A new wolf in town?

Pump-and-dump manipulation in cryptocurrency markets *

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Abstract

We investigate the puzzle of widespread participation in cryptocurrency pump-and-dump manipulation schemes. Unlike stock market manipulators, cryptocurrency manipulators openly declare their intentions to pump specific coins, rather than trying to deceive investors. Puzzlingly, people join in despite negative expected returns. In a simple framework, we demonstrate how overconfidence and gambling preferences can explain participation in these schemes. Analyzing a sample of 355 cases in six months, we find strong empirical support for both mechanisms. Pumps generate extreme price distortions of 65% on average, abnormal trading volumes in the millions of dollars, and large wealth transfers between participants.

Keywords: market manipulation, pump-and-dump, cryptocurrencies, overconfidence, gambling

JEL classification: G14, G41

The Internet Appendix accompanying this study can be found at this link (https://bit.ly/2GTCPn3).

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1. Introduction

Traditional pump-and-dump manipulation, which has existed in financial markets for centuries, typically falls into one of two categories: information-based manipulation or trade-based manipulation. Information-based manipulation involves spreading false information about the value of the security in the hope that traders will believe the false information (Vila, 1989; Van Bommel, 2003). It requires uncertainty about the fair value of a security and information asymmetry as the underpinnings of the manipulation. If there is little or no uncertainty about value, or no information asymmetry, then uninformed traders will not act on the rumors or false information circulated by the manipulators. Trade-based manipulation involves buying and then selling profitably, or vice versa, which is possible if there is asymmetry in liquidity-motivated trading or price momentum (Allen and Gorton, 1992; Jarrow, 1992).

We examine a new form of pump-and-dump manipulation that has a different underpinning and has become widespread in cryptocurrency markets. We begin by showing that this form of manipulation is prevalent and accounts for considerable cryptocurrency trading. Combining hand-collected data with audited data from a pump-and-dump aggregator, we identify as many as 355 cases of pump-and-dump manipulation within a period of six months on two cryptocurrency exchanges. Up to 23 million individuals are involved in these manipulations. We estimate that the 355 pumps in our sample are associated with approximately $350 million of trading on the manipulation days, and that manipulators extract profits of approximately $6 million from other participants. In all, 197 distinct cryptocurrencies or “coins” are manipulated, which implies that approximately 15% of all coins in our sample of exchanges are targeted by manipulators at least once in the six-month period. There are, on average, two pumps per day. This rate of manipulation is considerably higher than pump-and-dump manipulation in stock markets in recent decades.¹

Interestingly, while pump-and-dump manipulation of cryptocurrencies is similar to manipulation of stocks in some regards, it is completely different in others. The most important difference is that in cryptocurrency pump-and-dumps manipulators typically make no pretense of having private information or claiming that a coin is undervalued, unlike in typical stock market

¹ Market manipulation in modern equity markets is significantly lower. For example, Aggarwal and Wu (2006) only identify 142 pump-and-dump cases on US stock exchanges in an 11-year period, which implies that pump-and-dump rates in cryptocurrency markets are in the order of 40 times higher than those in equity markets.
manipulations.\textsuperscript{2} Instead, pump group administrators (manipulators) publicly declare that they are pumping a given coin (releasing a “pump signal”) and call on others to join.\textsuperscript{3} Others then rush to buy the coin, presumably hoping to sell before the collapse of the pumped coin’s price. Economically, this means that manipulation schemes orchestrated by cryptocurrency pump groups do not exploit the classic mechanisms of information asymmetry and uncertainty about the fundamental value of an asset to “fool” market participants into buying a security.\textsuperscript{4} Nor do they exploit asymmetry in price impact, which underpins trade-based market manipulation.\textsuperscript{5}

This novel feature of cryptocurrency pump-and-dumps raises two interesting questions. First, why do individuals participate in these pumps? Second, how do manipulators profit if they are neither fooling participants nor exploiting asymmetry in price impacts? We present a simple theoretical framework to address both these questions. We show that rational individuals lacking a speed or skill advantage would not participate in pump-and-dump manipulations because for participants other than the manipulators (who can buy ahead of the pump signal) pumps provide negative expected returns. The intuition is simple. Pumps are a zero-sum game involving redistribution of wealth between players. Given that manipulators use their advantage to extract profit and given the existence of trading costs, pumps become a negative-sum game for participants other than the manipulator. While the fastest or most skilled participants can profit at the expense of slower or less skilled participants, non-manipulators, in aggregate, lose money, presenting a puzzle of how these pumps can sustain participation.

We use the theoretical framework to illustrate two types of individuals who willingly participate in pumps, despite the negative expected returns. The first is overconfident individuals, who overestimate their ability to sell at a price close to the peak. From their

\textsuperscript{2} In conventional pump-and-dump schemes, manipulators try to convince investors to buy the stock by spreading positive news about the stock through e-mails, phone calls, and newsletters and by claiming that the stock has the potential for large gains. Prices rise as investors who are convinced by the manipulators’ promotional campaign buy the stock. After the manipulators’ promotional campaign is over, these investors sell their holdings, leading to a fall in the stock price (Leuz et al., 2017).

\textsuperscript{3} While this transparency of the manipulators’ intentions is a feature of the manipulations that we examine (those orchestrated by organized pump groups), it is possible that traditional forms of pump-and-dump manipulation that rely on information asymmetry or asymmetry in price impacts also exist in cryptocurrency markets outside of these organized pump groups.

\textsuperscript{4} Although manipulators trigger the pump-and-dump episodes through an information release, the information that is released is not false information about the value of the security as is typical of information-based manipulation. Rather, the information reveals the intended manipulation. Manipulators do not exploit information asymmetry or uncertainty about the fair value, in contrast to typical cases of information-based manipulation. The data support these arguments: we find that the probability of a pump-and-dump manipulation is not higher when there is more uncertainty about a coin’s value as proxied by the lagged volatility of the coin (Table IA1 in the Internet Appendix).

\textsuperscript{5} See Section B.1 in Appendix B.
perspective, pumps appear (incorrectly) to be a profitable game *ex-ante*. The second type is individuals who use pumps as a form of gambling, attracted by the possibility of large gains and the right-skewed payoff distribution that pumps can generate under certain conditions.

We find strong empirical support for both these explanations. We estimate regressions of pump participation on measures of overconfidence and gambling. The overconfidence proxy is based on the tendency for past success to increase overconfidence through self-attribution bias. The gambling proxy measures gambling in cryptocurrency-based gambling services such as SatoshiDICE, normalized by the level of cryptocurrency activity. The results show that overconfidence and gambling are statistically significant and economically meaningful determinants of the amount of participation in cryptocurrency pumps. The magnitudes of both mechanisms are similar. Therefore, we conclude that cryptocurrency pump-and-dumps are, to a large extent, a type of trading game that attracts overconfident traders and people looking for gambles.\(^6\)

We study various other properties of cryptocurrency pump-and-dumps, both empirically and theoretically. We show that while pump-and-dump episodes tend to be rather short-lived, they generate extreme price distortions and abnormal volumes. The average cryptocurrency pump-and-dump manipulation is associated with a price rise of 65% within minutes. These average returns are approximately four times larger than the standard deviation of daily cryptocurrency returns. Therefore, even after considering the high volatility of cryptocurrencies, pump-and-dump episodes generate extreme price distortions. On average, it takes about eight minutes for a pumped coin to reach its peak price, after which the dumping phase commences and the price collapses. The trading volume on manipulation days is approximately 13.5 times the usual daily volume. We also find spillover effects into other markets that trade the manipulated coins but are not directly targeted by the manipulators; both volume and volatility increase significantly on these other markets during the pumps.

We also examine the characteristics of coins that are most likely to be targeted by manipulators and we test how manipulation affects these coins. We find that manipulators target relatively illiquid coins. This observation is consistent with our framework, which predicts that

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\(^6\) Despite functioning as a type of trading game, cryptocurrency pump-and-dumps are nevertheless a form of market manipulation as they involve a deliberate intention on the part of the manipulators to influence the price of a traded security. Therefore, these schemes not only expose unwitting and naïve investors to exploitation by manipulators but are also likely to involve similar costs as other forms of manipulation, e.g., a loss of confidence in the integrity of markets.
individuals will be more attracted to pumps of illiquid coins. However, the most illiquid coins have a lower likelihood of manipulation, which is probably because a minimum level of liquidity is required to make the pump feasible and worthwhile on the part of manipulators, who need to build positions in the coin before sending a pump signal.

Finally, we find that although pumps create extreme price distortions during the pump, prices revert to their pre-pump levels within a day or two (often within an hour) following the manipulation. Therefore, pumps do not appear to have a permanent impact on the value of a targeted coin. The price distortions created by pumps are larger for less liquid coins and when more individuals participate in the pump. Over time, pumps tend to speed up and take less time to reach the peak price from the time the pump signal is sent.

Our paper contributes to the literature on behavioral biases in financial markets by showing how biases such as overconfidence and gambling preferences can lead to participation in speculative bubble games in markets. If we strip out the manipulation angle, at their core, cryptocurrency pump-and-dumps are a type of bubble game. In such games, agents disregard a security’s fundamentals and purchase it in the belief that they can sell it to others that will want to buy it in the future at higher prices. Such games have gained popularity in markets recently, with many prominent examples covered in the press and regulatory discussions. One example is the “meme stocks” phenomenon, whereby traders in social media forums co-ordinate their speculative purchasing of relatively illiquid companies to generate large price increases usually followed by a collapse of the price. For example, in 2021, users on the online forum Reddit urged others to purchase shares in GameStop, a video game retail company, resulting in a price increase of approximately 1,900% within a month without any substantial changes in the company fundamentals. Another example is celebrities and online influencers that serve as coordination mechanisms for speculative games in markets. For example, some market participants

7 Interestingly, some instruments in cryptocurrency markets are prone to speculative behavior by design. Consider the example of smart contracts that rely on “bonding curves” in their primary market. The primary market prices of such instruments increase with an increase in their supply. Such instruments can promote price speculation since they naturally advantage early investors and thereby trigger similar bubble games. Take, for example, Unisocks (SOCKS), a token that uses bonding curves. The price of SOCKS rose from $69,000 to $160,000 between February 27, 2021, and March 4, 2021, only to drop to $76,000 a day later. As an instrument, the only fundamental right that the SOCKS token grants a holder is that it can be redeemed for a non-fungible token and a pair of socks. Another innovation in the cryptocurrency ecosystem that can favor manipulators is automated market makers (AMMs), a form of decentralized exchange. Essentially, these systems can facilitate “rug pulls,” wherein manipulators create a coin, generate a market for the coin by supplying it to an AMM, publicize and drive up the prices of tokens, while exiting their own position via the AMM. The use of AMMs removes the need to obtain a centralized exchange listing of the token or rely on the liquidity provided by traditional market makers.
use Elon Musk’s tweets as co-ordination mechanisms for pump-and-dump games (essentially like Telegram pump signals), with specific words in a tweet triggering a pump of a coin or stock (Levine, 2021). Another example is social media influencer David Portnoy who announced his support for a token called SafeMoon in a tweet (May 17, 2021), despite acknowledging that “it could be a Ponzi scheme.” Consistent with these anecdotal accounts of recent speculative bubble games in various markets, we find that cryptocurrency pump-and-dump games have also increased in popularity in 2021 after a brief post-2018 hiatus (see Section 3.2).

Our paper also contributes to the market manipulation literature by characterizing a new form of manipulation that differs from typical cases of pump-and-dump manipulation in stock markets.\(^8\) Aggarwal and Wu (2006) provide a thorough analysis of stock market pump-and-dumps. Moreover, in cryptocurrency markets, we are able to exploit a more complete sample of manipulation instances and more granular information about those instances. For example, we can observe the exact start times for the pumps (when the pump group releases the “pump signal” to the participants). Our sample is also not contaminated by a prosecution bias, as we obtain the data on manipulations irrespective of whether these manipulations are prosecuted.\(^9\)

Four contemporaneous papers analyze pump-and-dump manipulation in cryptocurrency markets.\(^10\) Li, Shin, and Wang (2021) characterize the impact of pump-and-dump schemes on cryptocurrency markets. Xu and Livshitz (2019) and Kamps and Kleinberg (2018) develop approaches to predict cryptocurrency pumps \textit{ex-ante} and \textit{ex-post}, respectively. Finally, Hamrick et al. (2020) examine the factors that affect the price jumps in cryptocurrency pumps. While these four studies and this paper have some findings in common, our study has a different focus. For example, like this paper, Hamrick et al. (2020) and Li et al. (2021) find that coins with lower market capitalization have larger price jumps during pumps. Similar to the findings reported in this paper, Li et al. (2021) show that these schemes are widespread, generate large but short-lived price distortions, and result in substantial wealth transfers between market participants. A novel

\(^8\) For reviews of the market manipulation literature, see Fox, Glosten and Rautherberg (2018) and Putniņš (2020).

\(^9\) In contrast, the stock market manipulation prosecution cases that an empiricist can work with are a non-random “tip of the iceberg.” For example, Comerton-Forde and Putniņš (2014) show that the prosecuted cases of manipulation reflect a tiny and non-random fraction (0.3\%) of all manipulation.

\(^10\) Our paper is also related to two recent studies of other forms of cryptocurrency market manipulation. In both cases, the (alleged) perpetrators of market manipulation are cryptocurrency exchanges or parties associated with them. Griffin and Shams (2018) show that parties related to the cryptocurrency exchange Bitfinex used Tether (a USD-pegged stablecoin) to inflate the price of Bitcoin. Gandal et al. (2018) examine Bitcoin trading in 2013 and argue that fraudulent transactions conducted by the Mt. Gox exchange caused the Bitcoin price to rise by more than 500\% in two months.
feature of their analysis lies in testing the causal effects of these schemes on liquidity. Given the high trading volumes associated with these manipulations, it is somewhat surprising that they find that these schemes decrease the liquidity of cryptocurrency markets.

In contrast, the focus of this paper is on modeling and testing mechanisms that enable these schemes to exist and analyzing how they sustain participation. Theoretically, we show that two behavioral factors—overconfidence and gambling preferences—can explain pump participation. We find empirical support for both behavioral factors. We also characterize these schemes beyond what is presented in the other studies, showing their impact on the manipulated market as well as spillovers to other markets and identifying the characteristics of coins most susceptible to manipulation.

This paper is structured as follows. Section 2 provides an illustration of a cryptocurrency pump-and-dump manipulation. Section 3 introduces our data and sample. Section 4 investigates participation in cryptocurrency pumps theoretically and empirically. Section 5 analyzes the characteristics, determinants, and effects of pumps. Section 6 discusses the welfare effects of cryptocurrency pumps. Section 7 concludes.

2. Illustration of a Cryptocurrency Pump-and-Dump Manipulation

To explain the mechanics of a pump, we use an example from the Big Pump Signal (BPS) group, one of the largest pump groups in 2018 by number of members (around 63,000 members on Telegram in 2018).\footnote{Appendix A provides more details about pump groups and their operations.} This pump was on the Binance exchange and involved the cryptocurrency ChatCoin (CHAT). Figure 1 displays communication from the BPS administrators to the group members about the CHAT pump. First, the administrators announce the exchange, date, and time at which the pump will occur, but not the actual coin that will be pumped (top left-hand-side message in Figure 1). This pre-announcement of the pump prepares the participants, allowing them to transfer funds to the nominated exchange and be online and wait for the pump signal at the pre-specified time.

Then comes the “pump signal,” which is just the name of the coin being pumped (bottom left-hand-side message in Figure 1). In this illustration, the coin being pumped is “CHAT,” as indicated by the red dashed line around the text “CHAT” (the pump signal is displayed in such a
format to prevent machine readability). BPS sent the pump signal for the CHAT pump at 20:00:23 GMT on June 10, 2018.

< Figure 1 here >

Figure 2 Panel A shows the price of CHAT in 15-second intervals starting 15 minutes prior to the release of the pump signal and ending 90 minutes after the pump signal. Figure 2 Panel B shows the trading volume of CHAT in five-minute intervals during the same period. There is very little trading activity in the 15 minutes leading up to the pump signal and a sudden jump in the price and trading volume immediately after the pump signal at 20:00. Although the price fluctuates considerably during and after the pump, it peaks at around 17 seconds after the pump signal is sent (Panel C zooms in to the five minutes around the pump signal). The peak price is approximately 55% above the pre-pump price level. Following the peak, the price and volume of CHAT remain elevated until about one hour after the pump signal, at which time the price falls back down to around the pre-pump price level.

In addition to the extreme price movements, the pump is associated with a significant spike in trading volume. In the half hour before the pump signal is sent, the trading volume in CHAT is $17,313.47 (or 2.55 BTC), which is likely to be pre-pump position-building by the manipulators (the group administrators). In the half hour after the pump signal is released, the trading volume in CHAT jumps to $2.69 million, which is 3.6 times the median daily dollar volume for CHAT between December 2017 and July 2018.

< Figure 2 here >

3. Data and Prevalence of Pumps

3.1 Data

We identify cryptocurrency pump-and-dumps using two approaches. First, we hand-collect instances of pumps coordinated on one of the largest cryptocurrency exchanges, Binance, using the chat history data from 72 Telegram pump-and-dump channels. In our sample, we only

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12 BTC denotes the unit of measurement for Bitcoin. Most cryptocurrencies are traded in BTC pairs.
include cases in which the Telegram pump-and-dump administrator pre-specifies a date, time, and exchange for a pump and releases a “pump signal” containing the name of the pumped coin. Therefore, our sample only includes events in which the pump group administrator makes it explicit to its members that the intention is to pump the given coin. For each pump, we record the coin being pumped, the exchange, and the time at which the pump signal is sent. We also extract ancillary information, such as the number of pumps that a group has conducted prior to the pump, the number of groups participating in the pump, and the total number of members in the pump group(s) participating in the pump.

Second, we add instances of pump-and-dumps for a second cryptocurrency exchange, Yobit, from the database compiled by PumpAnalysis (PA). To verify the accuracy of the data from this second source, we conduct a data audit. In the audit, we take a random sample of the cases in the dataset and manually look up the chat history of the relevant pump group in Telegram and verify the existence of the pump signal, including the coin, exchange, and timestamp. We found no material inaccuracies in the dataset and were able to verify every case examined in the audit. Further, we imposed the same data requirements as per our sample of pumps on Binance. Because the data in the PA database match up with the records in the Telegram pump groups and many of the details in the database are only available from the Telegram chat histories, the underlying data source for the PA database is very likely to be the Telegram pump groups.

We couple the pump information with data on all trades on the Binance and Yobit exchanges (sourced from the official Binance API and the data provider Kaiko, respectively). We restrict our focus to Binance and Yobit because of the limited availability of reliable trade data. Our main sample for the pump-level analysis consists of 355 pumps (64 on Binance and 291 on Yobit) from December 29, 2017 to June 22, 2018. Based on the number of pump group members, up to 23.3 million participants were involved in the pump-and-dumps during our sample period. To examine the time-series trends in the prevalence of pumps, we also analyze an extended sample from 2018 to September 2021.

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13 Although the website hosting the dataset (PumpAnalysis.com) is no longer active, we downloaded a copy of the data before it went offline. Our copy of the PA dataset is available upon request. Adding data from the PA dataset allows us to obtain a more complete sample as the dataset contains records from Telegram pump groups that have subsequently ceased activity making their chat records unavailable.
We obtain daily market capitalization and price data for all cryptocurrencies from coinmarketcap.com, a cryptocurrency data aggregation website, and daily exchange-level price and volume data for all cryptocurrencies from cryptocompare.com, another cryptocurrency data aggregation website. We also obtain Google Search Volume Index data from the Google Trends website. Lastly, we obtain daily Bitcoin gambling volumes from WalletExplorer.com, a Bitcoin blockchain explorer website.

3.2 Prevalence of Cryptocurrency Pump-and-Dumps

Table 1 reports descriptive statistics for the trading activity on the two exchanges (Yobit and Binance) and the prevalence of pump-and-dump manipulation. In our main six-month sample, 1,307 cryptocurrencies (“coins”) are traded on the two exchanges, with a combined volume of around $20 billion. The 355 instances of pump-and-dump manipulation in our main sample, for which we have all necessary data, occur in 197 distinct coins. Therefore, approximately 15% of all coins (197/1,307) experience at least one pump-and-dump manipulation during the six-month period, with an average of 1.8 pumps per coin and 2.67 pumps per pump-day. These manipulation rates, which are a lower bound because they include only instances on which we have the necessary data, suggest that cryptocurrency pump-and-dump manipulation is widespread and frequent.

The volumes traded during pump-and-dump episodes are economically meaningful, with around $350 million traded during the 355 pumps in our sample. We estimate that manipulators buy approximately $24.38 million of coins in the two hours leading up to the pumps, resulting in a conservatively estimated aggregate profit to manipulators of approximately $6.04 million. This figure reflects the estimated wealth transfer from the pump participants (pump group followers) to the manipulators (pump group administrators) during our sample period. As a return, the manipulators earn around 24.77% within minutes or hours.

14 A “pump-day” is a day on which there is at least one instance of pump-and-dump manipulation.
15 Manipulator profits are estimated from the difference in the volume-weighted average price during the two hours preceding the pump signal and the volume-weighted average price during the pump (from start to peak). Factoring in transaction costs slightly reduces these profit estimates. For example, assuming that manipulators pay the highest trading fees on both the exchanges (0.1% of transaction value on Binance and 0.2% on Yobit; the actual fees may be lower, depending on factors such as trading volume), the profit estimate decreases only marginally to $5.98 million. If we further assume that manipulators pay an effective spread of 1% on their trades (which is 18 times larger than the average effective spread for Bitcoin trades on Gdax, see Dyhrberg, Foley and Svec, 2018), the profit estimate decreases to $5.44 million.
To examine the longer-term trends in the prevalence of pumps, we use three proxies for pump activity. The first is the number of pumps per week that we manually identify in cryptocurrency pump-and-dump groups on the Telegram and Discord social media platforms. Similar to our main sample, we add (without duplication) cases reported in a pump aggregation database, PumpOlymp, to this hand-collected sample. The second proxy is intraday reversals for all coins listed on Binance and Yobit. The reversals measure is calculated as the minimum of the percentage price change from the day’s open to the day’s high and the percentage price change from the day’s close to the high. The third is Google search activity for keywords related to cryptocurrency pump-and-dumps. Google searches are an indicator of public interest in cryptocurrency pumps, whereas reversals are an indicator of pump-and-dump activity and intensity, as pumps can cause sharp intraday price spikes and reversals.

Figure 3 plots these three pump activity proxies from March 2018 to October 2021. Pump-and-dump frequency is high in early 2018 and falls towards the end of 2018. Interestingly, pumps witness a sharp rise in late 2020 and early 2021, suggesting that cryptocurrency pumps have regained popularity in recent times. Our data indicate that at least 601 pumps took place between June 2018 and December 2020. The annualized figure for 2021 is 678 pumps. Evidently, cryptocurrency pumps persist beyond our main sample period in 2018. The two other proxies confirm these trends. Both search activity and reversals also increase in 2021, with the 2021 search activity exceeding its previous 2018 peak.

We also audit the PumpOlymp data to verify its accuracy. Given that pumps typically tend to occur at either the hour or half-hour mark, we apply a filter to the dataset that retains the observations that occur within one minute of the hour or half-hour mark, which removes some instances that could not be verified as pumps. We find no material discrepancies in the records for the remaining observations. We eliminate duplicates when merging with our hand-collected sample. As a robustness test, we also re-estimate the plot in Figure 3 without the PumpOlymp data (see Figure IIA1 in the Internet Appendix) and find that our main conclusion about the recent rise in cryptocurrency pump-and-dump activity is robust to the exclusion of the PumpOlymp data.
Other measures of pump activity suggest that participation in pumps has grown considerably through time and the scale of pumps in 2021 exceeds that of 2018. For example, if we consider the number of members in dedicated Telegram pump groups, the largest group in our 2018 sample had around 82,000 members. In contrast, the largest group in October 2021 has 3.2 million members. To put that into perspective, the single largest pump group in 2021 by membership has more members than the sum of the members in the top 100 pump groups in 2018. The driver is an increase in the total number of members of pump groups rather than just a consolidation of pump groups because, for example, the second, third, and fourth largest groups in October 2021 have 3.0 million, 1.8 million, and 1.6 million members, respectively.

Trading volumes also attest to the increasing scale of pumps. For example, if we take the five most recent pumps conducted by the largest pump group as of October 2021, the dollar volume traded during these five pumps (using data from Binance, as all five are conducted on Binance) exceeds the total dollar volume aggregated across all 355 pumps in our 2018 sample. The average volume in these most recent five pumps is approximately 14 times greater than the average in our 2018 sample.

4. Explaining Participation in Pumps

We use a simple framework to illustrate the mechanics of pump-and-dump manipulations and why it is puzzling that people participate. Below we describe the basic structure, the intuition, and key results and we provide the details in Appendix B. We then use the framework to show how behavioral mechanisms such as overconfidence and gambling preferences help resolve this puzzle. We then take those predictions to the data and test the drivers of cryptocurrency pump-and-dumps.

4.1 Framework for Understanding Cryptocurrency Pump-and-Dumps

We consider a four-period, simultaneous-move trading game. There are three types of agents: manipulators (pump group administrators), traders who can choose to participate in the pump following the release of a pump signal, and a simple market maker that facilitates trades. We assume that trades have linear price impacts given by $P_t = P_{t-1} + \beta x_t$, where $P_t$ is the price
in period \( t \), \( \beta \) is a price impact parameter between zero and one, and \( x_t \) is the net volume (buys minus sells) received by the market at time \( t \).

The game starts in Period 0, when a manipulator or a group of manipulators decides to pump a particular coin. The price of the coin at the time is \( P_0 \).

In Period 1, the manipulators take a long position of \( M > 1 \) units in the coin and notify their pump group members that there will be a pump in Period 2 (without releasing the name of the coin, as per a typical pump). The \( M \) units can be thought of as \( M \) manipulators, each buying one unit of the coin or one manipulator buying \( M \) units.

In Period 2, the manipulators send the pump signal to the \( N > 1 \) members of their pump group, notifying them of the coin being pumped. These \( N \) members simultaneously decide whether to participate in the pump (buy one unit of the coin) or not to participate (no trade). Players who decide to participate in the pump race to submit market buy orders to the market. The individual participants buy at prices \( \{ (P_1 + 1\beta), (P_1 + 2\beta), \ldots \} \) depending on their random latency, which determines their queue position.

In Period 3, players that participated exit the pump (along with the manipulators) by simultaneously submitting unit market sell orders. These orders are executed in the same way as the entry orders: random latencies determine the queue positions and execution prices.

Figure 4 illustrates the price dynamics of pumps in this simple framework under different parameter values. In the baseline illustration (\( P_0 = $5, M = 10, N' = 100, \beta = 0.2 \)), the price starts at \( P_0 = $5 \) and rises to \( P_1 = $7 \) before the pump signal due to the manipulators buying. The price rises further to \( P_2 = $27 \) once the pump group participants buy the coin, with \( P_2 \) being the peak price of the pump. Finally, the price falls back down to \( P_3 = $5 \) once the manipulators and participants exit the pump. With more manipulators (higher \( M \)), there is a larger run-up in Period 1 before the pump signal is sent and, consequently, a higher peak price. With more pump participants (higher \( N' \)), there is a sharper price rise in Period 2 and a higher peak. When there is less liquidity and a higher price impact parameter (\( \beta \)), there is a larger run-up in Period 1 before the pump signal is sent and a sharper price rise after the signal as participants buy the coin.

\(^{18}\) Section B.1 in Appendix B details the motivation for this pricing function.

\(^{19}\) Matching engines in financial markets, including cryptocurrency exchanges, typically process incoming orders sequentially by placing them in a queue. Therefore, small random latencies in order submission determine the queue position or the sequence in which the participants’ orders are executed by the market. These random latencies include the time taken to receive and interpret the pump signal, to make a decision, to enter the order, and for the order to be transmitted to the market.
4.2 Rational Agents

What types of individuals participate in cryptocurrency pump-and-dumps? We start by showing that the expected return to pump participants in aggregate is negative. We then show that a systematic skill or speed advantage can explain the participation of some individuals, shifting the puzzle to why less skilled or slower participants participate?

First, consider the simple case of homogenous participants with correct beliefs. Recall that the manipulators buy \( M \) units before sending the pump signal, driving the price to \( P_1 = P_0 + M\beta \) just before the pump signal is released. If all \( N \) pump group members choose to participate, they buy the coin at prices \( \{(P_0 + \beta(M + 1)), (P_0 + \beta(M + 2)), \ldots, (P_0 + \beta(M + N))\} \) depending on their random latency. Thus, their “entry prices” \( (P_{\text{entry}}) \) are uniformly distributed from \( P_0 + \beta(M + 1) \) to \( P_0 + \beta(M + N) \). Similarly, the “exit prices” at which they sell the coin in Period 3 \( (P_{\text{exit}}) \) are uniformly distributed from the first sell price following the peak, \( P_0 + \beta(M + N - 1) \), to the last sell price, \( P_0 \). Therefore, an individual \( i \)’s expected profit is:

\[
\mathbb{E}[\pi_i] = \mathbb{E}[P_{\text{exit}} - P_{\text{entry}}] = -\frac{\beta(M+2)}{2}.
\] (1)

Both \( \beta \) and \( M \) are strictly positive; therefore, the expected return, \( \mathbb{E}[\pi_i] \), is negative. The expected loss has two components: the round-trip trade cost \( (\beta) \) and the expected loss to the manipulator, which is half the manipulators’ initial price impact \( (\beta M/2) \).

In contrast, manipulators have an advantage because they can buy ahead of the pump signal at a more advantageous entry price than their followers. Therefore, pumps can have positive expected profits for manipulators if there is a sufficiently large number of participants \( (N') \) to cover their transaction costs:

\[
\mathbb{E}[\pi_m] = \frac{\beta M}{2} (N' - 2M),
\] (2)

which is positive if \( N' > 2M \).

Therefore, while manipulators can profit, other pump participants should expect to lose money in aggregate; collectively, they lose the sum of their transaction costs \( (\beta N') \) and the gross profits of manipulators \( (\beta MN'/2) \). A rational individual with correct beliefs should recognize

\[20\] Technically, the entry and exit prices follow discrete uniform distributions. However, given that there are typically many participants in pumps (\( N \) in the hundreds or thousands), the continuous distribution is a reasonable approximation that allows us to obtain a tractable solution.
that a cryptocurrency pump-and-dump is a zero-sum game across all participants including the manipulators in the absence of trading costs. Positive trading costs and the wealth transfers to the manipulators make it a negative-sum game for participants other than the manipulators. Therefore, risk-averse or risk-neutral rational individuals with correct beliefs and no advantage over other participants should choose not to participate in these pump-and-dump games.

**Result 1:** Rational individuals with correct beliefs do not participate in cryptocurrency pump-and-dumps.

What if some participants are faster or more skilled than others? Some participants might be able to react faster than others or they simply might be better at “picking the peak” and selling when the pump is about to enter the dump phase. Such individuals would be able to buy at a low price soon after the release of the pump signal and sell at a high price soon after the pump peaks.

To incorporate heterogeneity in speed or skill into the framework, we introduce a parameter that tilts the exit price distribution of fast (slow) players toward higher (lower) exit prices (tilting the entry prices as well would merely strengthen the effect). The speed/skill parameter, $S_i$, is the slope of the transformed exit price probability density function (pdf) for player $i$. When there is an equal proportion of fast and slow participants, $S_i > 0$ for fast players and $S_i < 0$ for slow players. The tilted pdfs are illustrated in Figure 5. In any given pump, players continue to face uncertainty around their exit prices, creating the possibility of profits or losses from any given pump. However, the tilted distributions of exit prices favor the fast players, allowing them to sell at higher prices on average, such that they earn higher payoffs from pumps on average. Section B.2 in Appendix B provides further details and computes the expected profits for fast and slow players.

If participants know their type (fast or slow), it is rational for sufficiently fast participants with sufficiently low risk aversion to participate in pumps. They might not profit from each pump, but they face positive expected returns. This shifts the puzzle of why people participate in pumps to the slow participants. In fact, participation becomes more puzzling because, in the
presence of fast participants, the slower individuals face even worse expected losses from participating in pumps.

However, if participants do not know their speed or skill relative to others, the puzzle of participation applies to all participants other than manipulators. For example, with an equal proportion of fast and slow participants (symmetric tilt of the exit price distribution), a participant’s expected exit price distribution if they do not know their type is uniform, as in the case of homogenous participants, resulting in negative expected returns. Intuitively, if a participant does not know their speed or skill relative to others, they can expect a random share of the aggregate outcomes of participants, which are losses equal to the aggregate trading costs plus the manipulators’ gross profits. Therefore, while the heterogeneity in speed potentially explains why some individuals willingly participate in pumps, it remains a puzzle as to why less skilled participants or participants who do not know their skill level participate in pumps.

4.3 Overconfident Individuals

To resolve the puzzle of participation, we propose two behavioral explanations. First, we consider overconfidence, which can give individuals the perception of having an advantage over others. A large literature on psychology and behavioral finance shows that most people, including financial market participants, assess their own abilities to be higher than those of the average person (Barber and Odean, 2000; Gervais and Odean, 2001; Alicke and Govorun, 2005; Deaves et al., 2008). This is known as the better-than-average effect. In cryptocurrency pump-and-dumps, an overconfident individual who believes they are more skilled than the average player can expect to enter and exit pumps faster than the average participant and, therefore, obtain more favorable prices, much like the fast individuals described above.

To model this overconfidence effect, we return to the baseline of homogenous individuals and add a bias to the perceived distribution of exit prices for overconfident individuals. The overconfidence parameter, $\varepsilon_i$, is the slope of the perceived pdf of exit prices. This bias can be interpreted as individuals believing they are better than average in “picking the peak” of the pump and exiting at a higher price than the average participant. Individuals exceeding a minimum overconfidence threshold of $\varepsilon_{\text{min}}$ expect to earn profits from cryptocurrency pump-and-dumps (see Section B.3 of Appendix B). Thus, we arrive at the first potential explanation for why individuals participate in cryptocurrency pump-and-dumps.
**Result 2:** Sufficiently overconfident individuals participate in cryptocurrency pump-and-dumps.

Figure 6 illustrates how the minimum overconfidence threshold varies with the other parameters. For the illustration, we set values for two of the three parameters and plot $\epsilon_{min}$ against the third parameter. Panel A shows that $\epsilon_{min}$ is decreasing in $\beta$, implying that pumps of less liquid coins tend to have more participation from overconfident individuals due to the lower minimum overconfidence required to induce participation. This effect occurs because less liquid coins tend to have a higher dispersion of exit prices, so a smaller bias is required to make the pump attractive to an overconfident individual. This effect also explains why pumps tend to occur in relatively illiquid coins. Panel B shows that $\epsilon_{min}$ is increasing in $M$, implying that pumps with more manipulator participation tend to have less participation from overconfident players. This effect occurs because manipulators impose a cost on other participants; therefore, higher overconfidence is required to make the pump attractive. Finally, Panel C shows that $\epsilon_{min}$ is decreasing in $N'$, implying that pumps with more participants are more attractive to overconfident players. This effect arises because a larger number of participants leads to a higher peak price and more dispersion in exit prices such that only a small bias in the perceived likelihood of exiting near the peak is required to make a pump attractive.

< Figure 6 here >

### 4.4 Gamblers

The second behavioral explanation that we consider is gambling preferences. Previous literature shows that individuals prefer “lottery-like” assets with positively skewed payoffs (Barberis and Huang, 2008; Kumar, 2009). In our framework, a single pump does not have a positively skewed payoff distribution; the gains and losses are approximately symmetrical. However, even a single bet on red or black at the roulette table does not have a right-skewed payoff. To explain the attraction of non-skewed games, such as bets in roulette, Barberis (2012) shows that gamblers view these games not in isolation but as a series of bets that collectively constitute a game. When a gambler intends to play a game repeatedly and stop if their losses exceed a “walk away” threshold, a game that has symmetric payoffs as a one-off gamble
becomes right-skewed for a series of bets. Other studies also suggest that gamblers favor repeated games over single games (Dickerson, 1984; Grinblatt and Keloharju, 2009).

Applying the mechanism proposed by Barberis (2012) to our setting, suppose a gambler starts with $a (a > 0)$ and considers whether to participate in a series of pumps until they either deplete their wealth to $b (b < a)$, incurring a loss of $a - b$, or accumulate a wealth of $c (c > a)$, making a gain of $c - a$. This strategy reduces to a binary gamble. Following Barberis (2012), we assume that gamblers exhibit preferences consistent with the Cumulative Prospect Theory (CPT) developed in Tversky and Kahneman (1992). Section B.4 in Appendix B provides details about the binary gamble, the gambler’s maximization problem, and their preferences. In essence, the gambler determines the optimal values of $b$ and $c$ that lead to the highest expected value.

We solve the gambler’s optimization problem numerically by determining the optimal $b$ and $c$ values for a given set of parameter values.\(^{21}\) We find that the optimal value of $b$ is $0$ and that of $c$ is $245$. This implies that a gambler starting off with $a = $6 participates in pumps either until they go bankrupt or until they accumulate a wealth of $245$. This strategy yields a positive expected value for the gambler with CPT preferences and, therefore, provides a second possible reason for why individuals participate in cryptocurrency pump-and-dumps.

**Result 3**: Individuals with Cumulative Prospect Theory preferences participate in cryptocurrency pump-and-dumps as a form of gambling.

In Figure 7, we illustrate how the attractiveness of cryptocurrency pump-and-dumps as a form of gambling varies with different parameters. We vary the parameters one at a time, plotting the gamblers’ expected value of participating in a series of pumps. The figure shows that gamblers are more attracted to cryptocurrency pump-and-dumps (higher expected value) when the pumped coins are relatively illiquid (high $\beta$), there are relatively few manipulators (low $M$), and there are many participants (high $N'$).

\[^{21}\text{We set} \ P_0 = $5, \ \beta = 0.01, \ M = 10, \ N' = 1,000, \ \text{and} \ a = $6. \ \text{Refer to Section B.4 in Appendix B for details about the CPT parameters and their values.}\]
4.5 Other Factors Influencing Participation in Pumps

We document two additional factors influencing participation. First, based on the illustrations in Figures 6 and 7, we know that more pre-pump trading by the manipulators ($M$) makes pumps relatively less attractive to individuals of all types—rational agents expect larger expected losses to manipulators, higher levels of overconfidence are required to induce participation when $M$ is higher, and the expected value of participating in a series of pumps decreases in $M$.

**Result 4:** Pumps with more manipulator participation are less attractive to non-manipulators and, therefore, have less non-manipulator participation.

Next, we model the long-run dynamics of pump-and-dumps by considering repeat iterations of the pump-and-dump game (for details, see Section B.5 in Appendix B). The primary empirical implication of this extension is that we expect to see increases in the volumes traded in pump-and-dumps through time when the participant inflow rate exceeds the outflow rate. This scenario can be expected when: (i) there is increasing interest in cryptocurrencies in general, (ii) overconfidence increases, for example, due to the self-attribution of success in past pumps, and (iii) there is a market-wide increase in the propensity to gamble, with cryptocurrency pump-and-dumps providing one outlet for gamblers.

**Result 5:** Participation in pump-and-dumps through time increases when the general level of interest in cryptocurrencies increases, when the returns of past pumps are higher, and when there is an increase in market-wide gambling activity.

A further implication is that, among pump participants, the mix of overconfident individuals and gamblers will vary over time. For example, all else equal, an increase in past returns on pumps is expected to increase the proportion of overconfident individuals among pump participants. Similarly, an increase in the market-wide propensity to gamble, all else equal, is expected to increase the proportion of gamblers.
4.6 Empirical Evidence

We now test the predictions in Results 2 and 3. Overconfidence and gambling preferences are individual characteristics that are best measured at an individual level. However, our data do not allow us to identify individuals and measure their individual characteristics. Instead, we use a pump-level proxy for overconfidence and a market-wide proxy for gambling activity.

Our main proxy for overconfidence exploits the past success or failure of the pump group; it is the average start-to-peak return earned in the two most recent pumps conducted by the Telegram pump groups orchestrating pump \( j \) of coin \( i \) on day \( t \) (Overconfidence\( _{j,i,t} \)).\(^{22}\)

Statman, Thorley, and Vorkink (2006) find that stock trading volumes are positively correlated with previous returns and attribute this effect to positive returns inducing overconfidence. Because of the self-attribution bias, investors tend to attribute positive outcomes to their own skill, fueling overconfidence in their abilities. Therefore, members of pump groups that have had recent success in conducting pumps with high returns are likely to be more overconfident about their prospects in subsequent pumps than others. Our hypothesis that overconfidence contributes to pump participation implies that we should expect to see higher participation in pumps conducted by groups likely to have more overconfident members.

One potential issue is that the proxy might capture group speed or skill instead of just overconfidence. To address this concern, we split past performance into its persistent component and the fluctuations around the persistent component. Because speed and skill are likely to have a degree of persistence, they should be reflected in the persistent component of performance. In contrast, the random fluctuations in performance are likely driven by other factors, yet are still likely to impact overconfidence through self-attribution bias. We therefore regress group-level pump returns on one lag of the group-level return (past performance) and save the residuals from this regression. The modified overconfidence proxy is the average of these residuals in the two most recent pumps for each group. The results using this modified overconfidence proxy (Table IA2 in the Internet Appendix) are consistent with the main overconfidence proxy. The results are also robust to the use of an alternative, less granular proxy for overconfidence, the past five-day cryptocurrency market return.

\(^{22}\) The results are robust to the use of the three most recent pumps instead of two.
Our main proxy for gambling among individuals in the cryptocurrency ecosystem is the revenue of Bitcoin gambling services. For example, SatoshiDICE is a relatively well-known cryptocurrency gambling site in which participants wager Bitcoin and receive a payoff determined by a random number generator. If individuals with gambling preferences use pump-and-dumps as another venue for gambling, pump participation rates are likely to positively correlate with the general demand for gambling within cryptocurrencies. Therefore, our proxy for gambling activity \((Gambling_t)\) is the daily log revenue of known Bitcoin gambling services identified in the Wallet Explorer (WE) database.\(^{23}\) We remove the effects of general cryptocurrency market activity from this gambling measure by regressing it on the contemporaneous value and the three lags of the average daily return and trading volume for all cryptocurrencies and using the residuals from this regression.

For each of the 355 pump-and-dump manipulations in our main sample, we measure the log total trading volume during pump \(j\) in coin \(i\) on day \(t\) from the release of the pump signal to three hours after the pump’s peak price is reached. We regress this participation measure \((Participation_{j,i,t})\) on the Overconfidence\(_{j,i,t}\) and Gambling\(_t\) proxies. We control for lagged volatility, which captures differences in uncertainty about the coin value. We also control for the number of Telegram groups participating in the pump as a proxy for the number of manipulators, because we expect fewer individuals to participate in pumps with more manipulators. Finally, we control for the number of members in Telegram groups participating in the pumps, the liquidity of the coin (log average daily trading volume), and the differences across the two exchanges by including exchange fixed effects (a Yobit\(_t\) indicator variable). While testing the overconfidence channel in Model 1, we also include week fixed effects to absorb other time-series factors.

The results in Table 2 Models 1 and 2 show that both overconfidence and gambling have statistically significant positive associations with the level of participation in pumps. The positive associations are consistent with the notion that both overconfidence and gambling contribute to participation in pump-and-dump manipulations, in line with the mechanisms illustrated in the theoretical framework (Results 2 and 3). The coefficient for

\(^{23}\) WE identifies the Bitcoin wallets of many different entities and reports all blockchain transactions associated with these wallets. WE has a separate section listing Bitcoin wallets of various gambling websites like SatoshiDICE. We use the transaction activity for these wallets to measure the overall gambling activity in cryptocurrencies. Our proxy includes combined gambling from 43 gambling websites. The use of actual transactions recorded on the blockchain enhances reliability since self-reported data from gambling sites may be fabricated.
Overconfidence_{j,t} is statistically significant at the 1% level, while that for Gambling_{t} is statistically significant at the 5% level.

The regressions in Table 2 (Model 3) also show that pump participation is negatively related to the number of manipulators, which is also consistent with the theory (Result 4). More manipulators imply greater aggregate losses for non-manipulators, thereby discouraging participation. Model 4 shows that uncertainty about the fundamental value of a coin (lagged volatility) does not explain pump participation, further supporting the notion that cryptocurrency pumps are not a form of information-based manipulation.

< Table 2 here >

Model 5 includes all regressors. Both overconfidence and gambling retain their positive signs and statistical significance. We use the overconfidence and gambling coefficients from this regression to compare the economic impact of these two drivers of pump participation. When overconfidence increases from its 25th percentile to its 75th percentile (an increase of 87% in past pump returns), pump participation increases by 37.97%. Similarly, when gambling increases from its 25th percentile to its 75th percentile (an increase of $45,321 in the daily Bitcoin gambling volume), pump participation increases by 24.33%.

As an alternative way to interpret the magnitudes, when the overconfidence proxy increases by 10% from its mean of 69.16%, pump participation increases by 2.62%. Similarly, when the Bitcoin gambling volume increases by 10% from its mean of $97,528.81, pump participation increases by 3.39%. The magnitudes of both mechanisms appear to be economically meaningful and are robust to controlling for other drivers. Therefore, we conclude that both overconfidence and gambling are reasons why people participate in pumps.

We also consider an alternative proxy for overconfidence motivated by the literature on self-attribution bias, the past five-day cryptocurrency market return. We do not rely on this measure in our main tests, as it is less granular than our main proxy and could be affected by confounding effects, such as the general level of interest or sentiment toward cryptocurrencies. Nevertheless, the time-series relation between this alternative overconfidence proxy and the level of pump activity is consistent with the overconfidence mechanism (unreported).
Figure 8 plots daily Bitcoin prices alongside the time series of the number of pumps per day (Panel A) and the average pump returns (Panel B). Both the number of pumps per day and pump returns follow patterns similar to the lagged Bitcoin price. This trend is consistent with the notion that overconfidence leads to higher participation in pumps and higher pump returns. Similarly, Figure 8 Panel C shows that the time series of our main proxy for participant overconfidence ($Overconfidence_t$) is positively related with daily pump participation (volume traded during pumps).

We also implement a more direct test of the time-series drivers of participation in pumps. Recall that Result 5 predicts an increase in pump participation over time when there is an increase in the general level of interest in cryptocurrencies, higher past returns on pumps, and increasing market-wide gambling activity. To test these predictions, we estimate time-series regressions in which the dependent variable is daily pump participation (calculated as the daily average of the pump participation measure, $Participation_{j,l,t}$) and the independent variables are daily averages of the overconfidence and gambling proxies used in our previous tests. We also add a time-series proxy for the level of interest in cryptocurrencies; this proxy is the log of the average Google Search Volume Index for cryptocurrency-related search terms on day $t$ ($SearchInt_t$).

The results support the three predicted drivers of pump participation dynamics. All three factors are individually positive and significant drivers of the time-series variation in cryptocurrency pump participation. The results show that much of the time-series variation in cryptocurrency pumps is attributable to variation in overconfidence, gambling, and general interest in cryptocurrencies.

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24 The search terms we include are “altpin,” “Bitcoin,” “crypto,” “cryptocurrency,” and “ICO.”

25 Given these tests are similar to those reported in Table 2 but with less statistical power and generally similar conclusions, we report the results in the Internet Appendix (Table IA3).
5. Characteristics, Determinants, and Effects of Pump-and-Dumps

In this section, we make some additional predictions about cryptocurrency pump-and-dumps from the theoretical framework and test these predictions and identify other characteristics of pumps using our data.

5.1 Price and Volume Dynamics of Pump-and-Dumps

Table 3 reports the characteristics of pump-and-dump manipulations. On average, pumps take around eight minutes to reach their peak price from the time the pump signal is sent (median time of 1.54 minutes) and generate an average return of 65.47% within this short period. For comparison, during our sample period, the highest daily return earned by Bitcoin is 22.72%, and that earned by the S&P 500 index is 2.72%. The return earned by the average pump in eight minutes is around three (24) times higher than the highest return earned by Bitcoin (S&P 500) in an entire day. The average pump return is also approximately four standard deviations higher than the pumped coin’s average daily return. This result suggests that pumps have a substantial effect on the prices of pumped coins, even after considering the high volatility of cryptocurrencies.

The impact of pumps is also evident in volume. The traded volume of pumped coins during manipulation days is, on average, approximately 13.5 times the average daily volume for the pumped coin. As pumps account for around 40% of the total pump-day volume, the trading volume generated by the average pump in eight minutes from start to peak is approximately five times the average daily trading volume for the pumped coin.

Finally, manipulators earn around 49% on an average pump. We use the same method as in Section 3.2 to calculate the percentage profit. Profits are estimated as the difference between the volume-weighted average price during the pump (from start to peak) and that in the two hours preceding the pump signal. The logic is that manipulators (pump group administrators who are aware of the coin being pumped before the pump signal) are likely to buy in the period preceding the release of the pump signal and sell after the release of the pump signal as other participants rush to buy. We calculate the percentage profit in each pump and take the average.
across pumps. This profit figure corroborates our previous observation that cryptocurrency pumps provide manipulators with high returns within a short period.\textsuperscript{26}

\textless Table 3 here \textgreater

Next, we examine the price and volume dynamics around pumps. In the theoretical framework (as illustrated in Figure 4), prices rise before the release of a pump signal as the manipulators build their positions. Prices rise sharply once a pump signal is released as non-manipulators join the pump. Finally, prices reach a turning point, after which they fall back to pre-pump levels.

Figure 9 Panel A provides an empirical analog of these predicted price dynamics, showing the cumulative returns from 15 minutes before to 45 minutes after the release of a pump signal. Prices rise by approximately 10\% in the 15 minutes preceding the pump signal, as manipulators build their initial positions ($M\beta$ in the theoretical framework). Prices rapidly rise by a further 40\% following the release of the pump signal as non-manipulators join the pump ($N'\beta$ in the theoretical framework).\textsuperscript{27} After reaching the peak, prices fall at a slower rate until they reach approximately the initial (pre-pump) level ($P_0$ in the theoretical framework). The price trajectory in Figure 9 is very similar to that in the theoretical framework.

Figure 9 Panel B plots the cumulative volume during the same one-hour window around the pump signal, expressing the cumulative volume as a percentage of the total volume in this one-hour window. Approximately 15\% of the total trading volume during the pump occurs in the 15 minutes leading up to the release of the pump signal as manipulators build their initial positions ($M$ in the theoretical framework). The highest trading rate occurs immediately following the release of the pump signal, as non-manipulators race to buy the coin being pumped. The rate of trading during the dump phase is more subdued.

\textless Figure 9 here \textgreater

\textsuperscript{26} In contrast, the profit number in Table 1 was a percentage calculated from the aggregate earnings and the aggregate position of manipulators.

\textsuperscript{27} The peak in Figure 2.7 (at around 40\%) is lower than the average peak return (around 65\% in Table 2.2) because in Figure 2.7, the individual pumps are aligned based on the pump signal ($t = 0$) but are not aligned in their peaks. Some pumps peak earlier than others, which is why Figure 2.7 does not reflect the average of the peak returns.
5.2 Factors Affecting Pump Outcomes

A basic yet important prediction that follows directly from the expressions for the peak price and manipulator profits is that, ceteris paribus, pumps have higher peak prices, larger peak returns, and higher profits for the manipulators when there are more participants (high $N'$) or the coin is less liquid (high $\beta$).\(^{28}\)

**Result 6:** Pumps with more participants and pumps in less liquid coins have higher peak prices and manipulators earn higher profits.

Interestingly, Results 4 and 6 imply manipulators face a trade-off; they naturally want to take a large position to earn large dollar profits but cannot take too large a position, otherwise there would be few or no non-manipulator participants and the pump would fail.

We test the predictions in Result 6 by regressing measures of pump outcomes on determinants at the pump level. Table 4 reports the results. First, we test the determinants of manipulator profits, approximated by the difference between the volume-weighted average price in the two hours preceding a pump signal and that during the pump (from start to peak) multiplied by the trading volume in the two hours leading up to the pump. Consistent with the theory, the results in Table 4, show a positive relation between manipulator profits and the level of pump participation. A 1% increase in pump participation is associated with a 0.96% increase in manipulator profits. The results are robust to the use of an alternative measure of pump participation, the log number of members in all Telegram groups participating in the pump (Table IA4 in the Internet Appendix). We find weak evidence in support of the prediction that manipulators earn higher profits in less liquid coins: the liquidity measure has the expected negative sign, but is not statistically significant.

Manipulators face a tradeoff in determining their optimal level of pre-pump trading; they want to trade a large volume to make a large dollar profit, but the more they trade, the lower the participation of non-manipulators. In the second regression, shown in Table 4, we find that manipulators tend to take larger positions before releasing the pump signal when they anticipate a higher rate of participation by non-manipulators and when the coin is more liquid since they

\(^{28}\) The expression for peak price is $P_2 = P_1 + N'\beta$, while the expression for manipulators’ profits is $\mathbb{E}[\pi_m] = \frac{\beta M}{2}(N' - 2M)$. 

26
can establish a larger position for a given level of price impact. A 1% increase in pump participation is associated with a 0.44% increase in the manipulators’ pre-pump inventory position and a 1% increase in liquidity increases the size of pre-pump positions by 0.46%.

The theory predicts that pumps have higher peak prices and thus higher peak returns when there is more participation (higher \( N' \)) and less liquidity (higher \( \beta \)). Both predictions are supported by the third regression in Table 4, which shows a positive (negative) relation between the peak returns and the level of pump participation (liquidity). A 1% increase in pump participation is associated with a 0.24% higher pump return.

Finally, we expect that, through time, pumps will become faster (the time from the pump signal to the pump peak will decrease) as slow individuals learn that they are at a disadvantage and cease to participate in pumps. The attrition of slow individuals leaves a higher concentration of fast individuals, thereby reducing the pump duration. This conjecture is supported by the fourth regression in Table 4. The pump duration is negatively related to our proxy for participant experience, which is the log number of pumps conducted in the past by the Telegram groups participating in the present pump. A 1% increase in participant experience reduces pump duration by 0.33%. Pumps conducted by groups that have conducted three pumps previously are, on average, 16.5% faster than those conducted by groups with only two previous pumps.

\(< \text{Table 4 here} >\)

5.3 Which Coins Are More Susceptible to Being Pumped?

Overconfident individuals and gamblers are more likely to participate in pumps of illiquid coins (see Figures 6 and 7), for which there are more extreme returns and greater dispersion in payoffs.

**Result 7:** Non-manipulators are more attracted to pumps in relatively illiquid coins.

Given the positive relation between pump participation and manipulator profits (Result 6), it follows from the framework that manipulators also will choose relatively illiquid coins to pump. However, coins require at least some minimum level of liquidity for the pump to be feasible; otherwise, manipulators cannot even establish their initial position in the coin.
therefore expect relatively illiquid coins, but not the most illiquid, to be the most likely to be manipulated.

To test these predictions, we estimate logistic regressions of the probability that a coin is subject to at least one pump-and-dump manipulation during our sample period. The results in Table 5 indicate that pumps are more likely to occur in smaller coins (coins with lower market capitalization). This result is highly statistically significant, and the magnitude suggests that as market capitalization is doubled the odds of being pumped reduce by 14.79%.29

To allow for the conjectured non-linearity between a coin’s liquidity and its manipulation probability, we include, as regressors, dummy variables for the coin’s liquidity quartile (quartiles of average daily number of trades and average daily dollar trading volume). As conjectured, we find that the likelihood of a coin being pumped is non-monotonically related to liquidity. The second lowest liquidity quartile is the most likely to be targeted by manipulators, followed by the third lowest quartile. Highly liquid coins and highly illiquid coins are less likely to be manipulated. The coefficients of TradesQ2i and TradesQ3i indicate that coins in the second and third quartiles by the number of trades have 263.28% and 118.15% higher odds of being pumped than those in the fourth (highest) quartile.

The finding that the coins in the middle of the liquidity spectrum are most likely to be manipulated mirrors results from stock markets, where the ideal target for a manipulator is a stock that is sufficiently illiquid to be successfully manipulated but sufficiently large and liquid for the manipulation to be worthwhile (Comerton-Forde and Putniņš, 2014). The results presented in Table 5 are robust to the use of an alternative measure of the likelihood that a coin is targeted by manipulators: the number of pumps conducted in the coin (Table IA5).

< Table 5 here >

29 MarketCap has a coefficient of −0.16. This coefficient implies an odds ratio of 0.8521 (e−0.16 = 0.8521). This odds ratio means that if MarketCap increases by one unit, then the odds of the coin being pumped reduce by 14.79%. Since MarketCap is the log to the base two of market capitalization, it increases by one unit when market capitalization is doubled.
5.4 Market Impact of Pump-and-Dumps

Finally, we analyze how pumps affect the market that is pumped and the other markets that trade the pumped coin.\textsuperscript{30} We measure trading volumes, returns, and volatility for each coin-day (for coins that are pumped at least once during the sample period) for the pumped market and the other markets that trade the pumped coin. We then regress these trading characteristics on an indicator for whether the coin was the target of a pump-and-dump manipulation that day (\textit{PumpDay}_{i,t}). We control for the coin’s market capitalization, market fixed effects (a dummy variable for the Yobit exchange), coin fixed effects, and time fixed effects.

The results in Table 6 Panel A show the effects of pumps on the pumped market. Traded volume on the pumped exchange increases significantly during pumps, even after controlling for coin and time effects. The coefficient for \textit{Volume}_{i,t} is statistically significant at the 1% level in all specifications. Trading volume is about 30 to 70 times higher when a coin is pumped.\textsuperscript{31}

Interestingly, the coin’s return measured from before the pump (day \( t - 1 \)) to after the pump (day \( t + 2, \) with day \( t \) being the day of the pump) is not significantly affected by the pump despite the earlier results showing that at intraday horizons, pumps generate large returns in the order of 65%. These results confirm that, consistent with the theory, the prices of pumped coins return to their pre-pump levels following the conclusion of a pump, with no permanent effects on coin valuations.

Lastly, the results show that volatility, measured from the high/low price range for the coin, is considerably higher on the pumped market when a pump-and-dump manipulation occurs. The coefficient for \textit{Volatility}_{i,t} is statistically significant in all specifications and indicates that intraday volatility is between six to eight times higher when a pump occurs, all else equal.\textsuperscript{32}

Although the impact of pumps on volatility is very large conditional on a pump occurring, overall, pumps are not the primary driver of the extremely high levels of volatility in cryptocurrencies. In our sample, the identified pumps occur on less than 5% of the coin-days. Given that the identified cases provide a lower bound on the prevalence of pump-and-dump

\textsuperscript{30} As illustrated in Section 2, pump group administrators typically specify not only a coin but also a cryptocurrency exchange on which the pump will occur, which we refer to as the “pumped market.” Other exchanges that also trade the same coin may be impacted differently and therefore we analyze them separately.

\textsuperscript{31} With the natural log of trading volume as the dependent variable, the estimated effect of a pump is to increase volume by \( e^{3.38} = 29.4 \) to \( e^{4.27} = 71.5 \) times its usual level.

\textsuperscript{32} With the natural log of high/low range-based volatility as the dependent variable, the estimated effect of a pump is to increase volatility by \( e^{1.86} = 6.4 \) to \( e^{2.04} = 7.7 \) times its usual level, all else equal.
manipulations in cryptocurrencies, we assume, for illustration, that pumps occur approximately 5% of the time. If cryptocurrency volatility in the absence of pumps is $\sigma$ and pumps increase this volatility to $7\sigma$ conditional on a pump occurring (as estimated in the regressions), then the overall, unconditional effect of pumps is to increase volatility by 30% of its natural level.\textsuperscript{33} While a 30% increase is a meaningful contribution to the overall volatility, it is only a small fraction of the “excess” volatility in cryptocurrencies as compared to other asset classes. For example, Liu and Tsyvinski (2021) show that Bitcoin returns are five to ten times more volatile than stocks, depending on the return frequency.

< Table 6 here >

Table 6 Panel B tests for spillover effects to other markets that trade the pumped coin. The results show that the trading volume for the pumped coin tends to increase in other exchanges that trade the coin during a pump. The coefficient for $PumpDay_{it}$ is positive in all specifications and statistically significant in Model 2 when we include coin fixed effects. Volatility of pumped coins is also significantly elevated on other exchanges during pump-and-dumps, although not as much as the increase in the pumped market. These results are consistent with arbitrageurs somewhat, but not fully, aligning the prices of coins across markets resulting in some of the price distortion in the manipulated market also being reflected in the prices of the coin in other markets.

6. Welfare Implications and Regulation

Cryptocurrency pump-and-dump schemes affect welfare in three main ways. First, pumps cause wealth transfers. In aggregate, wealth is transferred from the least sophisticated players (e.g., slow players, gamblers, and overconfident players) to manipulators and more sophisticated players (e.g., fast players). The losses incurred by gamblers do not necessarily decrease their welfare, because gamblers receive utility from the act of gambling itself (Conlisk, 1993). Their losses are gains for manipulators and sophisticated players; therefore, wealth transfers from gamblers might increase aggregate welfare by the amount of utility obtained from gambling.

\textsuperscript{33} Given these assumptions and estimates, the volatility in the presence of pumps is $0.95\sigma + 0.05(7\sigma) = 1.30\sigma$, i.e., 1.3 times its natural level, $\sigma$. 
There is, however, scope for harm to gamblers given the lack of regulatory oversight. In other settings, gambling tends to be regulated to reduce the risk of gamblers being excessively exploited by gambling service providers. No such controls exist in cryptocurrency pump-and-dump games.

In contrast, the transfers from slow and overconfident players to manipulators and more sophisticated players are likely to decrease aggregate welfare if the less sophisticated players tend to be less wealthy and, therefore, have a higher marginal utility of wealth than the more sophisticated players. In other financial markets, transfers from less sophisticated to more sophisticated participants are accompanied by an offsetting social benefit from information production and the provision of price discovery by sophisticated investors. No such offsetting benefit is present in cryptocurrency pump-and-dump manipulations.

Second, cryptocurrency pump-and-dumps, like other forms of market manipulation, cause price distortions that harm price accuracy and informativeness. The price distortions could, in theory, degrade the efficiency of resource allocation. However, because the price distortions from pumps are short-lived and tend to disappear within two days of the pump, it is difficult to imagine that cryptocurrency pump-and-dumps have a material effect on resource allocation.

Third, widespread manipulation can damage the perceived integrity of cryptocurrency markets and investor confidence in tokens and tokenization. The existing literature on manipulation of traditional financial markets finds that loss of confidence, reduced participation, and therefore decreased liquidity are among the harmful effects of market manipulation. Financial institutions that are concerned about their reputation might choose not to associate themselves with cryptocurrency markets or tokenization. Additionally, regulators cite manipulation as a reason to restrict the expansion of cryptocurrency markets, tokenization, and cryptocurrency-linked products. For example, the US Securities and Exchange Commission has rejected multiple applications for Bitcoin Exchange-Traded Funds because of concerns about market manipulation in the Bitcoin market. Lack of confidence/trust in cryptocurrency markets

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34 For example, see Comerton-Forde and Putniņš (2014). While it is difficult to measure the long-run impacts of market manipulation because of the challenges in establishing a counterfactual (a market free of manipulation), evidence from laboratory experiments in which it is possible to exogenously create a manipulated and a manipulation-free market suggests that liquidity is harmed by the possibility of the market being manipulated (e.g., Comerton-Forde and Putniņš, 2011). Consistent with this evidence, Cumming and Johan (2011) show that more detailed rules prohibiting practices such as market manipulation tend to increase market liquidity by increasing confidence in markets.
can impede the development and adoption of cryptocurrencies and tokenization of assets. These effects potentially have large negative welfare consequences.

While it is virtually impossible to quantify these welfare consequences, the effects of a stunted adoption of these new technologies could be an order of magnitude larger than the welfare implications of wealth transfers in cryptocurrency pump-and-dump schemes. The cryptocurrency ecosystem has many potential benefits. For example, initial coin offerings (ICOs) are a promising approach to raising capital—see Cong, Li and Wang (2018, 2020) and Li and Mann (2020) for models that show the benefits of using digital tokens. Howell, Niessner and Yermack (2019) find that platforms that list their tokens on exchanges post-ICO tend to be more successful, suggesting that a secondary market contributes to the success of token-based platforms. Therefore, widespread manipulation in cryptocurrency markets matters for reasons beyond the immediate and direct wealth transfers they create.

Currently, the lack of regulation and enforcement, as well as weak or absent oversight from exchanges, allows this form of manipulation to persist and flourish. If left unchecked, manipulation can lead to a loss of confidence in these markets and in the technology of tokenization more broadly. Therefore, there is potential for carefully designed regulation and enforcement that specifically limits manipulation to be beneficial. However, regulation also comes at a cost, including compliance and monitoring. Furthermore, the cryptocurrency ecosystem is currently in a phase of intense innovation, with the potential for substantial economic benefits from new financial system infrastructure. Poorly designed or excessive regulation could very easily suppress that innovation, potentially at a substantial cost to overall welfare. Therefore, any regulatory decisions should balance the benefits against the costs and, ideally, be very specifically targeted towards mitigating harmful activities without stifling the innovation or imposing regulatory burdens on the segments of the cryptocurrency ecosystem that are not involved in harmful activities.

35 Appendix C provides a background for the current regulatory and market surveillance environment in cryptocurrency markets.
7. Conclusion

Cryptocurrencies have given rise to a new form of pump-and-dump manipulation, which is similar in some respects to traditional pump-and-dump manipulation of stocks but completely different in other respects.

Like pump-and-dump manipulation of stocks, cryptocurrency pumps generate large price distortions (average price movements around 65%), generate abnormal trading volumes (13.5 times the average volume), and earn the manipulators millions of dollars. Similar to stock manipulation, manipulators target fairly illiquid coins, although they avoid coins with so little liquidity that manipulation would be infeasible or not sufficiently profitable. Although targeted coins experience extreme returns while being manipulated, their prices subsequently revert to their pre-manipulation levels, with no apparent long-lasting effects on their valuations.

However, in contrast to pump-and-dump manipulation in stock markets, cryptocurrency pump-and-dumps do not rely on information asymmetry and uncertainty about the value of the manipulated security—manipulators openly declare their intentions to manipulate. These manipulations also do not rely on asymmetry in price impacts, as in standard trade-based manipulation of stocks. Rather, our evidence suggests that cryptocurrency pump-and-dumps are akin to a gambling game in which players compete to buy a pumped coin ahead of others and sell near the peak before the price collapses. We show that rational individuals with correct beliefs would not participate in cryptocurrency pumps unless they have an advantage over other participants, because the pumps constitute a negative-sum game. However, we show that individuals with gambling preferences and overconfident individuals that overestimate their ability to sell near the peak price would find pumps attractive. We find empirical support for both of these explanations.

Our findings contribute more broadly to understanding the behavioral underpinnings of speculative activity in markets as there are many examples, particularly in recent years, of phenomena that resemble the pump-and-dump games played in cryptocurrency markets. These include meme stocks, celebrity influencers, “rug-pulls,” and the design of some tokens.
Appendix A. Pump-and-Dump Groups

The group Big Pump Signal (BPS) illustrates how pump-and-dump groups operate. Most groups communicate with their members on one of two instant messaging platforms, Telegram and Discord; BPS uses both. A unique feature of these messaging platforms is that they allow users to form public groups in which only the administrator can broadcast messages to the group members. These groups are public insofar as any Discord or Telegram user can find and join them.

Most messages sent by group administrators fit into one of the following four categories. The first is messages that convey the date/time/exchange of upcoming pumps, the coin being pumped, or the pump results. The second is messages that provide guidance on how pumps work and how members can profit from pumps. The right-hand-side message in Figure 1 provides an example in which the group’s administrators advise members to enter the pump as soon as possible and dump their holdings on outsiders, such as technical traders, who might buy the coin based on the upward price movements. The third is success stories of people profiting from pumps, likely intended to encourage participation. The fourth is messages that advertise the opportunity to become a paid member of the group. Paid members are provided pump-related information (e.g., the coin name) in advance of the general broadcast to all group members (who do not pay a subscription fee), allowing them to take positions ahead of the official pump signal.

Unlike conventional pump-and-dump manipulation, wherein manipulators typically try to mislead market participants into thinking the manipulated security is fundamentally undervalued (Leuz et al., 2017), in cryptocurrency pumps such as the one illustrated above, the manipulators’ goal is to convince people to participate in the pump. Cryptocurrency manipulators typically do not seek to trick people into believing that a coin is mispriced on the basis of fundamentals—they explicitly communicate to the pump group members that a coin is being pumped. We examine in detail a random sample of 70 pumps and find that in none of the 70 cases is there any suggestion that the target coin is undervalued. However, 27 of the 70 signals (39%) urge participants to hold the coin longer to attract outsiders to the pump. This feature of the schemes adds to the uncertainty about how many traders will be drawn to participate in the pump and, consequently, at what point the pump will peak.
Appendix B. Framework Details

B.1 Price Dynamics

We assume that market orders have linear price impacts, consistent with microstructure models of market making (Kyle, 1985). A further motivation for linear price impacts is that they rule out simple trade-based manipulation strategies that could otherwise make unlimited profits by simply buying and selling (Huberman and Stanzl, 2004). The previously discussed anecdotal evidence suggests that cryptocurrency pumps do not seek to exploit non-linearity or asymmetry in price impacts. Furthermore, we test for asymmetric price impacts and fail to reject the null hypothesis that price impacts are symmetric in our empirical data.36

As mentioned in the body of the paper, prices are determined by the function, \( P_t = P_{t-1} + \beta x_t \). Cumulating the net volume received up to time \( t \), \( X_t = \sum_{\tau=1}^{t} x_\tau \), we can rewrite the pricing function as \( P_t = P_0 + \beta X_t \). At the end of Period 1, after the manipulators have bought \( M \) units, pushing the price up by \( M \beta \), the price of the coin is \( P_1 = P_0 + M \beta \).

In Period 2, if \( N' \) players choose to participate, having a combined price impact of \( N' \beta \), the price at the end of Period 2 (which is the price paid by the participant whose order arrives at the market last) will be \( P_2 = P_1 + N' \beta = P_0 + M \beta + N' \beta \).

In Period 3, the individual sell orders posted by both manipulators and non-manipulators are executed at prices \( \{(P_2 - 1\beta), (P_2 - 2\beta), ..., P_0\} \) depending on their random latency and queue position. The price at the end of Period 3, which is the price received by the last participant to sell, will be \( P_3 = P_0 \), because once the manipulators and all pump participants have liquidated their long positions, the cumulative net volume of buys, \( X_3 \), is zero.

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36 We test whether price impacts are symmetric in our data by calculating the Amihud illiquidity ratio (Amihud, 2002) in 30 minute intervals and comparing the measure for price increases and decreases. Illiquidity ratios for price increases are not statistically different from the ratios for price decreases at the 5% significance level.
B.2 Fast and Slow Agents

The specification of the tilted exit price pdfs for fast and slow agents is as follows:

\[ f_i(P_{exit}) = \begin{cases} 
\frac{1}{\beta(M+N'-1)} + S_i P_{exit} - \frac{S_i(\beta(M+N'-1)+2P_0)}{2} & \text{if } P_0 \leq P_{exit} \leq P_0 + \beta(M + N' - 1) \\
0 & \text{otherwise}
\end{cases} \]  \quad (B1)

where \( S_i = s^* > 0 \) for fast players and \( S_i = s^* < 0 \) for slow players.

A fast (slow) player earns higher (lower) expected profits than an “average” participant, i.e., \( \mathbb{E}[\pi_i] \) in Eq. (1). The expected profit for fast (slow) players is higher (lower) than that for an average participant by \( \frac{\overline{\beta}^2 S_i}{2} (M + N - 1)^3 \). Manipulator profits remain unchanged; therefore, the increased expected profit of fast participants is at the expense of slow participants. Fast participants earn positive expected profits when they have a sufficiently large advantage, i.e., when \( S_i > \frac{6(M+2)}{\overline{\beta}^2(M+N'-1)^3} \).

B.3 Overconfident Agents

The perceived pdf of exit prices for overconfident actors is as follows:

\[ f_i(P_{exit}) = \begin{cases} 
\frac{1}{\beta(M+N'-1)} + \varepsilon_i P_{exit} - \frac{\varepsilon_i(\beta(M+N'-1)+2P_0)}{2} & \text{if } P_0 \leq P_{exit} \leq P_0 + \beta(M + N' - 1) \\
0 & \text{otherwise}
\end{cases} \]  \quad (B2)

Replacing the unbiased exit price distribution with the biased one, we find that the expected pump payoff, \( \mathbb{E}[\pi_i] \), for an overconfident player \( i \) is strictly positive when

\[ \varepsilon_i > \frac{6(M+2)}{\overline{\beta}^2(M+N'-1)^3} \equiv \varepsilon^\text{min}. \]  \quad (B3)

The condition in Eq. (B3) implies that cryptocurrency pump-and-dumps have positive expected payoffs for sufficiently overconfident individuals. Assuming risk neutrality, individuals with overconfidence exceeding the threshold \( \varepsilon^\text{min} \) would participate in pumps.

B.4 Gamblers

The series of pumps following the strategy \( q \) (participate until wealth reaches either $b$ or $c$) can be reduced to a binary gamble, \( \tilde{G}_q \),

\[ \tilde{G}_q \sim \left( (c-a), \mathbb{P}(c-a); -(a-b), \mathbb{P}(-(a-b)) \right) \]  \quad (B4)
where \( \mathbb{P}(c - a) \) represents the probability of achieving a \((c - a)\) gain and \( \mathbb{P}(-(a - b)) \) represents the probability of suffering a loss of \((a - b)\). We can estimate the probabilities \( \mathbb{P}(c - a) \) and \( \mathbb{P}(-(a - b)) \) by approximating the gambler’s wealth as a Brownian motion starting at \( \$a \) and terminating upon reaching one of two absorbing barriers on either side of the starting point, \( \$b \) and \( \$c \). Based on Dixit (1993), the estimates for \( \mathbb{P}(c - a) \) and \( \mathbb{P}(-(a - b)) \) are:

\[
\mathbb{P}(c - a) = \exp\left(\frac{-2a\mu}{\sigma^2}\right) - 1 \quad \text{and} \quad \mathbb{P}(-(a - b)) = 1 - \mathbb{P}(c - a) \quad (B5)
\]

where \( \mu \) and \( \sigma^2 \) are the mean and variance of the payoffs from a single pump: \( \mu = -\frac{B}{2}(M + 2) \) and \( \sigma^2 = \frac{B^2}{12}(M^2 + 2M(N' - 1) + 2(N' - 1)^2) \).

Following Barberis (2012), a gambler chooses a strategy \( q \) (the strategy gives the values \( b \) and \( c \) that determine when the gambler stops playing) from a set of strategies \( Q \) to solve the maximization problem:

\[
\max_{q \in Q} V(\tilde{G}_q) \quad (B6)
\]

where \( V(\cdot) \) is the expected value of the gamble based on the Cumulative Prospect Theory (CPT) developed by Tversky and Kahneman (1992). According to CPT, individuals overweight small probability outcomes and underweight large probability outcomes. Additionally, individuals’ valuation of payoffs is concave in the region of gains and convex in the region of losses. These features of CPT explain why individuals are attracted to positively skewed payoffs and serves as the basis for various theories of gambling (Barberis and Huang, 2008; Barberis, 2012). For the figures and the numerical solution, we set the CPT parameters as the benchmark estimates in Barberis (2012), \( \alpha = 0.95 \), \( \delta = 0.5 \), and \( \lambda = 1.5 \).

### B.5 Repeated Games

We examine the dynamics of repeated pump-and-dump games, which is crucial to understand how cryptocurrency pumps-and-dumps evolve through time. Participation in pumps is determined by various factors that can change over time. Let \( N_t^{OC}, N_t^{GP}, \) and \( N_t' \) denote the

---

37 Given that the payoff from a single pump follows a trapezoid distribution rather than a normal distribution, the Brownian motion approximation assumes a sufficiently large number of small bets.

38 The full set of equations for the value function and probability weighting function are in Section IA1 of the Internet Appendix.
number of sufficiently overconfident individuals (OC), the number of participants with gambling preferences (GP), and the total number of participants \( N'_t = N'O_C + N'_GP \), respectively, in the \( t^{th} \) iteration of the game (we also refer to these iterations as rounds).

As overconfident individuals observe the actual prices at which they buy and sell pumped coins and the profits or losses they incur, we expect them to revise their beliefs about their skill and, consequently, about their expected profits. Effectively, some of their overconfidence bias should attenuate over time as they learn about their skill and payoffs, consistent with other models of overconfidence (Gervais and Odean, 2001). In this process, as their overconfidence bias attenuates (as \( \varepsilon_i \to 0 \)), some overconfident individuals cross the threshold \( \varepsilon^{min} \) and switch from participating in pumps to not participating. Let \( \rho'_t^{OC} \) denote the number of overconfident individuals who switch to not participating after round \( t \). Additionally, let \( \lambda^{OC} \) be the Poisson arrival rate of new, sufficiently overconfident individuals.

Similarly, individuals with gambling preferences stop participating in pumps when they achieve their desired gains of \( $(c - a)$ \) or lose \( $(a - b)$ \). Let \( \rho'_t^{GP} \) denote the number of gambling-motivated participants who cease to participate in pumps after round \( t \). Furthermore, let \( \lambda^{GP} \) be the Poisson arrival rate of new participants with gambling preferences. Given these new parameters, the dynamics for the size of the participant pool can be expressed as follows:

\[
\mathbb{E} [\Delta N'_t] = \mathbb{E} [N'_t - N'_{t-1}] = (\lambda^{OC} + \lambda^{GP}) - (\rho'^{OC}_{t-1} + \rho'^{GP}_{t-1}). \tag{B7}
\]

According to the above equation, the change in the number of pump participants depends on the rate at which new overconfident individuals and individuals looking for a gamble arrive at the market and the rate at which existing participants cease to participate after learning about their ability or hitting their maximum gains or losses.
Appendix C. Cryptocurrency Markets and Regulation

Why is manipulation conducted so openly in cryptocurrency markets? There are at least four reasons. First, most cryptocurrency exchanges are underequipped to detect and prevent market manipulation such as pump-and-dump schemes. The Office of the New York State Attorney General (ONYSAG), the highest law office in New York, US, confirms this in a recent investigation into cryptocurrency exchanges. Out of the ten exchanges investigated, only four have formal policies defining actions that constitute manipulative activity. Surprisingly, none of the exchanges has adequate market surveillance tools to detect manipulation, and only two exchanges are working on implementing better surveillance tools. The lack of supervision by exchanges might be an issue of incentives—by turning a blind eye to manipulation, they generate higher trading volumes from the presence of manipulation schemes, thereby increasing their revenue from fees. However, according to the literature, competition between exchanges ensures that exchanges have an incentive to curb market manipulation since they stand to lose potential income if traders wary of manipulation take their trades elsewhere (e.g., Easterbrook, 1986; Daniel and David, 1991).

Second, there has been virtually no action from regulators or law enforcement agencies to counter these cryptocurrency pump-and-dump schemes. Currently, the only regulatory recognition of these schemes is a notice from the US Commodities and Futures Trading Commission advising the public to be wary of cryptocurrency pump-and-dump manipulation and announcing a reward for whistleblowers who report manipulators.

The last two factors that enable cryptocurrency pump-and-dumps are the increasing participation of the public in cryptocurrency markets and strong speculative sentiment among participants. Both factors ensure that there is no shortage of people from whom manipulators can extract profits. Cryptocurrency markets have recently witnessed a significant rise in trading activity, with the trading volume in 2018 exceeding the total trading volume in the preceding five

39 The ONYSAG conducted an in-depth investigation into the working practices of ten cryptocurrency exchanges: Bitfinex, Bitflyer, Bitstamp, Bittrex, Coinbase, Gemini, Hbus, Ibit, Poloniex, and Tidex. Among the exchanges with known instances of pump-and-dump manipulation (Yobit, Cryptopia, and Binance), one exchange (Binance) was contacted by the Attorney General’s office to join the investigation. Binance, however, refused to participate stating that their exchange does not allow trading from New York. ONYSAG conducted a preliminary investigation into whether Binance operated in New York and referred them to the New York Department of Financial Services for potential violation of the state’s virtual currency regulations. The report can be accessed at this link https://virtualmarkets.ag.ny.gov.

40 This advisory statement can be found at this link https://bit.ly/2NH3wj0.
years and an even stronger increase in 2020-2021. Investors entering cryptocurrency markets could increase participation in cryptocurrency pumps. Previous research shows that price movements in cryptocurrencies have a sizeable speculative component (Cheah and Fry, 2015), and speculation-driven investors exhibit a higher tendency to participate in pump-and-dump schemes (Leuz et al., 2017).
References


Levine, M. (2021) Fraud is no fun without friends. In: Bloomberg


Table 1
Aggregate trading and manipulation on cryptocurrency exchanges

This table reports descriptive statistics for the trading activity and prevalence of pump-and-dump manipulation on two cryptocurrency exchanges (Binance and Yobit) between December 2017 and June 2018. Panel A statistics are calculated for all coins listed on both exchanges during the sample period. Panel B statistics are calculated only for pumped coins. A “pump-day” refers to a day on which there is at least one manipulation. Pre-pump volume is the trading volume in a manipulated coin in the two hours preceding the release of the pump signal. Manipulators’ profit is calculated as the difference between the volume-weighted average price during the pump (from start to peak) and the volume-weighted average price in the two hours preceding the release of the pump signal, multiplied by the pre-pump volume.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Statistic</th>
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</thead>
<tbody>
<tr>
<td>Panel A: Market activity</td>
<td></td>
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<tr>
<td>Total coins</td>
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<tr>
<td>Total trading volume ($ million)</td>
<td>19,788.12</td>
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<tr>
<td>Panel B: Manipulation activity</td>
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<tr>
<td>Total number of pumps</td>
<td>355</td>
</tr>
<tr>
<td>Number of pumped coins</td>
<td>197</td>
</tr>
<tr>
<td>Average pumps per pumped coin</td>
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<tr>
<td>Number of pump-days</td>
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<tr>
<td>Average pumps per pump-day</td>
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</tr>
<tr>
<td>Total pump-day volume ($ million)</td>
<td>350.77</td>
</tr>
<tr>
<td>Total pre-pump volume ($ million)</td>
<td>24.38</td>
</tr>
<tr>
<td>Manipulators’ total profit ($ million)</td>
<td>6.04</td>
</tr>
<tr>
<td>Manipulators’ profit (% of pre-pump volume)</td>
<td>24.77%</td>
</tr>
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</table>
Table 2
Determinants of pump participation

This table reports regression results testing the determinants of participation in pump-and-dump manipulations. The dependent variable, $Participation_{j,t}$, is the log total trading volume during pump $j$ in coin $i$ on day $t$, measured from the release of the pump signal to three hours after the pump’s peak price is reached. $Overconfidence_{j,t}$ is the average percentage return in the two most recent pumps organized by the Telegram groups participating in the pump. $Gambling_t$ is the log daily dollar revenue of Bitcoin gambling services after removing the effects of cryptocurrency market activity. $Volatility_{t-1}$ is the log of intraday volatility for the coin on day $t-1$ (the difference between the highest and lowest trade prices scaled by the volume-weighted average price). For missing values of lagged volatility, we use the average volatility for the coin. $Manipulators_{j,t}$ is the log number of Telegram groups participating in the pump. $Members_{j,t}$ is the log number of members in these Telegram groups. $Yobit_t$ is an indicator variable that equals one if the coin is traded on the Yobit exchange. $Liquidity_t$ is the log average daily dollar trading volume of the coin. The sample consists of 355 manipulations on two exchanges (Binance and Yobit) between December 2017 and June 2018. $t$-statistics are in parentheses below the coefficient estimates. Standard errors are clustered by coin and day. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

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<td>$Overconfidence_{j,t}$</td>
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<td>0.35**</td>
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<td>(2.33)</td>
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<td>Observations</td>
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<td>291</td>
<td>355</td>
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</table>
Table 3

Characteristics of pump-and-dump manipulations

This table reports statistics describing the characteristics of the sample of 355 pump-and-dump manipulations. Pump duration, return, and volume statistics are calculated from the start of a pump (the release of the pump signal) to its peak. A “pump-day” refers to a day on which there is at least one manipulation. Manipulators’ percentage profit from a pump is calculated as the percentage difference between the volume-weighted average price during the pump (from start to peak) and the volume-weighted average price in the two hours preceding the release of the pump signal. Manipulators’ dollar profit is calculated as their percentage profit multiplied by the pre-pump volume (volume in the two hours preceding the release of the pump signal). The sample consists of 355 manipulations on two exchanges (Binance and Yobit) between December 2017 and June 2018.

<table>
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<tr>
<th>Variable</th>
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<tbody>
<tr>
<td>Pump duration (minutes)</td>
<td>8.07</td>
<td>21.27</td>
<td>1.54</td>
</tr>
<tr>
<td>Pump return (%)</td>
<td>65.47%</td>
<td>84.44%</td>
<td>34.75%</td>
</tr>
<tr>
<td>Pump return (number of standard deviations of the coin’s daily returns)</td>
<td>4.01</td>
<td>5.27</td>
<td>2.01</td>
</tr>
<tr>
<td>Pump volume (% of pump-day volume)</td>
<td>38.77%</td>
<td>24.22%</td>
<td>39.22%</td>
</tr>
<tr>
<td>Pump-day volume (% of the coin’s average daily volume)</td>
<td>1.351%</td>
<td>1.978%</td>
<td>628%</td>
</tr>
<tr>
<td>Manipulators’ profit (%)</td>
<td>49.02%</td>
<td>47.72%</td>
<td>39.36%</td>
</tr>
<tr>
<td>Manipulators’ profit ($ thousands)</td>
<td>16.77</td>
<td>85.94</td>
<td>0.17</td>
</tr>
</tbody>
</table>
Table 4
Determinants of pump outcomes

This table reports regression results testing how pump participation, participant experience, and liquidity affect manipulators’ profit, pre-pump volume, pump return, and pump duration. The unit of observation is a pump $j$ in coin $i$ on day $t$. $\text{ManipProf}_{j,i,t}$ is the manipulators’ log dollar profit from the pump, calculated as the difference between the volume-weighted average price during the pump (from start to peak) and the volume-weighted average price in the two hours preceding the release of the pump signal multiplied by the trading volume in the two hours leading up to the pump. $\text{PrePumpVol}_{j,i,t}$ is the log dollar trading volume in the two hours preceding the release of the pump signal. $\text{Return}_{j,i,t}$ is the percentage return from the time of the pump signal to the peak of the pump. $\text{Participation}_{j,i,t}$ is the log total dollar trading volume from the start of the pump to three hours after the pump’s peak price is reached. $\text{Experience}_{j,i,t}$ is a proxy for participant experience in the pump, calculated as the log average number of pumps conducted before pump $j$ by Telegram groups participating in pump $j$. $\text{Liquidity}_i$ is the log average daily dollar trading volume of the coin. The sample consists of 355 manipulations on two exchanges (Binance and Yobit) between December 2017 and June 2018. $t$-statistics are in parentheses below the coefficient estimates. Standard errors are clustered by coin and day. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

<table>
<thead>
<tr>
<th>Variable</th>
<th>$\text{ManipProf}_{j,i,t}$</th>
<th>$\text{PrePumpVol}_{j,i,t}$</th>
<th>$\text{Return}_{j,i,t}$</th>
<th>$\text{Duration}_{j,i,t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Participation}_{j,i,t}$</td>
<td>0.96***</td>
<td>0.44***</td>
<td>0.24***</td>
<td>-0.14*</td>
</tr>
<tr>
<td></td>
<td>(14.63)</td>
<td>(6.69)</td>
<td>(5.93)</td>
<td>(-1.49)</td>
</tr>
<tr>
<td>$\text{Experience}_{j,i,t}$</td>
<td>0.21**</td>
<td>0.17*</td>
<td>0.06</td>
<td>-0.33***</td>
</tr>
<tr>
<td></td>
<td>(2.38)</td>
<td>(1.69)</td>
<td>(0.94)</td>
<td>(-3.14)</td>
</tr>
<tr>
<td>$\text{Liquidity}_i$</td>
<td>-0.08</td>
<td>0.46***</td>
<td>-0.23***</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>(-1.62)</td>
<td>(8.65)</td>
<td>(-6.86)</td>
<td>(0.71)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>84.47%</td>
<td>86.51%</td>
<td>27.38%</td>
<td>6.88%</td>
</tr>
<tr>
<td>Observations</td>
<td>181</td>
<td>174</td>
<td>189</td>
<td>189</td>
</tr>
</tbody>
</table>
Table 5
Characteristics of pumped coins
This table reports the results of logistic regressions examining the characteristics of coins that are more likely to be pumped. The unit of observation is a coin i. The dependent variable, \(\text{Pumped}_i\), is an indicator variable that equals one if the coin is pumped at least once during the sample period. \(\text{MarketCap}_i\) is the log of the coin’s average market capitalization in dollars. \(\text{TradesQ1}_i\), \(\text{TradesQ2}_i\), and \(\text{TradesQ3}_i\) are indicator variables that equal one if the coin is in the first (lowest), second, or third quartile by average daily number of trades. \(\text{VolumeQ1}_i\), \(\text{VolumeQ2}_i\), and \(\text{VolumeQ3}_i\) are indicator variables that equal one if the coin is in the first (lowest), second, or third quartile by average daily dollar trading volume. The sample includes all coins on the Binance and Yobit exchanges from December 2017 to June 2018. Chi-square statistics are in the parentheses below the coefficient estimates. Standard errors are clustered by coin. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.05***</td>
<td>-2.29***</td>
<td>-2.35***</td>
</tr>
<tr>
<td>(\text{MarketCap}_i)</td>
<td>(4.00)</td>
<td>(-11.95)</td>
<td>(-12.07)</td>
</tr>
<tr>
<td>(\text{TradesQ1}_i)</td>
<td>-0.16***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\text{TradesQ2}_i)</td>
<td></td>
<td>1.29***</td>
<td></td>
</tr>
<tr>
<td>(\text{TradesQ3}_i)</td>
<td></td>
<td>0.78***</td>
<td></td>
</tr>
<tr>
<td>(\text{VolumeQ1}_i)</td>
<td></td>
<td></td>
<td>-1.10***</td>
</tr>
<tr>
<td>(\text{VolumeQ2}_i)</td>
<td></td>
<td>1.44***</td>
<td></td>
</tr>
<tr>
<td>(\text{VolumeQ3}_i)</td>
<td></td>
<td>0.92***</td>
<td></td>
</tr>
<tr>
<td>Pseudo-(R^2)</td>
<td>7.55%</td>
<td>5.36%</td>
<td>7.81%</td>
</tr>
<tr>
<td>Observations</td>
<td>609</td>
<td>1,307</td>
<td>1,307</td>
</tr>
</tbody>
</table>
Table 6
Effects of pump-and-dump manipulations

This table reports regression results testing how volume, return, and volatility are impacted by pump-and-dump manipulations. The unit of observation is a coin-day, i.e., \( \text{Volume}_{i,t} \) is the log dollar trading volume. \( \text{Return}_{i,t} \) is the percentage return for the coin from day \( t-1 \) to day \( t+2 \). \( \text{Volatility}_{i,t} \) is the log of intraday volatility for the coin on day \( t \) (the difference between the highest and lowest trade prices scaled by the volume-weighted average price). The independent variable of interest is \( \text{PumpDay}_{i,t} \), which equals one if there is a pump for the given coin on the given day and zero otherwise. \( \text{Yobit}_t \) is an indicator variable that equals one if the coin is listed on the Yobit exchange. \( \text{MarketCap}_t \) is the log of the coin’s average dollar market capitalization. Panel A displays the results for the exchange that is the target of the manipulation. Panel B displays the results for all exchanges on which the manipulated coin is listed except the target exchange. The sample includes coins targeted in 355 manipulations on two exchanges (Binance and Yobit) from December 2017 to June 2018. \( t \)-statistics are reported in parentheses below the coefficient estimates. Standard errors are clustered by coin and day. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

<table>
<thead>
<tr>
<th>Variable</th>
<th>( \text{Volume}_{i,t} )</th>
<th>( \text{Return}_{i,t} )</th>
<th>( \text{Volatility}_{i,t} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Panel A: Pump exchange</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \text{PumpDay}_{i,t} )</td>
<td>3.38*** (31.12)</td>
<td>3.50*** (35.57)</td>
<td>4.27*** (30.35)</td>
</tr>
<tr>
<td>( \text{Yobit}_t )</td>
<td>–9.21*** (–164.76)</td>
<td>–6.69*** (–79.80)</td>
<td>0.01 (0.57)</td>
</tr>
<tr>
<td>( \text{MarketCap}_t )</td>
<td>0.05*** (5.24)</td>
<td>0.35*** (29.63)</td>
<td>–0.01*** (–4.39)</td>
</tr>
<tr>
<td>Coin fixed effects</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Day fixed effects</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>82.23% (125.29)</td>
<td>4.13% (2.38)</td>
<td>69.34% (144)</td>
</tr>
<tr>
<td>Observations</td>
<td>14,542</td>
<td>24,816</td>
<td>14,542</td>
</tr>
<tr>
<td>Panel B: Other exchanges</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \text{PumpDay}_{i,t} )</td>
<td>0.09 (0.50)</td>
<td>0.25** (2.38)</td>
<td>0.25 (1.44)</td>
</tr>
<tr>
<td>( \text{MarketCap}_t )</td>
<td>1.00*** (125.29)</td>
<td>1.00*** (135.72)</td>
<td>–0.02*** (–5.86)</td>
</tr>
<tr>
<td>Coin fixed effects</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Day fixed effects</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>55.76% (0.00%)</td>
<td>0.00% (0.00%)</td>
<td>59.52% (0.14%)</td>
</tr>
<tr>
<td>Observations</td>
<td>11,995</td>
<td>13,240</td>
<td>11,995</td>
</tr>
</tbody>
</table>
Figure 1. Sample messages sent on the ‘Big Pump Signal’ Telegram group.
This figure shows messages sent by the administrators of the Telegram group ‘Big Pump Signal’ to its members. In these messages, the administrators announce the date, time, and exchange for a pump in advance of the actual pump (top left-hand-side message). Then, at the commencement of the pump, the group’s administrators send the pump signal by releasing the name of the coin being pumped (bottom left-hand-side message). In this illustration, the coin being pumped is ‘CHAT’, as indicated by the red dashed line around the text ‘CHAT’. The administrators also provide tips to pump participants on how to profit from pumps (right-hand-side message). The group’s administrators advise members to enter the pump as soon as possible and dump their holdings on outsiders who are likely to buy the coin based on rapid upward price movements.
Figure 2. Price and volume for ChatCoin during the ‘Big Pump Signal’ pump.
The pump signal for the ChatCoin pump was sent by the administrators of the ‘Big Pump Signal’ group at 20:00:23 GMT on June 10, 2018. Panel A shows the prices (in cents) for ChatCoin in 15-second intervals between 19:45 GMT and 21:30 GMT on June 10, 2018, i.e., from 15 minutes prior to the pump signal to 90 minutes after the signal. Panel B shows the trading volume ($ thousands) for ChatCoin in five-minute intervals. Panel C shows the prices (in cents) for ChatCoin in a narrower window, between 19:58 GMT and 20:03 GMT on June 10, 2018, i.e., from two minutes before the pump signal to three minutes after the signal.
Figure 3. Pump-and-dump activity through time.
This figure plots three proxies for the level of cryptocurrency pump-and-dump activity from March 2018 to October 2021. The first is intraday reversals for all coins listed on Binance and Yobit. The reversals measure is calculated as the minimum of the percentage price change from the day’s open to the day’s high and the percentage price change from the day’s close to the high. The second is Google search activity for keywords related to cryptocurrency pump-and-dumps. The third is the number of pumps identified in Telegram and Discord pump group chat records and audited pump analysis datasets. The figure plots a seven-week moving average of these measures. Search interest and number of pumps are plotted on a logarithmic scale.
The figure illustrates price paths during pumps based on the theoretical framework. For the baseline illustration, we set initial price $P_0 = $5, number of manipulators $M = 10$, number of participants $N' = 100$, and price impact parameter $\beta = 0.2$. In the high $M$ specification, we increase the number of manipulators to $M = 100$, keeping all other parameters at their baseline levels. In the high $N'$ specification, we increase the number of participants to $N' = 600$, keeping all other parameters at their baseline levels. In the high $\beta$ specification, we increase the price impact parameter to $\beta = 0.8$, keeping all other parameters at their baseline levels.

**Figure 4. Price dynamics in the theoretical framework.**

The figure illustrates price paths during pumps based on the theoretical framework. For the baseline illustration, we set initial price $P_0 = $5, number of manipulators $M = 10$, number of participants $N' = 100$, and price impact parameter $\beta = 0.2$. In the high $M$ specification, we increase the number of manipulators to $M = 100$, keeping all other parameters at their baseline levels. In the high $N'$ specification, we increase the number of participants to $N' = 600$, keeping all other parameters at their baseline levels. In the high $\beta$ specification, we increase the price impact parameter to $\beta = 0.8$, keeping all other parameters at their baseline levels.
This graph plots the probability density functions (pdf) of exit prices (the prices at which a pump participant expects to close their long position) for fast and slow participants. In this illustration, we use the following parameter values: initial price $P_0 = $5, number of manipulators $M = 2$, number of participants $N' = 100$, and price impact $\beta = 0.01$. Assuming an equal proportion of fast and slow agents, the exit price distribution for the average participant is uniform. Fast (slow) agents have a high (low) probability of receiving high exit prices and a low (high) probability of receiving low exit prices. The speed parameter, $S$, is the slope of the transformed pdf. $S$ takes the value $s^*(s^* > 0)$ for fast agents and the value $-s^*$ for slow agents. In this illustration, $s^* = 0.25$. 
Figure 6. Pump-and-dump participation thresholds as a function of overconfidence and other parameters.
This figure plots the minimum overconfidence level \( \epsilon^{\text{min}} \) above which individuals choose to participate in pump-and-dump manipulation games. Panel A plots this overconfidence threshold for different values of the price impact parameter \( \beta \). Panel B plots the threshold for different values of the manipulators’ pre-pump long position \( M \). Panel C plots the threshold for different values of the number of non-manipulators \( N' \). In all three plots, the shaded area is the region in which individuals participate in the pump. To plot the graphs, for illustrative purposes, we use the following parameter values: price impact parameter \( \beta = 0.1 \), number of manipulators \( M = 10 \), and number of non-manipulator participants \( N' = 250 \).
Panel A: Gamblers’ expected value from pumps vs. the price impact parameter ($\beta$)

Panel B: Gamblers’ expected value from pumps vs. the manipulators’ pre-pump long position ($M$)

Panel C: Gamblers’ expected value from pumps vs. the number of participants ($N'$)

Figure 7. Gamblers’ expected value from pumps for different parameter values.
The figure plots the expected value from participating in pumps for an individual with Cumulative Prospect Theory preferences (vertical axis). The horizontal axis is the price impact parameter ($\beta$) in Panel A, the manipulators’ pre-pump long position ($M$) in Panel B, and the number of non-manipulators ($N'$) in Panel C. For illustrative purposes, we set the price impact parameter $\beta = 0.1$, number of manipulators $M = 10$, number of non-manipulator participants $N' = 250$, and initial wealth $a = $6. We set the Cumulative Prospect Theory parameters as follows: value adjustment parameter $\alpha = 0.95$, probability weighting parameter $\delta = 0.5$, and loss aversion parameter $\lambda = 1.5$. We set the profit threshold, $c$, and the loss threshold, $b$, to their optimal values: $c = $245 and $b = $0.
Panel A: Number of pumps and Bitcoin price through time

Panel B: Pump returns and Bitcoin price through time

Panel C: Past pump return and pump volume through time

Figure 8. Pump dynamics through time.
Panel A plots the daily number of pumps and the volume-weighted average Bitcoin price. Panel B plots the average return on pumps (from start to peak) on a given day and the volume-weighted average Bitcoin price. Panel C plots the average return for the two most recent pumps conducted by the Telegram groups responsible for the pumps on a given day (our proxy for overconfidence) alongside the total trading volume during the pumps on that given day (our proxy for pump participation). All variables are smoothed using a ten-day moving average. The sample includes 355 pumps on the Binance and Yobit exchanges between December 2017 and June 2018.
Figure 9. Return and volume dynamics during pump-and-dump manipulations.
The figure plots average cumulative returns (Panel A) and average cumulative volumes (Panel B) before, during, and after a pump signal ($t = 0$). The cumulative returns and volumes are measured in 15-second intervals from 15 minutes (900 seconds) before the pump signal until 45 minutes (2,700 seconds) after the pump signal. Cumulative volume is measured as a percentage of the total trading volume from 15 minutes before the pump signal until 45 minutes after the pump signal. The sample includes 355 pumps on the Binance and Yobit exchanges between December 2017 and June 2018.