

A new wolf in town? Pump-and-dump manipulation in cryptocurrency markets *

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Abstract

We show that cryptocurrency markets are plagued by pump-and-dump manipulation, with at least 355 cases in seven months. 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 and 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. These manipulation schemes are likely to persist as long as regulators and exchanges turn a blind eye.

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

Cryptocurrencies have rapidly grown from a computer science curiosity to an asset class that is penetrating the traditional finance sector and the broader economy.¹ Around \$29 billion has been raised in the primary market for cryptocurrencies (initial coin offerings, ICOs) in just over five years.² The secondary market for the approximately 7,000 cryptocurrencies generated around \$100 trillion in trading volume in 2020.³ It is becoming increasingly important to understand cryptocurrency markets and the new challenges that they bring.

Regulators and central banks have expressed serious concerns about the prevalence of pump-and-dump manipulation in cryptocurrency markets. In these pump-and-dump schemes, manipulators first take a long position in a security and then inflate its price (the pump) before unloading their long positions at inflated prices (the dump). A Wall Street Journal (WSJ) report in 2018 exposed several examples of cryptocurrency pump-and-dump manipulation, claiming it accounts for millions of dollars of trading and showing examples of investors losing money in these schemes (Shifflett and Vigna, 2018). In the same year, the US Commodities and Futures Trading Commission (CFTC) issued a public warning about pump-and-dump manipulation of cryptocurrencies. Widespread manipulation can damage the integrity of cryptocurrency markets, harm investor confidence, and impede adoption of the related financial innovations.

We examine this new form of manipulation in cryptocurrency markets. First, we show that pump-and-dump manipulation in cryptocurrency markets is widespread and accounts for a substantial amount of cryptocurrency trading. Using hand collected data, we identify as many as 355 cases of pump-and-dump manipulation in the space of seven 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 around \$350 million of trading on the manipulation days and that manipulators extract profits of around \$6 million from other participants. A total of 197 distinct cryptocurrencies or “coins” are manipulated, which means

¹ For example, Bitcoin futures contracts are traded on the major US derivatives exchanges like index and commodity futures. More than 500 “crypto funds” manage billions of dollars of investments in cryptocurrencies. Cryptocurrency exchange-traded fund proposals are being evaluated by regulators including the US Securities and Exchange Commission. A number of central banks are issuing digital versions of their fiat currencies. A global consortium of major corporations led by Facebook has proposed a digital currency (Libra) intended to reach billions of users. Intercontinental Exchange (owner of the New York Stock Exchange) and the Swiss stock exchange are setting up their own digital/cryptocurrency exchanges.

² Source: ICOBench and Coinschedule.

³ Source: Coinmarketcap, annualizing the October 2020 monthly volume.

about 15% of all coins in our sample of exchanges are targeted by manipulators at least once in the seven-month period. There are two pumps per day on average. This rate of manipulation is much higher than pump-and-dump manipulation in stock markets in recent decades.⁴

Second, we show that while the 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% in the space of minutes. These average returns are around four standard deviations of the daily cryptocurrency returns, so 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 around 13.5 times the usual daily volume. We also find spillover effects into other markets that trade the manipulated coins but that were not directly targeted by the manipulators: both volume and volatility increase significantly on these other markets during pumps.

Interestingly, while pump-and-dump manipulation of cryptocurrencies is similar to pump-and-dump 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 typical stock market manipulations.⁵ Instead, pump group administrators (manipulators) publicly declare that they are pumping a given coin (releasing a “pump signal”) and call on others to join.⁶ 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

⁴ 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 pump-and-dump rates in cryptocurrency markets are in the order of 40 times higher than for equity markets.

⁵ 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, newsletters, and claiming 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, they sell their holdings, leading to a fall in the stock price (Leuz et al., 2017).

⁶ While this transparency of the manipulator’s intentions is a feature of the manipulations that we examine (those orchestrated by organized pump groups), it is likely that other forms of pump-and-dump manipulation also exist in cryptocurrency markets outside of these organized pump groups. These other forms may involve manipulators attempting to deceive other market participants into thinking a coin is undervalued, like the pump-and-dump manipulation that is found in stock markets.

and uncertainty about the fundamental value of an asset to “fool” market participants into buying a security. Nor do they exploit asymmetry in price impact, which underpins trade-based market manipulation.

This novel feature of cryptocurrency pump-and-dumps raises two interesting questions. First, why do individuals participate in these pumps? Second, how are manipulators able to profit if they are neither fooling participants nor exploiting asymmetry in price impacts? We present a simple theoretical framework to address both of these questions. We show that rational individuals, absent a speed or skill advantage, would not participate in pump-and-dump manipulations because for participants other than the manipulator (who can buy ahead of the pump signal) pumps provide negative expected returns. The intuition is simple. Pumps are a zero-sum game involving re-distributions of wealth between players. Given that manipulators use their advantage to extract a 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 framework to illustrate two types of individuals that would willingly take part in pumps, despite the unattractive returns. The first type is overconfident individuals that overestimate their ability to sell at a price close to the peak. From their perspective, pumps (incorrectly) seem like a profitable game *ex-ante*. The second type is individuals that 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 of these explanations. We estimate regressions of pump participation on measures of overconfidence and gambling. The overconfidence proxy that we use is based on the tendency for past success to increase overconfidence through the self-attribution bias. The gambling proxy measures the level of 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 a gamble.

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 manipulator to influence the price of a traded security. These schemes therefore not only expose unwitting and naïve investors to being exploited by manipulators but are also likely to involve similar costs as other forms of manipulation. For example, a loss of confidence in the integrity of markets, which can inhibit the growth of cryptocurrency markets since institutional investors are likely to steer clear of markets with such widespread manipulation.

We also examine the characteristics of coins that are most likely to be targeted by manipulators and we test how manipulation affects those coins. We find that manipulators target relatively illiquid coins. This observation is consistent with our framework, which predicts 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 back to their pre-pump levels within one or two days (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 in less liquid coins and when more individuals participate in the pump. Through time, pumps tend to speed up; they take less time to reach the peak price from the time the pump signal is sent.

There are many potential benefits from the cryptocurrency ecosystem. A contribution of our paper is to increase our understanding of the downsides so that the sector can be efficiently regulated, rather than shut down entirely. For example, initial coin offerings (ICOs) are a promising new way to raise 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. Our results suggest that, without regulation and enforcement, widespread manipulation will prevail in cryptocurrency secondary markets. Widespread manipulation can harm confidence in cryptocurrencies and tokens and impede their growth and adoption.

Therefore, without proper regulation and enforcement of manipulation, some of the benefits of a token-based ecosystem might remain unrealized.

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.⁷ Aggarwal and Wu (2006) provide a thorough analysis of stock market pump-and-dumps. The cryptocurrency pump-and-dumps that we examine exploit mechanisms that are quite different to those in typical stock market manipulations. There are also data advantages in analyzing cryptocurrency pump-and-dumps. For example, we can observe the exact start times for the pumps (when the pump group releases the “pump signal” to participants) and our sample is not contaminated by a prosecution bias as we obtain data on manipulations irrespective of whether they are prosecuted.⁸ The cryptocurrency markets that we analyze are electronic limit-order-book markets like most of the world’s equity and derivatives exchanges. Thus, our findings about market manipulation can be useful for equity and derivatives markets as well.

Four contemporaneous papers also analyze pump-and-dump manipulation in cryptocurrency markets. Li, Shin, and Wang (2020) characterize the impact of pumps-and-dump schemes on cryptocurrency markets. Xu and Livshits (2019) and Kamps and Kleinberg (2018) develop approaches to predict cryptocurrency pumps *ex-ante* and *ex-post*, respectively. Lastly, Hamrick et al. (2020) examine the factors that affect price jumps in cryptocurrency pumps. While these four studies and our paper have some findings in common, our study has a different focus. For example, like our paper, Hamrick et al. (2020) and Li et al. (2020) find that coins with lower market capitalization have larger price jumps during pumps. Similar to our paper, Li et al. (2020) also find that these schemes are widespread, generate large but short-lived price distortions, and result in substantial wealth transfers between market participants. A novel feature of their analysis is testing the causal effects of these schemes on liquidity. Somewhat surprisingly, they find that these schemes decrease the liquidity of cryptocurrency markets.

In contrast, the focus of our paper is on modelling and testing the mechanisms that enable these schemes to exist in the first place and analyzing how they sustain participation. Theoretically, we show that two behavioral factors—overconfidence and gambling

⁷ For reviews of the market manipulation literature, see Fox, Glosten, and Rautherberg (2018) and Putniņš (2020).

⁸ 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 prosecuted cases of manipulation reflect a tiny and non-random fraction (0.3%) of all manipulation.

preferences—can explain pump participation and we find empirical support for both of these behavioral factors. We also provide further characterization of these schemes beyond what is 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 such manipulation.

This 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 (2020) show that parties related to the cryptocurrency exchange Bitfinex used Tether (a USD-pegged cryptocurrency) 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.

The paper is structured as follows. Section 2 provides background on pump-and-dump groups and the cryptocurrency ecosystem. Section 3 discusses existing market manipulation theories and develops a simple new framework of cryptocurrency pumps. Section 4 details the empirical tests and results. Section 5 discusses the welfare effects of cryptocurrency pumps. Section 6 concludes.

2. Institutional setting

2.1 Illustration of a cryptocurrency pump-and-dump manipulation

To explain the mechanics of a pump, we provide an illustration of a pump by the Big Pump Signal (BPS) group, one of the largest pump groups by number of members (around 63,000 members on Telegram at the time of writing). This pump was on the Binance exchange and involved the cryptocurrency ChatCoin (CHAT). Figure 1 displays communication from BPS administrators to its 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 participants, allowing them to transfer funds to the nominated exchange and be online and waiting 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 format is intended to prevent

machine readability of the message content). 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 fifteen-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 a lot 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 manipulators (the group administrators).⁹ 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 >

2.2 *Pump-and-dump groups*

BPS provides a nice illustration of 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 of the group can broadcast messages to the

⁹ BTC denotes the unit of measurement for Bitcoin. Most cryptocurrencies are traded in BTC pairs.

members of the group. These groups are public insofar as any Discord or Telegram user can find and join these groups.

Most messages sent by group administrators fit into one of four categories. The first category is messages that convey information about pumps, such as details about the date/time/exchange of upcoming pumps, the coin being pumped, or pump results. The second category 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 that might buy the coin based on the upward price movements. The third category is success stories of people profiting from pumps. It is likely that these success stories are intended to encourage participation by creating the perception of large potential profits. Lastly, the fourth category is messages that advertise the opportunity to become a paid member of the group. Paid members (as distinct from the individuals that follow the group messages at no cost) are provided pump-related information (e.g., the coin name) in advance of the general broadcast to all group members, allowing them to take positions in coins ahead of the official pump signal.

Unlike conventional pump-and-dump manipulation, where manipulators typically try to mislead market participants into thinking the manipulated security is fundamentally undervalued (Leuz et al., 2017), in cryptocurrency pumps like 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, as opposed to representing a great investment opportunity. We randomly sample 70 of the pumps and manually categorize each of the messages sent to the pump group members. In none of the 70 cases is there any suggestion that the target coin is undervalued.

Although manipulators are explicit in telling their group members about the intention to pump, they may also hope to attract others, such as technical traders, to buy the manipulated coin following the initial sharp increase in price. As an example, the message in Figure 1 urges pump group members to hold for a long period so that outsiders have a chance to get in and “we can all profit.” Such messages can appear in isolation as general “how to pump better” messages or accompany the pump signal.

In the sample of 70 pump messages that we manually categorize, we find that 27 of them (39%) urge participants to hold the coin for 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. We show later that this uncertainty is crucial in attracting overconfident traders that overestimate their ability to exit at close to the peak price and in attracting gamblers as the uncertainty creates volatility in the outcomes.

2.3 Cryptocurrency markets and regulation

Why is such manipulation conducted so openly in cryptocurrency markets? The answer to this question is four-fold. First, cryptocurrency exchanges are underequipped to detect and prevent most forms of market manipulation, including pump-and-dump schemes. The Office of the New York State Attorney General (ONYSAG), the highest law office in the state of New York in the US, confirms this in a recent investigation into cryptocurrency exchanges.¹⁰ Out of the ten exchanges investigated, only four have formal policies defining actions that constitute manipulative activity. Surprisingly, none of the exchanges have adequate market surveillance methods to detect manipulation, and only two exchanges are working on implementing better surveillance tools. The lack of supervision by exchanges may 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, the previous literature suggests that 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 is 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 (CFTC) advising the public to be wary of pump-and-dump manipulation on

¹⁰ The ONYSAG conducted an in-depth investigation into the working practices of ten cryptocurrency exchanges: Bitfinex, Bitflyer, Bitstamp, Bittrex, Coinbase, Gemini, Hbus, Itbit, 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>).

cryptocurrency exchanges and announcing a reward for whistleblowers who report manipulators.¹¹ This lack of attention from exchanges and regulators implies that cryptocurrencies are vulnerable to market manipulation.

The last two factors that enable cryptocurrency pump-and-dumps are increasing participation of the public in cryptocurrency markets and strong speculative sentiment among participants. Both of these factors ensure that there is no shortage of people from whom manipulators can extract profits. Cryptocurrency markets have witnessed a significant rise in trading activity recently, with trading volume in 2018 exceeding the total trading volume in the preceding five years. Investors entering cryptocurrency markets could increase participation in cryptocurrency pumps, as manipulators can attract a bigger audience into their pump groups. Previous research shows that price movements in cryptocurrencies have a sizeable speculative component (Cheah and Fry, 2015). Previous research also shows that speculation-driven investors have a higher tendency to participate in pump-and-dump schemes (Leuz et al., 2017).

In summary, cryptocurrency pump-and-dump manipulations occur openly in cryptocurrency markets because these markets have little oversight by regulators and exchanges, high levels of investor speculation, and a growing pool of participants.

3. Theoretical framework

3.1 Existing theories

Cryptocurrency pumps-and-dump manipulations cannot be explained by existing market manipulation theories. The two main types of manipulation that have been modelled theoretically are *information-based* manipulation and *trade-based* manipulation (Putniņš, 2012). 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). Information-based manipulation theories require uncertainty about the fair value of a security and information asymmetry as underpinnings of the manipulation (Van Bommel, 2003). If there is little or no uncertainty about the fair value, or no information asymmetry, then uninformed traders will not act on the rumors or false information circulated by manipulators.

¹¹ This advisory statement can be found at this link (<https://bit.ly/2NH3wj0>).

Trade-based manipulation involves manipulating the price of a security by buying and then selling or vice versa. Allen and Gale (1992) show that successful trade-based manipulation can occur if non-manipulators believe that the manipulator is an informed trader and follow the manipulator by trading in the same direction. Such manipulation also requires uncertainty about the fair value of a security and information asymmetry. Additionally, Allen and Gorton (1992) and Jarrow (1992) respectively show that asymmetry in liquidity-motivated trading and price momentum can both drive trade-based manipulation.

Cryptocurrency pump-and-dumps, like the one illustrated in the previous section, do not fit well into either of the two existing market manipulation theories. Manipulators in cryptocurrencies trigger the pump-and-dump episodes through an information release (the pump signal) rather than through buying or selling and as such the manipulation is not trade-based. Yet, 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. Therefore, neither information asymmetry nor uncertainty about the fair value is exploited in cryptocurrency pump-and-dumps, 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 lagged volatility of the coin (Table IA1 in the Internet Appendix). Therefore, a new framework is needed to explain the mechanics of cryptocurrency pumps.

3.2 *A framework for cryptocurrency pump-and-dumps*

We model cryptocurrency pump-and-dumps as a four-period, simultaneous-move trading game. There are three agents: a manipulators (pump group administrators), traders that can choose to participate in the pump following the release of a pump signal, and a simple market maker that facilitates trades.

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 units ($M > 1$) in the coin and send a message to their pump group members stating there will be a pump in Period 2 (without releasing the name of the coin, as per the previous example of 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 of the coin.

We assume 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 simply by buying and selling (e.g., Huberman and Stanzl, 2004). The anecdotal evidence discussed previously suggests that cryptocurrency pumps do not seek to exploit non-linearity or asymmetry in price impacts. We also fail to reject the null hypothesis that price impacts are symmetric in our empirical data.¹² Therefore, prices are determined by the function, $P_t = P_{t-1} + \beta x_t$, where P_t is the price in period t , β is a price impact parameter between zero and one, and x_t is the net volume of buys (buys minus sells) received by the market at time t . Cumulating the net volume received up to time t , $X_t = \sum_{\tau=1}^t x_\tau$ the pricing function can be rewritten 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 $M\beta$, the price of the coin is $P_1 = P_0 + M\beta$.

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 each simultaneously decide whether to participate in the pump (buy one unit of the coin) or not participate (no trade). We restrict trade sizes to one unit to keep the framework simple and focus on the participation decision. Players that decide to participate in the pump race to submit their unit market buy orders to the market. 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 sequence in which the orders of participants 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. The individual participants will buy at prices $\{(P_1 + 1\beta), (P_1 + 2\beta), \dots\}$ depending on their random latency, which determines their queue position. 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 $P_2 = P_1 + N'\beta = P_0 + M\beta + N'\beta$.

¹² We test whether price impacts are symmetrical 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 to the ratios for price decreases at the 5% significance level.

Conditional on participation, in Period 3, players exit the pump (along with the manipulator) by simultaneously submitting unit volume market sell orders. These orders are executed in the same way as the entry orders: random latencies determine the queue positions and execution prices. To keep things simple, we assume the exit queue position is independent of the entry queue position. Therefore, in Period 3, the individual sell orders are executed at prices $\{(P_2 - 1\beta), (P_2 - 2\beta), \dots, P_0\}$ depending on their random latency and queue position. The price at the end of Period 3 (which is the price received by the participant whose order arrives at the market last) 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.

Figure 3 illustrates the timing and price dynamics 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 $P_1 = \$7$ once the manipulators buy 10 units. The price rises further to $P_2 = \$27$ once the 100 pump group participants buy, 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 a larger number of manipulators (higher M), there is a larger run-up in Period 1 before the pump signal is sent and consequently also a higher peak price. With a larger number of 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 (β), 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.

< Figure 3 here >

3.3 *Who participates in pumps?*

What types of individuals would choose to participate in cryptocurrency pump-and-dumps? We start by showing that it is puzzling why individuals would choose to participate in pumps given that the expected return to pump participants in aggregate is negative. We then show that a systematic skill or speed advantage could explain why some individuals participate, shifting the puzzle to the less skilled or slower participants. Lastly, we show that a preference for skewness (gambling preferences) and/or overconfidence can explain the remainder of the participation puzzle.

Start with the simple case of homogenous participants with correct beliefs and consider the prices at which a participant expects to buy and sell the coin. 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 $\{(P_0 + \beta(M + 1)), (P_0 + \beta(M + 2)), \dots, (P_0 + \beta(M + N))\}$ depending on their random latency. Thus, their “entry prices” (P_{entry}) are uniformly distributed from $P_0 + \beta(M + 1)$ to $P_0 + \beta(M + N)$. Similarly, their “exit prices” at which they sell the coin in Period 3 (P_{exit}) are uniformly distributed from P_0 (once all positions are liquidated there are zero net cumulative buys) to $P_0 + \beta(M + N - 1)$, which is the highest price received by the first seller following the peak.¹³ Therefore, individual i ’s expected profit is:

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

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

In contrast, manipulators have an advantage over others by being able to buy the coin ahead of the pump signal, effectively getting a more advantageous entry price than their followers. Therefore, pumps can have positive expected profits for manipulators as long as there are sufficiently many participants (N') in the pump to cover their transaction costs:

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

which is positive if $N' > 2M$.

So, while it is clear that manipulation can be profitable for manipulators, 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 ($\beta M N'/2$). Intuitively, a rational individual with correct beliefs would recognize that a cryptocurrency pump-and-dump is a zero sum game across all participants including the manipulator, in the absence of trading costs. Positive trading costs and the wealth transfer to the manipulator make it a negative-sum game for participants other than the manipulator. Therefore, risk averse or risk neutral rational individuals

¹³ Technically, the entry and exit prices follow discrete uniform distributions. However, given there are typically many participants in pumps (N' in the hundreds or thousands), the continuous distribution is a reasonable approximation and allows us to obtain a tractable solution.

with correct beliefs and no advantage over others would 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.*

But what if participants are not homogenous and instead some are faster or more skilled than others? Some participants might be able to systematically react faster than others, or might have lower latencies in getting orders filled at the exchange, or they simply might be better at “picking the peak” and sensing when the pump is about to enter the dump phase. In effect they would be able to buy at a lower price soon after the release of the pump signal and sell at a higher price soon after the pump peaks.

To incorporate this heterogeneity into the framework, we allow for fast and slow players by tilting the exit price distribution of fast (/slow) players toward higher (/lower) prices (tilting the entry prices as well would merely strengthen the effect). We introduce a speed parameter, S_i , that is the slope of the transformed exit price pdf for player i . For fast players, $S_i = s^* > 0$ whereas for slow players, $S_i = -s^* < 0$ when there are equal proportions of fast and slow participants. The tilted exit price pdfs become:

$$f_i(P_{exit}) = \begin{cases} \frac{1}{\beta(M+N'-1)} + S_i P_{exit} - \frac{S_i(\beta(M+N'-1)+2P_0)}{2} & \text{if } P_0 \leq P_{exit} \leq P_0 + \beta(M+N'-1) \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

The tilted pdfs are illustrated in Figure 4. The extent of the tilt (magnitude of s^*) determines the magnitude of the difference in speed or skill. In any given pump, players still face uncertainty around their exit price, creating the possibility of profits or losses from any given pump. But 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.

< Figure 4 here >

Unsurprisingly, a fast (slow) player earns higher (lower) expected profits than an “average” participant (e.g., $\mathbb{E}[\pi_i]$ in Eqn. (1)). The expected profit for fast (slow) players is

higher (lower) than for an average participant by $\frac{\beta^3 S_i}{2} (M + N - 1)^3$. Manipulator profits remain unchanged and 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, that is, when $S_i > \frac{6(M+2)}{\beta^2(M+N'-1)^3}$.

There are two interpretations of these results. First, it could be that participants know their type (fast or slow). In this case, it is rational for sufficiently fast participants (with sufficiently low risk aversion) to participate in pumps. They may not profit from every pump, but under the conditions given above, 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.

A second interpretation is that participants do not know their speed or skill relative to others. In this case, the puzzle of participation that we described for the homogenous case remains. For example, with an equal proportion of fast and slow participants (implying symmetric tilts of the exit price distributions), a participant's expected exit price distribution if they do not know their type is uniform just like 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 manipulator's gross profit. So, 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 that do not know their skill level participate in pumps.

To resolve this 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 in psychology and behavioral finance shows that most people (including financial market participants) assess their own abilities as being higher than those of the average person (Barber and Odean, 2000; Gervais and Odean, 2001; Alicke and Govorun, 2005; Deaves, Lüders and Luo, 2008). This is known as the better-than-average effect. In cryptocurrency pump-and-dumps, an overconfident individual that believes they are more

skilled than the average player could expect to enter and exit pumps faster than the average participant and therefore obtain more favorable prices, much like the fast individuals 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. 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. Let the overconfidence parameter, ε_i , be the slope of the *perceived* probability density function (pdf) of exit prices:

$$f_i(P_{exit}) = \begin{cases} \frac{1}{\beta(M+N'-1)} + \varepsilon_i P_{exit} - \frac{\varepsilon_i(\beta(M+N'-1)+2P_0)}{2} & \text{if } P_0 \leq P_{exit} \leq P_0 + \beta(M + N' - 1) \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

The overconfidence bias, ε_i , tilts the distribution to increase the perceived probability of exiting the pump at a high price.

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 is strictly positive when:

$$\varepsilon_i > \frac{6(M+2)}{\beta^2(M+N'-1)^3} \equiv \varepsilon^{min}. \quad (5)$$

The condition in (5) implies that cryptocurrency pump-and-dumps have positive expected payoffs for sufficiently overconfident individuals. Assuming risk neutrality, individuals with overconfidence exceeding the threshold, ε^{min} , would participate in pumps. We therefore arrive at the first possible explanation for why individuals participate in cryptocurrency pump-and-dumps.

Result 2: *Sufficiently overconfident individuals participate in cryptocurrency pump-and-dumps.*

Figure 5 illustrates how the minimum overconfidence threshold varies with the other parameters. For the illustration, we set values for two of three of the parameters and plot ε^{min} against the third parameter. Panel A shows that ε^{min} is decreasing in β , implying that pumps of less liquid coins (higher price impact parameter, β) 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 (higher pre-pump to peak return). Consequently, a smaller bias is required in the perceived probability of being able to exit the pump near the peak to make the pump attractive to an

overconfident individual. This effect also provides an explanation for why pumps tend to occur in relatively illiquid coins. Panel B shows that ε^{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 (losses equivalent to manipulator gains) on other participants, so a greater perceived ability to exit near the peak price (higher overconfidence) is required to make the pump attractive. Finally, Panel C shows that ε^{min} is decreasing in N' , implying that pumps with a high number of participants are more attractive to overconfident players. This effect arises because a greater number of participants leads to a higher peak price and more dispersion in exit prices, so only a small bias in the perceived likelihood of exiting the pump near the peak is required to make a pump attractive to an overconfident individual.

< Figure 5 here >

Next, we consider whether gambling preferences can explain why individuals participate in pump-and-dumps. Previous literature shows that individuals have a preference for “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. Similarly, 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 red/black 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 $c - a$. The series of pumps following this strategy q can be reduced to a binary gamble, \tilde{G}_q ,

$$\tilde{G}_q \sim ((c - a), \mathbb{P}(c - a); -(a - b), \mathbb{P}(-(a - b))) \quad (6)$$

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 these probabilities 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 $\$c$.¹⁴ Based on Dixit (1993), the estimates for $\mathbb{P}(c - a)$ and $\mathbb{P}(-(a - b))$ are

$$\mathbb{P}(c - a) = \frac{\exp\left(\frac{-2a\mu}{\sigma^2}\right) - 1}{\exp\left(\frac{-2c\mu}{\sigma^2}\right) - 1} \quad \text{and} \quad \mathbb{P}(-(a - b)) = 1 - \mathbb{P}(c - a) \quad (7)$$

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

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

$$\max_{q \in Q} V(\tilde{G}_q) \quad (8)$$

where $V(\cdot)$ is the expected value of the gamble based on the Cumulative Prospect Theory (CPT) developed by Tversky and Kahneman (1992). In essence, the gambler determines the optimal b and c that lead to the highest expected payoff. 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 the CPT explain why individuals are attracted towards positively skewed payoffs and serves as the basis for various theories of gambling (Barberis and Huang, 2008; Barberis, 2012).

We solve the gambler's optimization problem numerically, determining the optimal b and c for a given set of parameter values.¹⁵ We find the optimal b is $\$0$ and the optimal c is $\$245$. This implies that a gambler starting off with $a = \$6$ participates in pumps either until they go bankrupt or until they have accumulated a wealth of $\$245$. This strategy yields a positive

¹⁴ 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.

¹⁵ We set $P_0 = \$5$, $\beta = 0.01$, $M = 10$, $N' = 1,000$, $a = \$6$. We set the CPT parameters as the benchmark estimates in Barberis (2012), $\alpha = 0.95$, $\delta = 0.5$, and $\lambda = 1.5$. The full set of equations for the value function and probability weighting function are in Section IA1 of the Internet Appendix.

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 6 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 gambler’s expected value of participating in the series of pumps, $V(\tilde{G}_q)$. The figure shows that gamblers are more attracted to cryptocurrency pump-and-dumps (higher expected value) when the pumped coins are relatively illiquid (high β), there are relatively few manipulators (low M), and there are many participants (high N'). These relations are similar to those of overconfident individuals.

< Figure 6 here >

3.4 Pump characteristics

Having established two possible reasons for why individuals participate in cryptocurrency pump-and-dumps—overconfidence and gambling—we now summarize some other empirically testable predictions from the framework. A basic but important prediction that follows directly from the expressions for the peak price ($P_2 = P_1 + N'\beta$) and the manipulator profits ($E[\pi_m] = \frac{\beta M}{2}(N' - 2M)$) is that, *ceteris paribus*, pumps have higher peak prices, larger pre-pump-to-peak returns, and higher profits for the manipulator when there are more participants (high N') or the coin is less liquid (high β).

Result 4: *Pumps with more participants and pumps in less liquid coins have higher peak prices and earn manipulators higher profits.*

From the illustrations in Figures 5 and 6, we know that more pre-pump trading by manipulators (M) makes pumps relatively less attractive to individuals of all kinds—rational

agents would expect larger expected losses to manipulators, higher levels of overconfidence are needed to induce participation when M is higher, and the expected value of participating in a series of pumps decreases in M .

Result 5: *Pumps with more manipulator participation are less attractive to non-manipulators and therefore have less non-manipulator participation.*

Figures 5 and 6 also show that overconfident individuals and individuals that consider pumps as a form of gambling are more likely to participate in pumps of relatively illiquid coins, for which there are more extreme returns and greater dispersion in payoffs. However, coins do require at least some minimum level of liquidity to be feasible otherwise manipulators cannot even establish their initial position in the coin.

Result 6: *Non-manipulators are more attracted to pumps in relatively illiquid coins.*

Interestingly, Results 4 to 6 imply considerations on the strategy of manipulators. Manipulators face a trade-off in determining the size of the position to take initially: they would 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. Similarly, when it comes to the choice of coin, a manipulator would want to select relatively illiquid coins to make the pumps attractive to non-manipulators and generate high peak prices, but highly illiquid coins are probably not feasible to pump.

3.5 Repeated games

Next, 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 through time. Let N_t^{OC} , N_t^{GP} , and N_t' denote the number of sufficiently overconfident individuals (OC), the number of participants with gambling preferences (GP), and the total number of participants ($N_t' = N_t^{OC} + N_t^{GP}$) in the t^{th} iteration of the game (we also refer to these iterations as rounds). Now consider how these numbers can change through time.

As overconfident individuals observe the actual prices at which they buy and sell pumped coins and the profits or losses that they incur, we expect them to revise their beliefs about their skill and therefore about their expected profits. Effectively, some of their overconfidence bias should attenuate through 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 $\varepsilon_i \rightarrow 0$), some overconfident individuals will cross the threshold ε^{min} and switch from participating in pumps to not participating. Let ρ_t^{OC} denote the number of overconfident individuals that switch to not participating after round t . Additionally, let λ^{OC} be the Poisson arrival rate of new, sufficiently overconfident individuals that participate in pumps.

Similarly, individuals with gambling preferences stop participating in pumps if they achieve their desired gains of $\$(c - a)$ or lose $\$(a - b)$. Let ρ_t^{GP} denote the number of gambling-motivated participants that cease to participate in pumps after round t . Also, let λ^{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 are given by,

$$\mathbb{E}[\Delta N'_t] = \mathbb{E}[N'_t - N'_{t-1}] = (\lambda^{OC} + \lambda^{GP}) - (\rho_{t-1}^{OC} + \rho_{t-1}^{GP}). \quad (9)$$

Equation (9) simply states that 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 overconfident individuals and gamblers cease to participate in pumps due to learning about their ability or hitting their maximum gains or losses. Importantly, as stated in Result 4, the number of participants determines the peak prices in pump-and-dumps as well as the manipulator profits.

The empirical implication of equation (9) is that we expect to see increases in the volumes traded in pump-and-dumps, increases in pump-and-dump peak returns, and increases in manipulator profits through time when the participant inflow rate ($\lambda^{OC} + \lambda^{GP}$) exceeds the outflow rate ($\rho_t^{OC} + \rho_t^{GP}$). This scenario can be expected when: (i) there is increasing interest in cryptocurrencies in general, (ii) overconfidence increases, for example, due to 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 7:** 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 of equation (9) is that among pump participants, the mix of overconfident individuals and gamblers will vary through 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. Empirical tests

4.1 Data

We identify cases of pump-and-dump manipulation in cryptocurrency exchanges using chat history data from Telegram pump-and-dump channels. We hand-collect pump data for the cryptocurrency exchange Binance and add to it pump data for the cryptocurrency exchange Yobit from the database compiled by PumpAnalysis (PA).¹⁶ In our sample, we only 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. Our sample therefore only includes events in which the pump group administrator is 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 the pump signal is sent. We also extract ancillary information such as the number of pumps 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.

We couple the information on pumps with data on all trades on the Binance and Yobit exchanges (sourced from the official Binance API and data provider Kaiko, respectively). After reconciling the information on pumps with the trades data and restricting our focus to Binance

¹⁶ Although the website hosting the dataset (PumpAnalysis.com) is no longer active, we downloaded a copy of the data before it went offline. We conducted a data audit to verify the quality of dataset and did not find any material inaccuracies. In this audit, we verified the pump-related information in the database against the actual information found in the chat history of the pump-and-dump group for a random sample of pumps. Our copy of the PA dataset is available upon request.

and Yobit due to the availability of reliable trade data, our sample consists of 355 pumps (64 on Binance and 291 on Yobit). The earliest pump in our sample occurs on December 29, 2017, while the last pump is on June 22, 2018. Based on the number of pump group members, up to 23.3 million total participants are involved in the pump-and-dumps during our sample period.

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.

4.2 Pump-and-dump prevalence and characteristics

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 seven-month sample, there are 1,307 cryptocurrencies (“coins”) traded on the two exchanges with a combined volume of around \$20 billion. The 355 instances of pump-and-dump manipulation that we identify and for which we have all the necessary data occur in 197 distinct coins. Therefore, around 15% of all coins (197/1,307) experience at least one pump-and-dump manipulation during the seven-month period with an average of 1.80 pumps per coin and 2.67 pumps per pump-day.¹⁷ These manipulation rates (being a lower bound as 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 around \$24.38 million of coins in the two hours leading up to the pumps, resulting in a conservatively estimated aggregate profit to manipulators of around \$6.04 million.¹⁸ This figure

¹⁷ A “pump-day” is a day in which there is at least one instance of pump-and-dump manipulation.

¹⁸ 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 exchanges (0.1% of transaction value on Binance and 0.2% on Yobit; the actual fees could be lower, depend 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

reflects the estimated wealth transfer from pump participants (pump group followers) to manipulators (pump group administrators) during our sample. As a return, manipulators earn around 24.77% in the space of minutes or hours.

< Table 1 here >

Table 2 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% in that short space of time. For comparison, the highest daily return earned by Bitcoin during our sample period is 22.72%, and that for 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 around 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, around 13.5 times the average daily volume for the pumped coin. Since 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 around five times the average daily trading volume for the pumped coin.

Finally, manipulators earn around 49% on an average pump. Here we calculate the percentage profit in each pump and take the average across pumps, whereas the profit number in Table 1 was a percentage calculated from the aggregate earnings and aggregate manipulator position. This profit figure corroborates our previous observation that cryptocurrency pumps provide manipulators with high returns in a short period of time.

< Table 2 here >

average effective spread for Bitcoin trades on Gdax, see Dyhrberg, Foley, and Svec (2018)), the profit estimate decreases to \$5.44 million.

Next we examine price and volume dynamics around pumps. In the theoretical framework (as illustrated in Figure 3), prices rise before the release of a pump signal as 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 7 Panel A provides the empirical analogue of these predicted price dynamics, showing the cumulative returns from 15 minutes before to 45 minutes after a pump signal is released. Prices rise around 10% in the 15 minutes preceding the pump signal, most likely due to the price impact of manipulators building their initial positions ($M\beta$ in the theoretical framework). Prices rapidly rise a further 40% following the release of the pump signal due to the price impact of non-manipulators joining the pump ($N'\beta$ in the theoretical framework).¹⁹ 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 7 is very similar to that in the theoretical framework.

Panel B in Figure 7 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 that 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. This pre-pump trading activity is likely a result of manipulators building their initial positions in the pumped coin (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 phase in which the price returns to its pre-pump level is more subdued.

< Figure 7 here >

4.3 Determinants of pump participation

Results 1 to 3 in the theoretical framework predict that while rational individuals would not participate in pumps, overconfident individuals and individuals seeking to gamble would

¹⁹ The peak in Figure 7 (at around 40%) is lower than the average peak return (around 65% in Table 2) because in Figure 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 7 does not reflect the average of the peak returns.

potentially be attracted to cryptocurrency pump-and-dumps as games in which they perceive positive expected value. We now test these predictions. Overconfidence and gambling preferences are individual characteristics and 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 proxy for overconfidence measured at the pump level and an aggregate 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 ($Overconfidence_{j,i,t}$).²⁰ Statman, Thorley, and Vorkink (2006) find that trading volumes in stock markets are positively correlated with previous returns and attribute this effect to positive returns inducing investor overconfidence. Due to self-attribution bias, investors have a tendency to attribute positive outcomes (e.g., earning high returns) to their own skill, thereby fueling overconfidence in their abilities. Given this logic, members of pump groups that have had recent success in conducting pumps with high returns are more 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 that are conducted by groups likely to have more overconfident members. Our results are robust to using an alternative, less granular proxy for overconfidence, being the past five-day cryptocurrency market returns.

Our main proxy for gambling among individuals that are part of the cryptocurrency ecosystem is the revenue of known gambling services that accept gambles in Bitcoin. For example, SatoshiDICE is a relatively well-known cryptocurrency gambling site in which participants wager an amount of Bitcoin and receive a payoff determined by a random number generator. If individuals with gambling preferences use pump-and-dumps as yet another venue for gambling, pump participation rates are likely to be positively correlated with the general demand for gambling within cryptocurrencies. Thus, our proxy for gambling activity ($Gambling_t$) is the daily log revenue of known Bitcoin gambling services identified in the

²⁰ The results are robust to the use of three most recent pumps instead of two.

Wallet Explorer (WE) database.²¹ We remove the effects of general cryptocurrency market activity from this gambling measure by regressing it on the contemporaneous value and three lagged values 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 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 that individuals are less likely to participate in pumps the more manipulators participate. Finally, we also control for the number of members in Telegram groups participating in the pumps, the liquidity of the coin (log average daily trading volume), and differences across the two exchanges by including exchange fixed effects (a $Yobit_i$ 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 3 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 $Overconfidence_{j,i,t}$ is statistically significant at the 1% level while the coefficient for $Gambling_t$ is statistically significant at the 5% level. The regressions in Table 3 (Model 3) also show evidence that pump participation is negatively related to the number of manipulators, consistent with the theory (Result 5). 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

²¹ WE identifies the Bitcoin wallets of many different entities and reports all blockchain transactions associated with those wallets. The use of actual transactions recorded on the blockchain enhances reliability since self-reported data from gambling sites could be fabricated. Overall, our proxy includes combined gambling from 43 gambling websites.

supporting the notion that cryptocurrency pumps are not a form of information-based manipulation.

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 mechanisms on pump participation. When overconfidence increases from its 25th percentile to its 75th percentile (an increase in prior pump returns by 87%), pump participation increases by 37.97%. Similarly, when gambling increases from its 25th percentile to its 75th percentile (an increase in daily Bitcoin gambling volume of \$45,321), 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 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. We therefore conclude that both overconfidence and gambling are reasons why people participate in pumps.

< Table 3 here >

We also consider an alternative proxy for overconfidence motivated by the literature on self-attribution bias: the past five-day cryptocurrency market returns. We do not rely on this measure in our main tests as it is less granular than our main proxy and it could capture other confounding effects such as the general level of interest or sentiment towards cryptocurrencies. Nevertheless, the time-series relation between this alternative overconfidence proxy and the level of pump activity is consistent with the overconfidence mechanism.

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 similar patterns as 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 ($Overconfidence_t$) has a positive relation with daily pump participation (volume traded during pumps).

< Figure 8 here >

We also implement a more direct test of the time-series drivers of participation in pumps. Recall that Result 7 predicts pump participation increases through 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, $Participation_{j,i,t}$) 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, being the log of the average Google Search Volume Index for cryptocurrency related search terms on day t ($SearchInt_t$).²²

The results support the three predicted drivers of the pump participation dynamics.²³ 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 can be attributed to variation in overconfidence, gambling, and general interest in cryptocurrencies.

4.4 Determinants of pump outcomes

Our theoretical framework predicts that a number of factors such as the coin liquidity and the level of participation determine pump-and-dump outcomes such as manipulator profits and pump returns. We now test these predictions by regressing measures of outcomes on determinants at the individual 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 the volume-weighted average price during the pump (from start to peak) multiplied by the trading volume in the two hours leading up to the pump. The theory (Result 4) predicts that manipulator profits are higher when more non-manipulators participate in the pump (higher N') and for

²² The search terms we include are “altcoin”, “Bitcoin”, “crypto”, “cryptocurrency”, and “ICO”.

²³ Given these tests are similar to those reported in Table 3, but with less statistical power and generally similar conclusions, we report the results in the Internet Appendix (Table IA4).

pumps in less liquid coins (higher β). We find that former prediction is supported by the results in Table 4, which show a positive relation between manipulator profits and the level of pump participation. The estimates suggest that a 1% increase in pump participation is associated with a 0.96% increase in the manipulators' profit. Recall that manipulator profits come at the expense of non-manipulator pump participants. Intuitively, with more participants, manipulators are able to extract greater payoffs from pumps. The results are robust to using an alternative measure of pump participation: the log number of members in all Telegram groups participating in the pump (Table IA2 in the Internet Appendix). We find weak evidence, at best, in support of the second prediction regarding manipulators earning more profits for pumps in less liquid coins. Although our liquidity measure has the predicted direction (negative), it 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 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 such that they are able to establish a larger position for a given level of price impact. The estimates suggest that 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 (Result 4) predicts that pumps have higher peak prices, and thus higher pre-pump-to-peak returns, when there is more participation in the pump (higher N') and less liquidity (higher β). Both of these predictions are supported by the third regression in Table 4, which shows a positive (/negative) relation between pre-pump-to-peak returns and the level of pump participation (/liquidity). The estimates suggest that 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 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 relatively slow individuals leaves a higher concentration of relatively fast individuals, thereby reducing the duration of pumps. We find support for this conjecture in the fourth regression of Table 4. The duration of pumps 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. The estimates suggest that a 1% increase in participant experience reduces pump duration by 0.33%. This magnitude implies that pumps conducted by groups that have conducted three pumps previously are, on average, 16.50% faster than pumps conducted by groups that have only conducted two pumps previously.

< Table 4 here >

4.5 Which coins are more likely to be pumped?

The characteristics of coins more likely to be targeted by a pump-and-dump groups will be driven by what coins are most attractive to manipulators given that manipulators choose which coins to pump. The theoretical framework suggests that, all else equal, a manipulator's profits increase with the illiquidity of the coin (β) as larger price impacts lead to higher returns, and the number of pump participants (N'). The manipulator's profits do not depend on the type of participant or their motivation (e.g., overconfident individuals vs. gamblers), but simply on the aggregate number of participants that the manipulator is able to attract. Therefore, we can expect that manipulators will target relatively illiquid coins and coins that are attractive to a large number of non-manipulators.

Considering the preferences of non-manipulators, both overconfident individuals and gamblers are likely to prefer coins that are less liquid and have larger price impacts (see Result 6). Therefore, we expect that liquidity, whether measured directly or proxied by coin market capitalization, will be the primary driver of which coins are more 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 during our sample period. The results in Table 5 indicate that pumps are more likely 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%.²⁴

²⁴ $MarketCap_i$ 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 $MarketCap_i$ increases by one unit, then the odds of the coin being pumped reduce by 14.79%. Since $MarketCap_i$ is the log to the base two of market capitalization, it increases by one unit when market capitalization is doubled.

While the theory predicts that both manipulators and non-manipulators have a preference for illiquid coins, for a pump to be feasible, there must be at least some minimum level of liquidity, otherwise it is not even possible for manipulators to establish a sufficient initial position to warrant pumping the coin. To allow for this potential non-linearity, as regressors we include dummy variables for the coin's liquidity quartile (quartiles of average daily number of trades and average daily dollar trading volume). We find that indeed the likelihood of a coin being pumped is not monotonically related to liquidity. The second lowest liquidity quartile is most likely to be targeted by manipulators, followed by the third lowest quartile. The highly liquid coins and highly illiquid coins are less likely to be manipulated. The coefficients of $TradesQ2_i$ and $TradesQ3_i$ indicate that coins in the second and third quartile by number of trades have 263.28% and 118.15% higher odds of being pumped than coins in the fourth (highest) quartile, while the lowest quartile coins have 42.31% lower odds of being pumped than the highest quartile coins.

The finding that 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 in Table 5 are robust to using an alternative measure of the likelihood that a coin is targeted by manipulators: the number of pumps conducted in the coin (Table IA3).

< Table 5 here >

4.6 Impact of pump-and-dumps on market characteristics

Finally, we analyze how pumps affect market characteristics, both on the market that is pumped and on other markets that trade the pumped coin.²⁵ We measure trading volumes, returns, and volatility 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

²⁵ 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.

pump-and-dump manipulation that day ($PumpDay_{i,t}$). 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 is significantly increased during pumps on the pumped exchange, even after controlling for the various other coin and time effects. The coefficient for $Volume_{i,t}$ is statistically significant at the 1% level in all specifications. The coefficient suggests that trading volume is about 30 to 70 times higher when a coin is pumped.²⁶

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 regression results therefore confirm that, consistent with the theory, the prices of pumped coins return back to their pre-pump levels following the conclusion of a pump, with no permanent effects on the valuations of the coins.

Lastly, the results show that volatility, measured from the high/low price range for the coin on day t , is considerably higher on the pumped market when a pump and dump occurs. The coefficient for $Volatility_{i,t}$ is statistically significant in all specifications and indicates that intraday volatility is between six and eight times higher when a pump occurs than it is at other times, controlling for other factors.²⁷

Although the impact of pumps on volatility is very large *conditional* on a pump occurring, pumps are not the major driver of the extremely high levels of volatility in cryptocurrencies overall. In our sample, the pumps that we have been able to identify occur on less than 5% of the coin-days. Given the cases that we identify provide a lower bound on the prevalence of pump-and-dump manipulation in cryptocurrencies, assume for illustration that pumps occur approximately 5% of the time. If cryptocurrency volatility in the absence of pumps is σ and pumps increase that volatility to 7σ conditional on a pump occurring (as estimated in the regressions) then the overall, unconditional, effect of pumps is to increase volatility by 30%

²⁶ 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.

²⁷ 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.

of its natural level.²⁸ While a 30% increase is a meaningful contribution to overall volatility, it is only a small fraction of the “excess” volatility in cryptocurrencies compared to other asset classes. For example, Liu and Tsyvinski (2020) 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 onto other markets that trade the pumped coin but that were not directly targeted by the pump group administrators. The results show that trading volume for the pumped coin tends to increase on other exchanges that trade the coin during a pump. The coefficient for $PumpDay_{i,t}$ 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, however not as much as the increase in volatility on the pumped market. These results are consistent with arbitrageurs somewhat, but not fully, aligning the prices of coins across markets so that some of the price distortion of a manipulated coin on a manipulated market is reflected in the prices of that coin on other markets.

5. Welfare implications

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 the 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 and therefore the wealth transfers from gamblers may increase aggregate welfare by the amount of utility obtained from gambling. There is, however, scope for harm to the gamblers given the lack of regulatory oversight. In other settings, gambling tends to be regulated to reduce the risk that

²⁸ Given these assumptions and estimates, volatility in presence of pumps is $0.95\sigma + 0.05(7\sigma) = 1.30\sigma$, i.e., 1.30 times its natural level, σ .

gamblers are 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 payers 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, being 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 harm 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 cryptocurrency pump-and-dump schemes have any material effects on resource allocation.

Third, widespread manipulation damages the integrity of cryptocurrency markets and investor confidence with respect to tokens and tokenization. Financial institutions that are concerned about their reputation might choose not to associate themselves with cryptocurrency markets or tokenization more broadly. 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 applications for Bitcoin Exchange-Traded Funds (ETFs) multiple times due to concerns about market manipulation in the Bitcoin market. Lack of confidence/trust in cryptocurrency markets can impede the development and adoption of cryptocurrencies and tokenization of financial securities. These effects potentially have large negative welfare consequences.

While it is virtually impossible to quantify these welfare consequences, it seems likely the effects of stunted adoption of these new technologies could be an order of magnitude larger than the welfare implications of the wealth transfers from participating in cryptocurrency pump-and-dump schemes. Therefore, widespread manipulation in cryptocurrency markets matters for reasons beyond the immediate and direct wealth transfers that they create.

6. Conclusion

We show that cryptocurrencies have given rise to a new form of pump-and-dump manipulation. This manipulation is similar in some respects to traditional pump-and-dump manipulation of stocks, but it is 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 average volume), and earn manipulators millions of dollars. Similar to manipulation of stocks, 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 particular coins. These manipulations also do not rely on asymmetry in price impacts like 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 out ahead of others, 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) as they constitute a negative-sum game. However, individuals with gambling preferences would participate under certain conditions and so too would overconfident individuals that overestimate their ability to sell near the peak price. We find empirical support for both of these explanations for why people participate in pumps.

Despite the finding that many pump participants treat them as a form of game or gambling, cryptocurrency pump-and-dumps nevertheless constitute market manipulation as they involve trading and actions (inducing others to trade) undertaken with the intention to influence the price of a traded security (see Fox, Glosten, and Rauterberg (2018) and Putniņš (2020) for a discussion of what constitutes market manipulation). Currently, a lack of regulation and enforcement, as well as weak or absent oversight from exchanges, allows this form of manipulation to persist and flourish. For example, we find well over 300 cases of cryptocurrency pump-and-dump manipulation in the space of a mere seven months. If regulators and exchanges

continue to turn a blind eye, cryptocurrency pump-and-dumps are likely to continue. If left unchecked, widespread manipulation in cryptocurrency markets can lead to a loss of confidence in these markets and in the technology of tokenization more broadly. Stunted adoption of what is potentially a very promising technological development in finance could have substantial negative effects on welfare.

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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 in 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.

Characteristic	Statistic
Panel A: Market activity	
Total coins	1,307
Total trading volume (\$ million)	19,788.12
Panel B: Manipulation activity	
Total number of pumps	355
Number of pumped coins	197
Average pumps per pumped coin	1.80
Number of pump-days	133
Average pumps per pump-day	2.67
Total pump-day volume (\$ million)	350.77
Total pre-pump volume (\$ million)	24.38
Manipulators’ total profit (\$ million)	6.04
Manipulators’ profit (% of pre-pump volume)	24.77%

Table 2
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 the peak price observed during the pump. A “pump-day” refers to a day in which there is at least one manipulation. Manipulators’ percentage profit from a pump 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. 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.

Variable	Mean	Standard deviation	Median
Pump duration (minutes)	8.07	21.27	1.54
Pump return (%)	65.47%	84.44%	34.75%
Pump return (number of standard deviations of the coin’s daily returns)	4.01	5.27	2.01
Pump volume (% of pump-day volume)	38.77%	24.22%	39.22%
Pump-day volume (% of the coin’s average daily volume)	1,351%	1,978%	628%
Manipulators’ profit (%)	49.02%	47.72%	39.36%
Manipulators’ profit (\$ thousands)	16.77	85.94	0.17

Table 3
Determinants of pump participation

This table reports regression results testing the determinants of participation in pump-and-dump manipulations. The dependent variable, $Participation_{j,i,t}$ 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. $Overconfidence_{j,i,t}$ is the average percent 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. $Volatility_{i,t-1}$ 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. $Manipulators_{j,i,t}$ is the log number of Telegram groups participating in the pump. $Members_{j,i,t}$ is the log number of members in these Telegram groups. $Yobit_i$ is an indicator variable that equals one if the coin is traded on the Yobit exchange. $Liquidity_i$ 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.

Variable	Dependent variable = $Participation_{j,i,t}$				
	(1)	(2)	(3)	(4)	(5)
$Overconfidence_{j,i,t}$	0.57*** (4.89)				0.37*** (2.93)
$Gambling_t$		0.28** (2.04)			0.35** (2.33)
$Manipulators_{j,i,t}$			-0.20** (-2.38)		-0.23** (-2.59)
$Members_{j,i,t}$			0.57*** (6.08)		0.51*** (5.26)
$Volatility_{i,t-1}$				0.03 (0.68)	0.08 (1.49)
$Liquidity_i$	0.15* (1.78)	0.20*** (2.65)	0.20*** (2.76)	0.21*** (2.86)	0.09 (1.18)
$Yobit_i$	-6.35*** (-7.84)	-4.77*** (-6.89)		-4.68*** (-6.98)	
Week fixed effects	Yes	No	No	No	No
R^2	87.58%	77.72%	21.51%	77.45%	23.80%
Observations	264	355	291	355	211

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 . $ManipProfit_{j,i,t}$ 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. $PrePumpVol_{j,i,t}$ is the log dollar trading volume in the two hours preceding the release of the pump signal. $Return_{j,i}$ is the percentage price change from the time of the pump signal to the peak of the pump. $Duration_{j,i,t}$ is the number of seconds from the release of the pump signal to the peak of the pump. $Participation_{j,i,t}$ is the log total dollar trading volume from the start of the pump to three hours after the pump's peak price is reached. $Experience_{j,i,t}$ 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 . $Liquidity_i$ 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.

Variable	Dependent variable =			
	$ManipProfit_{j,i,t}$	$PrePumpVol_{j,i,t}$	$Return_{j,i,t}$	$Duration_{j,i,t}$
$Participation_{j,i,t}$	0.96*** (14.63)	0.44*** (6.69)	0.24*** (5.93)	-0.14* (-1.49)
$Experience_{j,i,t}$	0.21** (2.38)	0.17* (1.69)	0.06 (0.94)	-0.33*** (-3.14)
$Liquidity_i$	-0.08 (-1.62)	0.46*** (8.65)	-0.23*** (-6.86)	0.05 (0.71)
R^2	84.47%	86.51%	27.38%	6.88%
Observations	181	174	189	189

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, $Pumped_i$, an indicator that equals one if the coin is pumped at least once during the sample period. $MarketCap_i$ is the log of the coin's average market capitalization in dollars. $TradesQ1_i$, $TradesQ2_i$, and $TradesQ3_i$ are indicator variables that equal one if the coin is in the first (lowest), second, or third quartile by average daily number of trades. $VolumeQ1_i$, $VolumeQ2_i$, and $VolumeQ3_i$ 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.

Variable	Dependent variable = $Pumped_i$		
	(1)	(2)	(3)
<i>Intercept</i>	2.05*** (4.00)	-2.29*** (-11.95)	-2.35*** (-12.07)
<i>MarketCap_i</i>	-0.16*** (-7.30)		
<i>TradesQ1_i</i>		-0.55* (-1.77)	
<i>TradesQ2_i</i>		1.29*** (5.65)	
<i>TradesQ3_i</i>		0.78*** (3.25)	
<i>VolumeQ1_i</i>			-1.10*** (-2.92)
<i>VolumeQ2_i</i>			1.44*** (6.24)
<i>VolumeQ3_i</i>			0.92*** (3.85)
Pseudo- R^2	7.55%	5.36%	7.81%
Observations	609	1,307	1,307

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, t . $Volume_{i,t}$ is the log dollar trading volume. $Return_{i,t}$ is the percentage return for the coin from day $t - 1$ to day $t + 2$. $Volatility_{i,t}$ 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 $PumpDay_{i,t}$, which equals one if there is a pump for the given coin on the given day and zero otherwise. $Yobit_i$ is an indicator variable that equals one if the coin is listed on the Yobit exchange. $MarketCap_i$ 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.

Variable	Dependent variable =								
	$Volume_{i,t}$			$Return_{i,t}$			$Volatility_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Pump exchange									
$PumpDay_{i,t}$	3.38*** (31.12)	3.50*** (35.57)	4.27*** (30.35)	-0.02 (-0.60)	0.01 (0.48)	0.03 (0.97)	1.86*** (37.60)	1.87*** (36.97)	2.04*** (34.89)
$Yobit_i$	-9.21*** (-164.76)		-6.69*** (-79.80)	0.01 (0.57)		-0.01 (-1.06)	0.00 (0.07)		-0.08*** (-2.58)
$MarketCap_i$	0.05*** (5.24)		0.35*** (29.63)	-0.01*** (-4.39)		-0.01*** (-4.63)	-0.03*** (-3.72)		-0.02*** (-3.35)
Coin fixed effects	No	Yes	No	No	Yes	No	No	Yes	No
Day fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
R^2	82.23%	4.13%	69.34%	0.39%	0.00%	0.23%	2.32%	2.48%	2.63%
Observations	14,542	24,816	14,542	14,542	24,814	14,542	13,295	20,826	13,295
Panel B: Other exchanges									
$PumpDay_{i,t}$	0.09 (0.50)	0.25** (2.38)	0.25 (1.44)	-0.09*** (-4.95)	-0.00 (-0.02)	-0.04** (-2.30)	0.30*** (4.30)	0.26*** (3.89)	0.38*** (5.45)
$MarketCap_i$	1.00*** (125.29)		1.00*** (135.72)	-0.02*** (-5.86)		-0.02*** (-5.83)	-0.03*** (-11.05)		-0.03*** (-10.60)
Coin fixed effects	No	Yes	No	No	Yes	No	No	Yes	No
Day fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
R^2	55.76%	0.00%	59.52%	0.14%	0.00%	0.14%	1.18%	0.09%	1.19%
Observations	11,995	13,240	11,995	14,452	19,276	14,452	11,887	13,094	11,887

Saturday, June 9, 2018



Big Pump Signal

The next pump will be:

Exchange: Binance

Date: 10-06-2018

Time: 8PM GMT

Advantage: The pump will be Free-For-All (FFA)

30K edited 11:19:33 AM

Big Pump Signal 63542 subscribers

Show recent messages

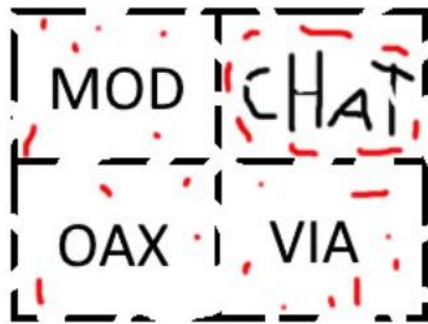


Big Pump Signal

2 minutes left



Big Pump Signal



As a lot of outsiders are watching and see the coin move up quickly, they will FOMO in. We have been observing this coin and saw it almost breakout a few times today. Currently, the coin is up to the exact point where a breakout is certainly possible. The last push of our combined effort can certainly achieve this! In addition to this, we will use our contacts in order to spread the call across social media to get even more outsiders in. Today it's even more important than at other times to hold so outsiders can get on the train and we can all sell at a profit.

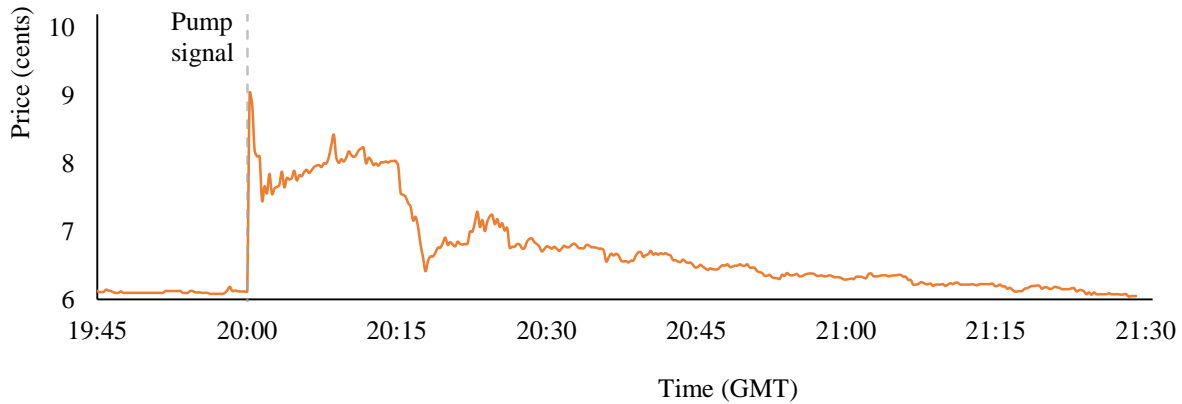
Some tips for this free for all pump:

- Have both your mobile telegram app and the webapp open.
- It is smart to split your screen, so have telegram on the left side and binance on the right side of your screen so you can react quickly.
- If you are in early market buy and limit sell (never market buy 100%, they will not work).
- IF YOU ARE IN LATE, DO NOT MARKET BUY (or if you are really late do not invest at all).

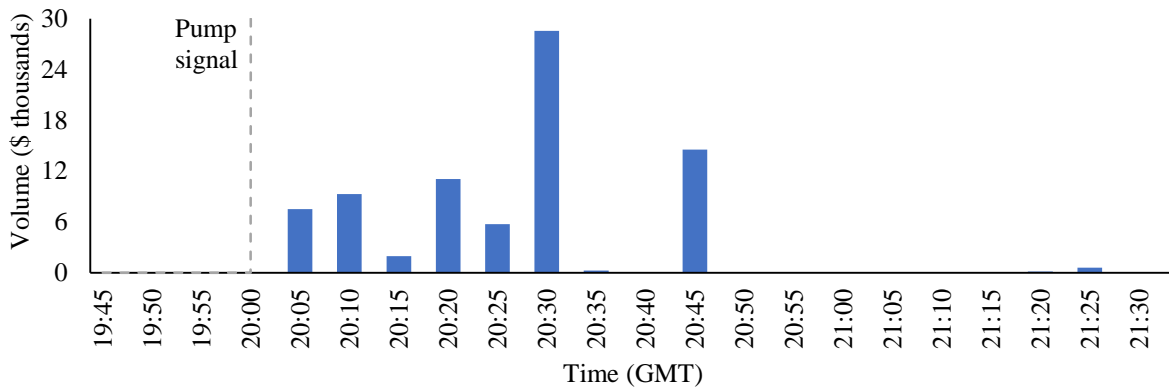
Figure 1. Sample messages sent on the 'Big Pump Signal' Telegram group.

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.

Panel A: Price movement for ChatCoin before, during, and after the ‘Big Pump Signal’ pump



Panel B: Trading volume for ChatCoin before, during, and after the ‘Big Pump Signal’ pump



Panel C: Magnified price movement graph for ChatCoin during the ‘Big Pump Signal’ pump

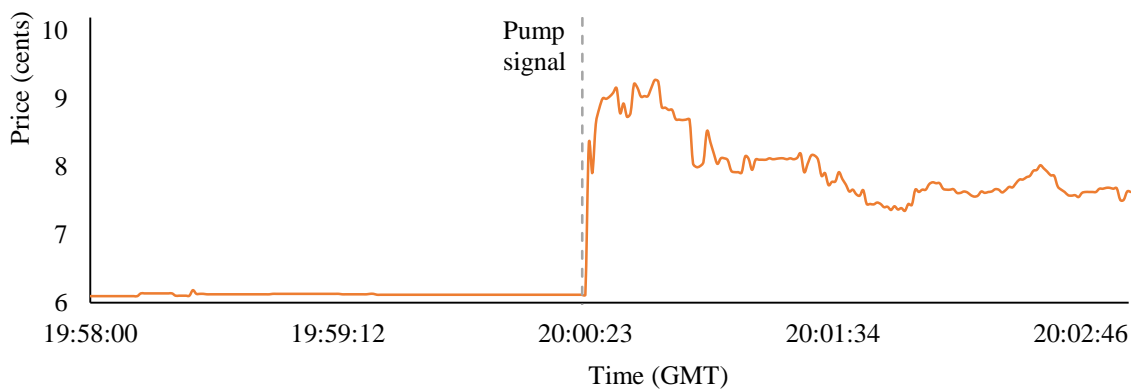


Figure 2. Price and volume for ChatCoin during the ‘Big Pump Signal’ pump.

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) in 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.

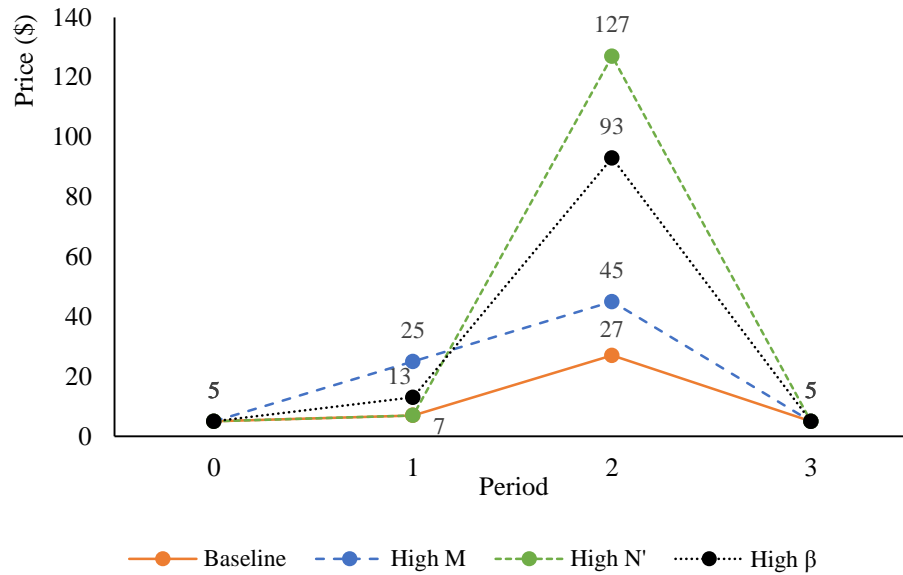


Figure 3. Price dynamics in the theoretical framework.

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 β specification, we increase the price impact parameter to $\beta = 0.8$, keeping all other parameters at their baseline levels.

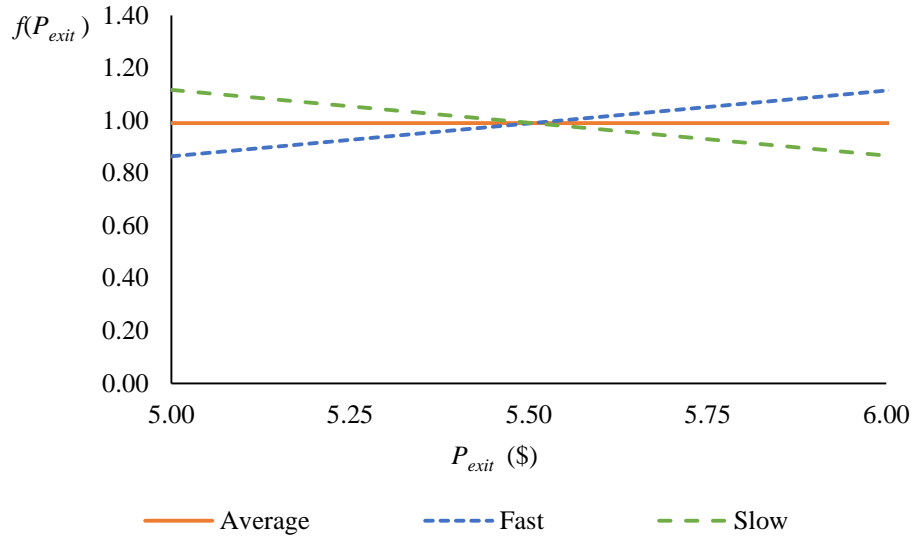
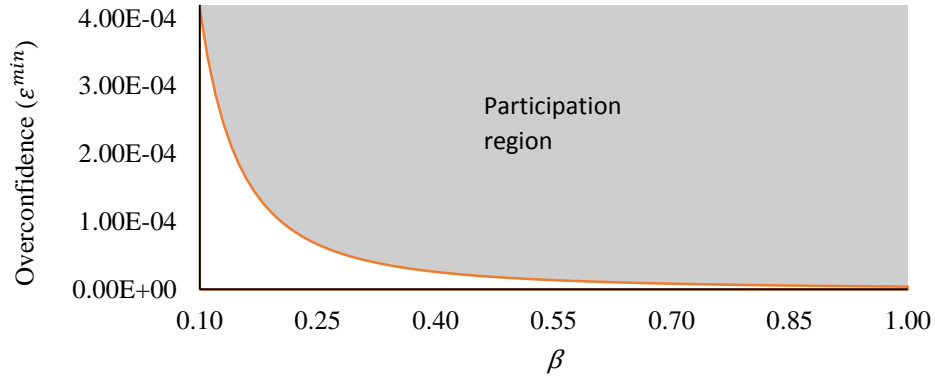


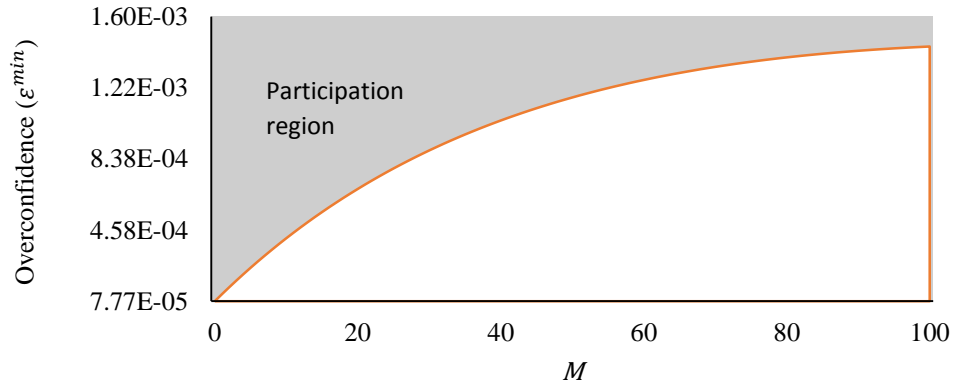
Figure 4. Exit price distributions for fast and slow individuals.

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, $s^* = 0.25$.

Panel A: Participation region for different levels of overconfidence (ϵ^{min}) and price impact (β)



Panel B: Participation region for different levels of overconfidence (ϵ^{min}) and manipulators' pre-pump long position (M)



Panel C: Participation region for different levels of overconfidence (ϵ^{min}) and number of participants (N')

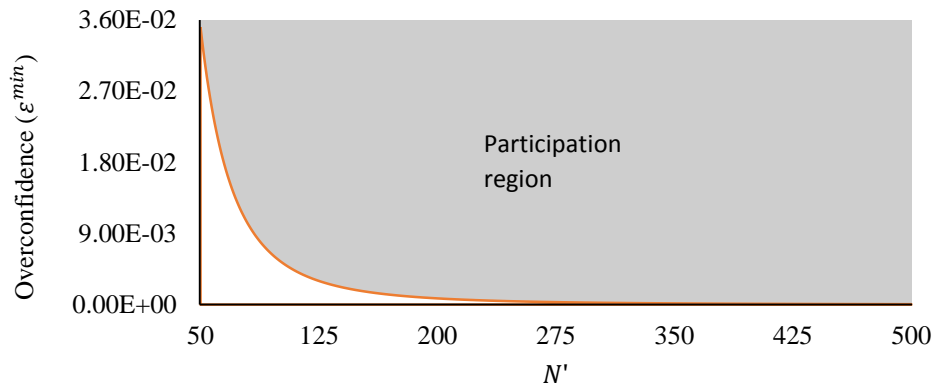
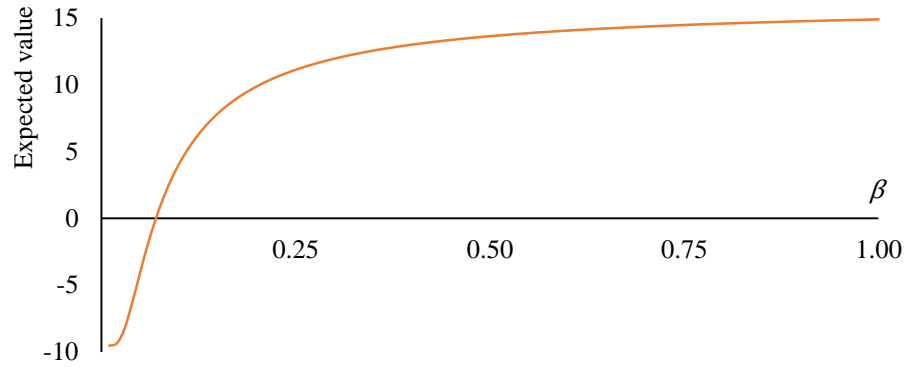


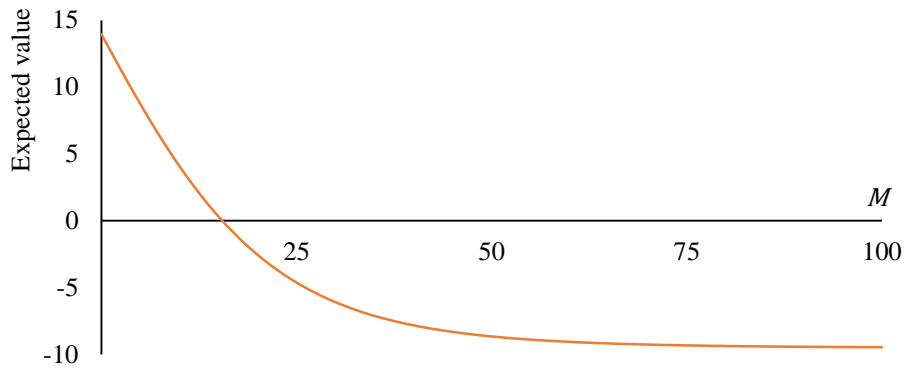
Figure 5. Pump-and-dump participation thresholds as a function of overconfidence and other parameters.

This figure plots the minimum overconfidence level (ϵ^{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 (β). 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: Gambler's expected value from pumps vs. the price impact parameter (β)



Panel B: Gambler's expected value from pumps vs. the manipulators' pre-pump long position (M)



Panel C: Gambler's expected value from pumps vs. the number of participants (N')

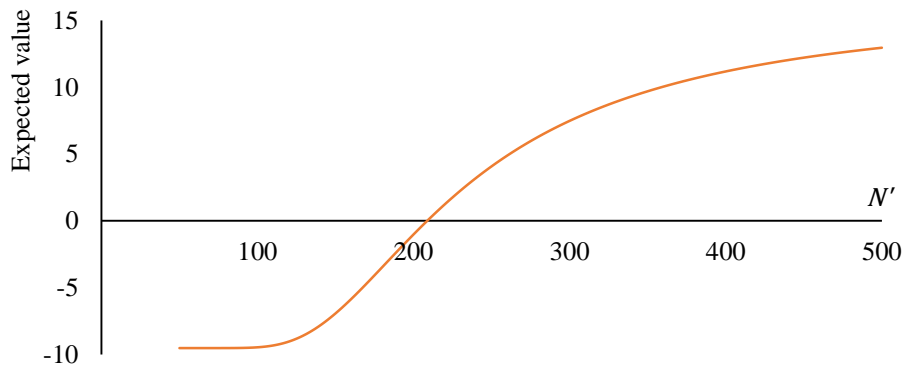
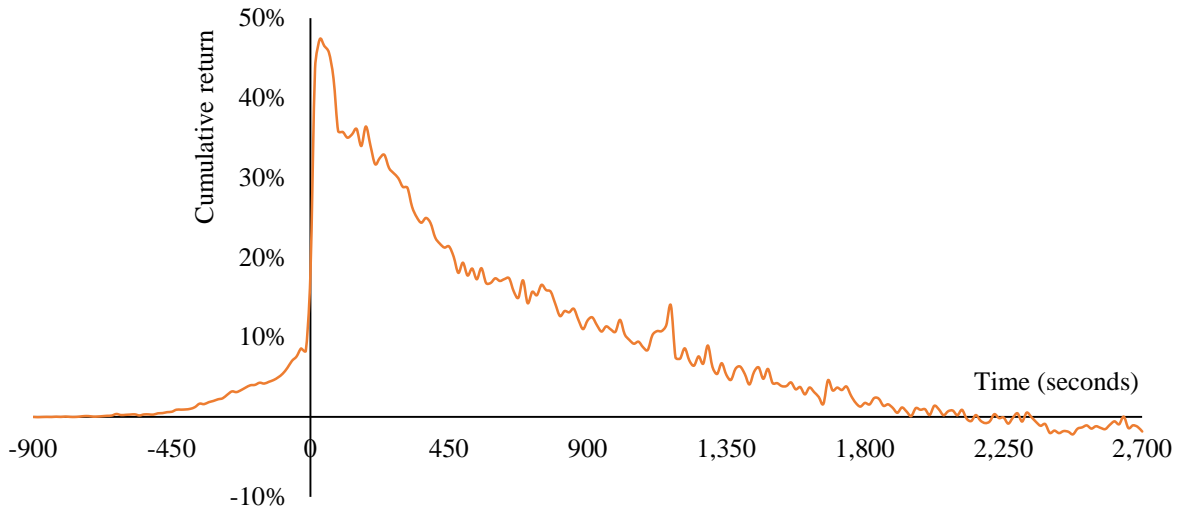


Figure 6. Gambler's expected value from pumps for different parameter values.

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 (β) in Panel A, the manipulators' pre-pump long position (M) in Panel B, and the number of non-manipulator participants (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: Return during pumps



Panel B: Volume during pumps

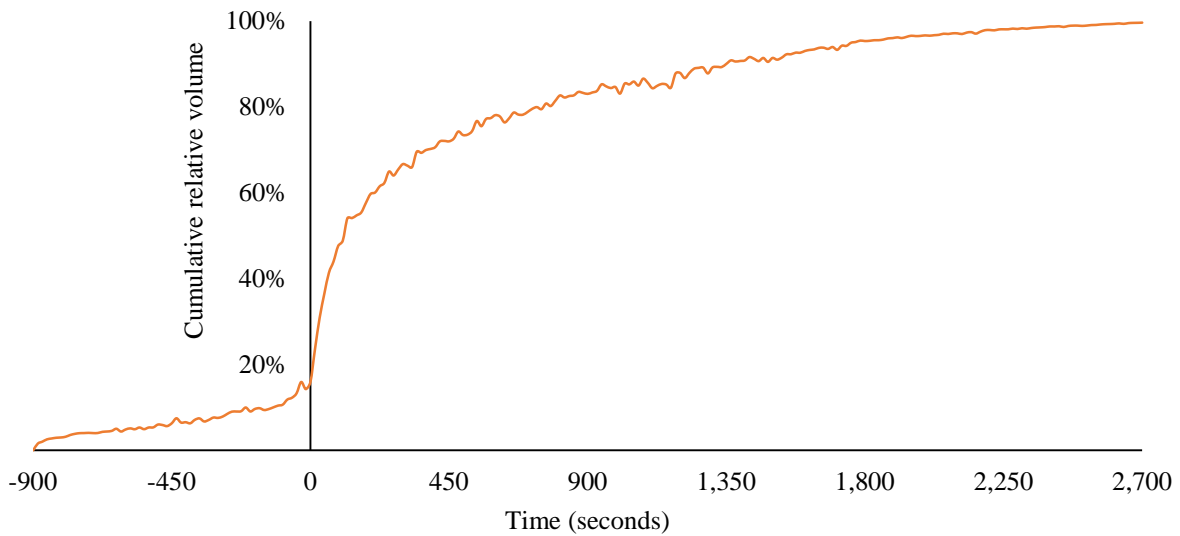
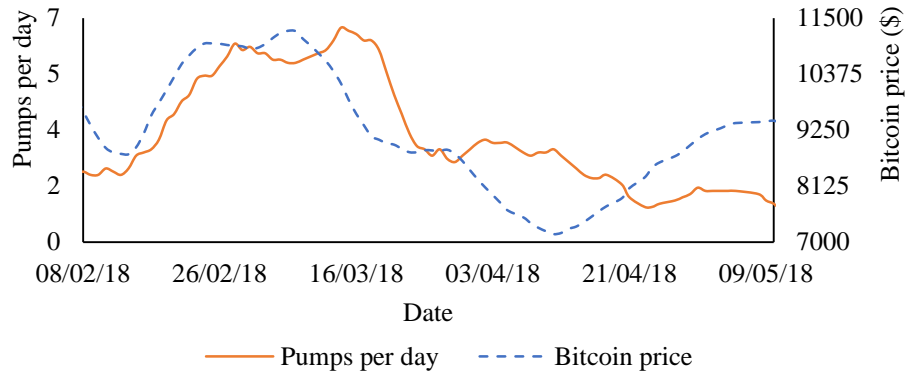


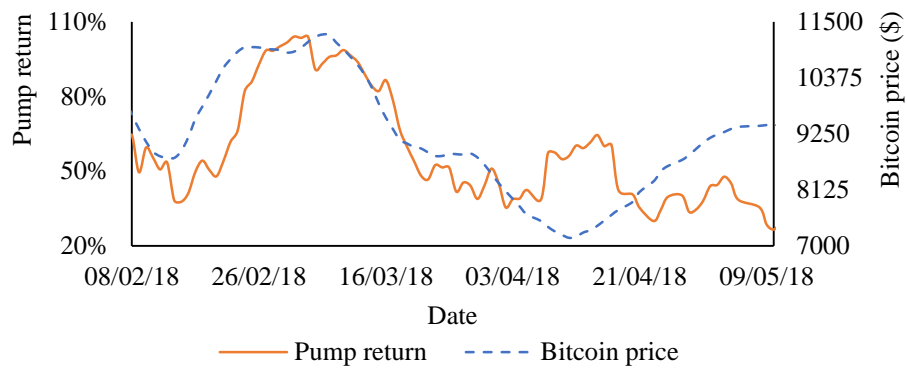
Figure 7. Return and volume dynamics during pump-and-dump manipulations.

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.

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

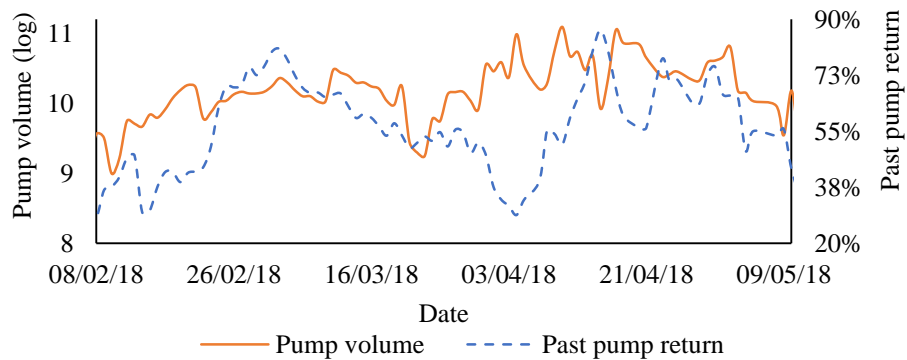


Figure 8. Pump dynamics through time.

Panel A plots the daily number of pumps and the volume-weighted average Bitcoin price. Panel B plots the average return on pumps (from pump 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 pump groups responsible for the pumps on a given day (our proxy for participant 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.