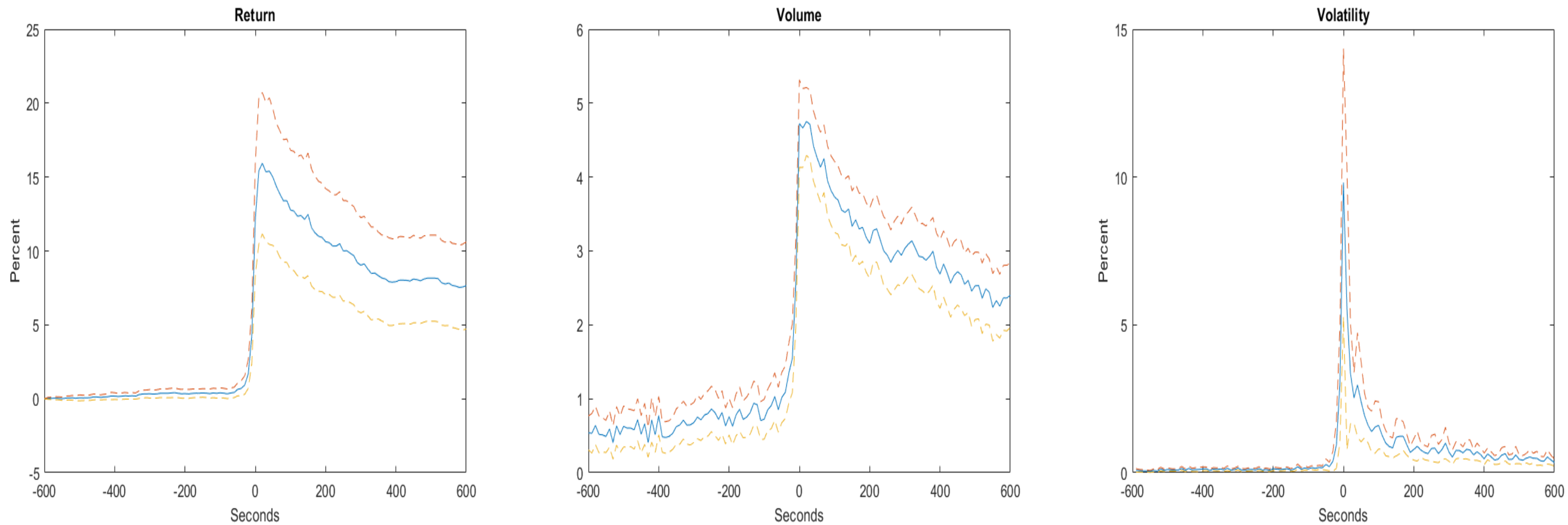
Part A2: Pump-and-Dump Schemes in the Past Six Months

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



Part A3: Pump and Dumps on Binance

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



Part A4. Spillovers to Ethereum Trading Pairs and Other Exchanges

This table reports results pertaining to potential spillovers. The figures in Panel A show whether there is any spillover to trading pairs in Ethereum for the same pumped tokens, while those in Panel B represent trading pairs in Bitcoin on other exchanges. In Panel A, for pumped tokens with trading data on Ethereum pairs, we report maximum returns, abnormal volume, and the volatility of the Ethereum pairs. In Panel B, for pumped tokens with trading data from other exchange(s), we report maximum returns, abnormal volume, and the volatility of these cross-listed tokens on the non-targeted exchange(s). If a token is cross-listed on two other exchanges besides the target exchange, we take the average of maximum returns, abnormal volume, and volatility across the two exchanges. The *t*-values and the Wilcoxon *p*-values are calculated based on the paired sample.

Panel A. Spillovers to Ethereum pairs

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

Panel B. Spillovers to other exchanges

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