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

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January 10, 2020

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. Through a simple model, we demonstrate how overconfidence and gambling preferences can explain participation in these schemes, with gambling having stronger empirical support. 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

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[*] The Internet Appendix accompanying this study can be found at this link (https://bit.ly/2QkfgJY).
We thank Sean Foley, Gerhard Hambusch, Petko Kalev, Adrian Lee, Benjamin Loos, Lee Smales, Elvira Sojli, Terry Walter, David Yermack, and seminar participants at the 2nd UWA Blockchain, Cryptocurrency and FinTech Conference, the 32nd Australasian Finance and Banking Conference, the University of Technology Sydney, and RoZetta Institute for helpful comments. A. Dhawan gratefully acknowledges funding from the RoZetta Institute. T. Putniņš gratefully acknowledges funding from the Australian Research Council (ARC DP200101445).
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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. 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.[1] Cryptocurrency ETF (exchange traded fund) proposals are being evaluated by regulators including the US Securities and Exchange Commission (SEC). 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] Around $29 billion has been raised in the primary market for cryptocurrencies (initial coin offerings, ICOs) in just over five years.[3] The secondary market for the approximately 3,000 cryptocurrencies generated around $10.8 trillion in trading volume in 2019.[4] Clearly, cryptocurrencies are no longer just a fringe asset.

Regulators and central banks have expressed serious concerns about cryptocurrencies, with one of the major concerns being the prevalence of pump-and-dump manipulation in cryptocurrency markets. Pump-and-dump is a manipulation technique in which manipulators first take a long position in a security and then artificially 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 to be wary of and avoid pump-and-dump manipulation on cryptocurrency exchanges.

This paper examines this new form of pump-and-dump manipulation that is found in cryptocurrency markets. First, we show that pump-and-dump manipulation in cryptocurrency

[1] Source: Autonomous Research.
[2] Intercontinental Exchange has recently launched 'Bakkt', a cryptocurrency spot and futures trading platform. SIX, the owner of the Swiss stock exchange, is working towards introducing 'SIX Digital Exchange', a platform to trade, settle, and provide custodian services for cryptocurrencies.
[3] Source: ICOBench and Coinschedule.
[4] Source: Coinmarketcap.

markets is widespread and accounts for 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 about 15% of all coins in our sample of exchanges are targeted by manipulators at least once in the seven-month period. There is at least one pump on 133 days out of the 175 days in our sample, indicating that there is almost one pump per day on average. Such a high rate of manipulation is unprecedented in financial markets.

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.

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, unlike typical stock market manipulations, in cryptocurrency pump-and-dumps, manipulators make no pretense of having private information or claiming that a coin is undervalued.[5] Instead, pump group administrators (manipulators) publicly declare that they are pumping a given coin (releasing a "pump signal") at a specific time and invite others to join. Others then rush to buy the coin, presumably hoping to exit their position before the eventual collapse of the pumped coin's price. Economically, this means that cryptocurrency pumps do not exploit the classic mechanisms of information asymmetry and uncertainty about

[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, Meyer, Muhn, Soltes, and Hackethal, 2017).

the 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 develop a simple model to address both of these questions. We show that rational individuals would not participate in pump-and-dump manipulations because, for a participant other than the manipulator (who has the advantage of being able to buy ahead of the pump signal), pumps provide negative expected returns. The intuition is simple. Absent the profits extracted by the manipulator and ignoring trading costs, pumps are a zero-sum game involving re-distributions of wealth between players. With the addition of a manipulator that extracts a profit and with trading costs, pumps become a negative-sum game for all non-manipulator participants.

If rational individuals do not participate, then who does? We use the model to demonstrate that at least two types of individuals would willingly take part in pumps. The first type includes overconfident individuals that overestimate their ability to sell at a price close to the peak; from their perspective, pumps seem like a profitable game *ex-ante*. The second type consists of individuals that use pumps as a form of gambling, generating a right-skewed payoff distribution by playing a series of pumps. We test both of these explanations for cryptocurrency pump participation. While both explanations find some support in the data, the evidence in support of gambling is the strongest. We, therefore, conclude that to a large extent, cryptocurrency pump-and-dumps reflect a new form of unregulated gambling.

Despite functioning as a form of gambling, 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.

Finally, we examine the characteristics of coins that are most likely to be targeted by manipulators and how manipulation affects those coins. We find that manipulators target relatively illiquid coins. This observation is consistent with our model, which predicts individuals are more likely to participate in pumps of illiquid coins, which enables manipulators to extract higher profits. 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.

We also 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.

Our paper 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.[6] A thorough analysis of stock market pump-and-dumps can be found in Aggarwal and Wu (2006). An advantage of examining market manipulation in cryptocurrency markets is that manipulation of cryptocurrencies happens in the open without concealment other than the anonymity of participants. This feature allows us to construct a virtually complete record of all manipulations with detailed information on each instance. In contrast, the stock market manipulation prosecution cases that an empiricist can work with are a non-random "tip of the iceberg".[7] Furthermore, 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, but have a different focus. Li, Shin, and Wang (2019) document several stylized facts about cryptocurrency pumps and pump groups and find that these pumps harm liquidity and prices. Xu and Livshits (2019) and Kamps and Kleinberg (2018) attempt to predict cryptocurrency pumps *ex-ante* and *ex-post* respectively. Lastly, Hamrick et al. (2019) examine the factors that affect price jumps in cryptocurrency pumps. Our study provides new theoretical insights into the economic mechanisms that underpin cryptocurrency pump-and-dumps, tests the

[6] For reviews of the market manipulation literature, see Fox, Glosten, and Rautherberg (2018) and Putnins (2019).
[7] Comerton-Forde and Putniņš (2014) show that prosecuted cases of manipulation reflect a tiny and non-random fraction (0.3%) of all manipulation.

role of overconfidence and gambling in facilitating this new form of manipulation, and provides further characterization of these schemes and their impact on cryptocurrency markets.

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 (2018) show that parties related to Bitfinex, a cryptocurrency exchange, used Tether, a cryptocurrency pegged to the US Dollar, to artificially inflate the price of Bitcoin. Gandal, Hamrick, Moore and Oberman (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 some background on pump-and-dump groups and the cryptocurrency ecosystem. Section 3 discusses existing market manipulation theories and develops a simple new model of cryptocurrency pumps. Section 4 details the empirical tests and results. Section 5 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).[8] 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 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

[8] BTC denotes the unit of measurement for Bitcoin. Most cryptocurrencies are traded in BTC pairs.

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 who are likely to buy the coin based on rapid 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 given benefits such as pump-related information (e.g., the coin name) in advance of the general broadcast to all group members. This allows paid members to take positions in coins ahead of the official pump signal, presumably increasing their ability to profit from pumps.

Unlike conventional pump-and-dump manipulation, where manipulators typically try to mislead market participants into thinking the manipulated security is appreciating in price due to fundamentals (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 participants 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. Although manipulators are explicit in telling their group members about the intention to pump, they may also hope to attract technical traders that are not part of the pump group to buy the manipulated coin following the initial sharp increase in price at the start of the pump.

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.[9] Out of

[9] 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

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.

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 cryptocurrency exchanges and announcing a reward for whistleblowers who report manipulators.[10] 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.

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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/).

[10] This advisory statement can be found at this link (https://bit.ly/2NH3wj0).

3. Theory

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.

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 model is needed to explain the mechanics of cryptocurrency pumps.

3.2. A simple model of cryptocurrency pump-and-dumps

3.2.1. Structure of the model

We model cryptocurrency pump-and-dumps as a four-period, simultaneous-move trading game. 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 in different trade sizes (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. Therefore, prices are determined by the function, $P_t = P_0 + \beta X_t$, where P_t is the price in period t, β is a price impact parameter between zero and one, and X_t is the cumulative net volume of buys (buys minus sells) received by the market up to time 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 ($N > 1$) members of their pump group. This signal contains the name 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 model 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 each participant's order being received by the market 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 $\{(P_1 + 1\beta), (P_1 + 2\beta), \ldots\}$ 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 $P_2 = P_1 + N'\beta = P_0 + M\beta + N'\beta$.

Conditional on participation, in Period 3, players exit the pump by simultaneously submitting unit volume market sell orders. We assume that manipulators also close their positions in Period 3. These exit orders are also 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 of prices $\{(P_2 - 1\beta), (P_2 - 2\beta), \ldots, P_0\}$ depending on their random latency and queue position. The price at the end of Period 3 (which is the price paid 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 model 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 >

3.2.2. *Who participates in pumps?*

We now consider the conditions under which individuals choose to participate in cryptocurrency pump-and-dumps. We start by showing that in our setting, rational individuals would not choose to participate in a pump. To see why, 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.[11] Given this information, we can determine individual i's expected profit:

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

Both β and M are strictly positive. Therefore, in the presence of manipulators, a rational player i expects to make a loss by participating in a cryptocurrency pump-and-dump. The expected loss has two components: half the manipulator's initial price impact ($\beta M/2$) and the round-trip trade cost (β). Hence, risk averse, or risk neutral rational individuals would choose not to participate in these pump-and-dump games.

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

Intuitively, a rational individual would recognize that a cryptocurrency pump-and-dump is a zero sum game across all participants (manipulators and pump group followers) minus trading costs. Positive trading costs make it a negative-sum game across all participants, making it unattractive to anyone that does not have an advantage or perceived advantage over others. Manipulators have an actual advantage over others by being able to buy the coin ahead of the pump signal (effectively getting a more advantageous entry price than pump group followers). Therefore, pumps can have positive expected profits for them as long as there are sufficiently many participants (N') in the pump to cover their transaction costs: $\mathbb{E}[\pi_m] = \frac{\beta M}{2}(N' - 2M)$. The manipulators' profits, however, equate to losses for pump group followers. Consequently, these

[11] 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.

followers face a negative-sum game in which the expected loss for an individual is a fraction of the manipulators' profit and the trading costs.

This baseline result about non-participation by rational players formalizes the puzzle of why people (other than the manipulators) participate in cryptocurrency pump-and-dump schemes. To resolve this puzzle, we consider what modifications are able to induce participation.

First, we consider overconfidence bias, which may 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. This means that overconfident individuals are likely to expect they will obtain lower entry prices and/or higher exit prices than the average participant.

To model this overconfidence effect, we add a bias to the *perceived* distribution of exit prices for overconfident individuals (adding a bias to the entry prices as well would merely strengthen the effect). 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. To obtain the perceived exit price distribution for an overconfident agent, we start with the actual uniform distribution of exit prices and merely tilt it so that it places more likelihood on higher exit prices. The extent of the tilt (strength of the overconfidence) for an individual i is given by the overconfidence parameter, $\varepsilon_{OC,i}$, which is the slope of the transformed perceived probability density function (pdf) of exit prices:

$$f_i(P_{exit}) = \begin{cases} \frac{1}{\beta(M+N'-1)} + \varepsilon_{OC,i}P_{exit} - \frac{\varepsilon_{OC,i}}{2}\left(\beta(M+N'-1) + 2P_0\right) & \text{if} \quad P_0 \leq P_{exit} \leq P_0 + \beta(M+N'-1) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where N' is the number of individuals that participate in the pump. When the overconfidence parameter $\varepsilon_{OC,i} = 0$ (e.g., an unbiased rational individual), the exit price pdf collapses down to the true uniform distribution of exit prices. When $\varepsilon_{OC,i} > 0$ (an overconfident individual), the pdf is tilted as shown in Figure 4. Higher ε_{OC} implies a greater overestimation of the likelihood of exiting the pump near the peak and greater underestimation of exiting at a low price once the pump collapses.

< Figure 4 here >

We can now determine the expected payoffs of participating in a pump for an overconfident individual, much like we did for a rational individual, just replacing the unbiased exit price distribution with the biased one. We find that the expected pump payoff, $\mathbb{E}\left[P_{exit} - P_{entry}\right]$ is strictly positive if the following condition on $\varepsilon_{OC,i}$ is satisfied,

$$\varepsilon_{OC,i} > \frac{6(M+2)}{\beta^2(M+N'-1)^3} = \varepsilon_{OC}^{min}. \tag{3}$$

The condition in (3) implies that cryptocurrency pump-and-dumps have positive expected payoffs for sufficiently overconfident individuals. Assuming risk neutrality, individuals with overconfidence exceeding a threshold, ε_{OC}^{min}, choose to participate in pumps. We therefore arrive at the first possible explanation for why some 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 model parameters. For the illustration, we set values for two of three of the model parameters and plot ε_{OC}^{min} against the third parameter. Panel A shows that ε_{OC}^{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_{OC}^{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_{OC}^{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 as an alternative departure from rationality 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 model, a single pump does not have a positively skewed payoff structure; the gains and losses are approximately symmetrical. But neither does a single bet on red or black at the roulette table. To explain the attraction of non-skewed games such a 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 when considering 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 formalized 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 s can be reduced to a binary gamble, $\tilde{G}_s$,

$$\tilde{G}_s \sim ((c - a), P_{c-a}; -(a - b), P_{-(a-b)}) \tag{4}$$

where P_{c-a} represents the probability of achieving a $(c - a)$ gain and $P_{-(a-b)}$ 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 $\$c$.[12] Based on Dixit (1993), the estimates for P_{c-a} and $P_{-(a-b)}$ are

$$P_{c-a} = \frac{\exp\left(-\frac{2a\mu}{\sigma^2}\right)-1}{\exp\left(-\frac{2c\mu}{\sigma^2}\right)-1} \qquad \text{and} \qquad P_{-(a-b)} = 1 - P_{c-a} \tag{5}$$

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), we assume that a gambler chooses a strategy s (a strategy consists of the values b and c that determine when the gambler stops playing) from a set of strategies S_0 to solve the maximization problem,

$$\max_{s \in S_0} V(\tilde{G}_s) \tag{6}$$

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, an individual overweighs small probability outcomes and underweights large probability outcomes. Additionally, the individual's valuation of payoffs is concave in the region of gains and convex in the region of losses, implying that individuals are risk-seeking in the domain of losses and risk-averse in the domain of gains. These features of the CPT explain why individuals are attracted towards positively skewed payoff structures 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 model parameter values.[13] For the given parameters, 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 expected value for the gambler with CPT preferences and therefore provides a second possible reason for why individuals participate in cryptocurrency pump-and-dumps.

[12] 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.

[13] 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.

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 the model parameters. We take the numerical solution to the gambler's optimization problem found previously for a given set of model parameter values and vary the model parameters one at a time, plotting the gambler's expected value of participating in the series of pumps, $V(\tilde{G}_s)$. 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 >

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

3.2.3. 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 in the course of repeated pumps. Let N_t^{OC}, N_t^{GP}, and N_t' denote the number of sufficiently overconfident individuals, the number of participants with gambling preferences, 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 expected exit prices. Effectively, some of their overconfidence bias should attenuate through learning about actual ability and payoffs, consistent with other models of overconfidence, which suggest individuals become more aware of their true ability with experience (Gervais and Odean, 2001). In this process, as their beliefs converge towards the true expected exit prices (as $t \rightarrow \infty$, $\varepsilon_{OC} \rightarrow 0$), some overconfident individuals will cross the threshold ε_{OC}^{min} and go from participating in pumps to not participating. Let ρ_t^{OC} denote the number of overconfident individuals that switch to not participating in the game after round t. Additionally, let λ^{OC} be the Poisson arrival rate of new individuals that are sufficiently overconfident to participate in pumps upon arriving.

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,

$$\mathbb{E}[\Delta N_t'] = \mathbb{E}[N_t' - N_{t-1}'] = (\lambda^{OC} + \lambda^{GP}) - (\rho_{t-1}^{OC} + \rho_{t-1}^{GP}). \tag{7}$$

Equation (7) 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 the ability or hitting their maximum gains or losses. Importantly, as stated in Result 4, the number of participants determines the peak prices achieved in pump-and-dumps as well as the manipulator profits.

The empirical implication of equation (7) is that we expect to see increases in the volumes traded in pump-and-dump episodes, in pump-and-dump peak returns, and 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 in at least three different instances. First, when there is increasing interest in cryptocurrencies in general. Second, when overconfidence increases due to self-attribution of success in past pumps or in cryptocurrency returns in general. Third, when there is a market-wide increase in the propensity to gamble, with cryptocurrency pump-and-dumps providing one outlet for gamblers.

Result 8*: The dynamics of pump-and-dump activity, peak prices, and manipulator profits through time are affected by the general level of interest in cryptocurrencies, past returns on pumps and cryptocurrencies, and the market-wide propensity to gamble.*

Finally, we consider how pump-and-dump episodes themselves are likely to change through time by considering two types of participants: fast and slow. Fast players are faster at entering pumps (buying at low prices) and exiting pumps (selling near the peak). Therefore, they are able to earn higher profits. Suppose each individual is either a fast or slow type by nature, but initially individuals are not sure about their type. Individuals will be able to learn about their type by participating in pumps and observing their success rates. Individuals that realize they are of the slow type will come to understand that they are systematically disadvantaged in pumps and destined to make losses on average to faster individuals. Therefore slow types are likely to cease participating at a faster rate than fast types and through time, the speed of pumps should increase. That is, the time from the start of the pump (release of the pump signal) through to the peak and subsequent return to pre-pump prices is likely to get shorter through time. In the limit as all but the very fastest participants cease to participate, cryptocurrency pump-and-dumps could eventually cease to exist.

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-related data for one cryptocurrency exchange (Binance) and rely on a database compiled by PumpAnalysis (PA) for another cryptocurrency exchange (Yobit).[14] Only cases in which the Telegram pump-and-dump channel administrator explicitly states that a signal is for a pump are counted as pump-and-dump cases. For each pump, we record the coin being pumped, the exchange on which the pump takes place, and the time the pump signal is sent. Additionally, from these chat groups, we also obtain 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.

[14] 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.

We couple the information on pumps with data on all trades on the Yobit exchange, sourced from the cryptocurrency market data provider Kaiko, and all trades on the Binance exchange, sourced from the official Binance API. After reconciling the information on pumps with the trades data and restricting our focus to Binance 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 popular cryptocurrency market capitalization data aggregation website, and daily Bitcoin gambling volume data 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.[15] 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 million.[16] This figure reflects the estimated wealth transfer from pump participants (pump group followers) to

[15] A "pump-day" is a day in which there is at least one instance of pump-and-dump manipulation.

[16] 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).

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 >

Next we examine price and volume dynamics around pumps. In our model of cryptocurrency pump-and-dump games, as illustrated in Figure 3, prices rise before a pump signal is released as manipulators build their initial 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 model). 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 model).[17] After reaching the peak, prices fall at a slower rate until they reach approximately the initial (pre-pump) level (P_0 in the model). The price trajectory in Figure 7 is very similar to that in our simple theory model.

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 model). 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 our model predict that while rational individuals would not participate in pumps, overconfident individuals and individuals seeking to gamble would 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 rely on proxies for

[17] 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.

overconfidence and gambling at an aggregate market-wide level and measure how they relate to the rates of pump participation. We expect pump participation to increase when cryptocurrency investors are more overconfident and when there is a higher prevalence of cryptocurrency gambling.

We use the past cryptocurrency returns as a proxy for aggregate investor overconfidence. Statman, Thorley and Vorkink (2006) find that trading volumes are positively correlated with previous returns and attribute this effect to positive returns inducing investor overconfidence. Self-attribution bias results in investors attributing positive outcomes (e.g., earning high returns) to their own skill, thereby fuelling overconfidence in their own abilities. Consequently, individuals that own cryptocurrencies are likely to increase in overconfidence following positive cryptocurrency returns, which according to our model, could lead them to start participating in pump-and-dump manipulations. Individuals that are already members of pump groups are likely to have long exposure to cryptocurrencies due to the involvement in pumps or general participation in the cryptocurrency ecosystem. Therefore, following positive cryptocurrency returns they may be more eager to participate in pumps due to an increase in overconfidence. Our aggregate proxy, $Overconfidence_t$, is the average daily return earned by all cryptocurrencies in the five days before day t.

Before estimating any regressions, a simple plot of cryptocurrency returns and pump participation rates is already rather telling. Figure 8 plots daily Bitcoin prices and the number of pumps and average pump returns per day. Recall from the model that pump returns are a proxy for pump participation because a larger number of participants, N', leads to higher peak prices. Both the number of pumps per day and pump returns follow a similar pattern as the lagged Bitcoin price. This trend is consistent with the notion that overconfidence is related to cryptocurrency returns and that overconfidence leads to higher participation in pumps, thereby generating higher pump returns. This high demand from pump participants also prompts manipulators to conduct more pumps.

< Figure 8 here >

As a proxy for the aggregate prevalence of gambling among individuals that are part of the cryptocurrency ecosystem, we use 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 demand in cryptocurrencies ($Gambling_t$) is the daily log revenue of known Bitcoin gambling services identified in the Wallet Explorer (WE) database. 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.

For each of the 355 pump-and-dump manipulations in our sample, we measure the log total trading volume in pump j of coin i on day t from the release of the pump signal to three hours after the pump's peak price is reached.[18] We regress this pump-level participation measure ($Participation_{j,i,t}$) on the aggregate $Overconfidence_t$ 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 according to the model, individuals are less likely to participate in pumps the more manipulators participate.[19] Finally, we also control for 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).

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. The positive associations are consistent with the notion that both overconfidence and gambling contribute to participation in pump-and-dump manipulations, consistent with the mechanisms illustrated in the simple theory model (Results 2 and 3).

The regressions in Table 3 (Model 3) also show weak evidence that pump participation is negatively related to the number of manipulators, consistent with the model (Result 5). More

[18] We standardize this participation measure to make it comparable across coins by regressing it on average trade size during the pump and saving the residuals.
[19] We standardize this proxy for manipulator participation by regressing it on the number of members in all participating groups and saving the residuals.

manipulators mean greater aggregate losses for non-manipulators, thus discouraging participation. Model 4 shows that uncertainty about the fundamental value of a coin (lagged volatility) does not explain pump participation, further supporting the notion that cryptocurrency pump-and-dumps are not a form of information-based manipulation. Finally, in Model 5, when all regressors are included concurrently (also reducing the number of observations), only gambling remains statistically significant of the two proxies for why individuals participate in pumps. Overconfidence retains its sign and the lack of significance could be an issue of low statistical power, given the low number of observations and relatively noisy measures. The magnitude of the effects suggests that, on average, a 1% increase in the total dollar volume of gambling with Bitcoin results in a 0.33% increase in pump participation.

< Table 3 here >

4.4. Determinants of pump outcomes

Our model 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 model (Result 4) predicts that manipulator profits are higher when more non-manipulators participate in the pump (higher N' in the model) and for pumps in less liquid coins (higher β in the model). 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 0.47%.

The model (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' in the model) and less liquidity (higher β in the model). 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 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?

To test which characteristics make a coin more susceptible to being targeted by a pump-and-dump group, 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%.[20]

The model predicts that both manipulators and non-manipulators have a preference for illiquid coins. However, as discussed earlier, for a pump to be feasible, there must be at least some minimum level of liquidity in the coin, 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 to 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 274.34% and 136.31% higher odds of being pumped than coins in the fourth (highest) quartile, while the lowest quartile coins have 62.09% 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 >

[20] $MarketCap_i$ 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.

4.6. Impact of pump-and-dumps on coin trading characteristics

Finally, we analyze how pumps affect market activity for the coins being pumped. We measure trading volumes, returns, and volatility each coin-day and regress these trading characteristics on an indicator for whether the coin was the target of a 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 show that traded volume is significantly higher when coins are pumped, 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 more than three-and-a-half times higher when a coin is pumped.

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 affected by the pump despite the earlier results showing that intraday, pumps generate large returns in the order of 65%. These regression results therefore confirm that, consistent with our simple model, 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 suggest that volatility, measured as the difference between the highest and lowest log prices for the coin on day t, is considerably higher on pump-days compared to other days and for pumped coins compared to other coins. The coefficient for $Volatility_{i,t}$ is statistically significant in all specifications and indicates that intraday volatility is almost twice as high when a coin is being pumped.

< Table 6 here >

5. 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 while rational individuals would not participate in cryptocurrency pumps as they constitute a negative-sum game, individuals with gambling preferences would participate and so too would overconfident individuals that overestimate their ability to sell near the peak price. While our empirical analysis supports both explanations for participation, the evidence likening cryptocurrency pump-and-dumps to a form of gambling is stronger.

Despite the finding that many of the participants in these pumps treat them as a form of 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 et al. (2018) and Putnins (2019) 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 that there are 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.

While there may be some utility in these games for their participants, such as utility from gambling, there is also a lot of potential for harm. First, most forms of gambling have a degree of regulatory oversight to ensure gamblers are not excessively exploited by gambling service providers. No such checks exist for cryptocurrency pump-and-dump games. Second, to the extent that some pump participants are not doing it for the utility of gambling but instead may be overconfident individuals, pumps cause wealth transfers from less sophisticated participants to manipulators, together with deadweight costs associated with trading. Both of these effects can harm aggregate welfare. In other financial market contexts, transfers from less sophisticated to more sophisticated participants are accompanied by an offsetting social benefit, that being information production and the provision of price discovery by sophisticated investors. No such offsetting benefit is present in cryptocurrency pump-and-dump manipulations. Third, market manipulation itself is associated with a variety of negative consequences including loss of confidence in markets, which can impede the development and adoption of cryptocurrencies and their potential benefits.

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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. Total coins and trading volume include all coins listed on both exchanges during the sample period. 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 the level of participation in pump-and-dump manipulations. The dependent variable, $Participation_{j,i,t}$ is the log total trading volume in pump j on coin i in day t, measured from the release of the pump signal to three hours after the pump's peak price is reached. $Overconfidence_t$ and $Gambling_t$ are aggregate proxies for overconfidence and gambling in cryptocurrency markets. $Overconfidence_t$ is the average daily percent return on all coins listed on Coinmarketcap between day $t-5$ and day t. $Gambling_t$ is the log daily dollar revenue of Bitcoin gambling services. $Volatility_{i,t-1}$ is the log of the difference between the highest and lowest prices for the coin on day $t-1$. $Manipulators_{j,i,t}$ is the log number of Telegram groups participating in the pump, adjusted to remove the effects of the number of group members. $Yobit_i$ is an indicator variable that equals one if the coin is listed 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. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable = $Participation_{j,i,t}$				
Variable	(1)	(2)	(3)	(4)	(5)
$Overconfidence_t$	6.47***				1.93
	(2.70)				(0.64)
$Gambling_t$		0.48***			0.33*
		(4.11)			(1.93)
$Manipulators_{j,i,t}$			-0.20*		-0.18
			(-1.88)		(-1.55)
$Volatility_{i,t-1}$				0.02	0.01
				(0.56)	(0.31)
$Liquidity_i$	0.20***	0.18***	0.22***	0.14*	0.12*
	(2.96)	(2.73)	(3.26)	(1.88)	(1.68)
$Yobit_i$	-4.76***	-4.92***		-7.00***	
	(-7.75)	(-8.08)		(-8.35)	
R^2	77.52%	74.04%	4.45%	46.18%	4.02%
Observations	355	355	291	242	237

Table 4
Determinants of pump outcomes

This table reports regression results testing how the level of 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 log of the manipulators' 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 a proxy for the amount of participation in a pump, calculated as 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 number of pumps conducted before pump j by all 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. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable =			
Variable	$ManipProfit_{j,i,t}$	$PrePumpVol_{j,i,t}$	$Return_{j,i,t}$	$Duration_{j,i,t}$
$Participation_{j,i,t}$	0.96***	0.44***	0.24***	-0.15*
	(14.57)	(6.56)	(6.26)	(-1.80)
$Experience_{j,i,t}$	0.21**	0.17*	0.06	-0.33***
	(2.36)	(1.77)	(1.10)	(-2.85)
$Liquidity_i$	-0.08	0.47***	-0.23***	0.06
	(-1.55)	(8.66)	(-7.53)	(0.90)
R^2	84.74%	86.58%	26.54%	7.13%
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 dollar market capitalization. $TradesQ1_i$, $TradesQ2_i$, 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. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable = $Pumped_i$		
Variable	(1)	(2)	(3)
$Intercept$	2.09***	-2.29***	-3.56***
	(14.70)	(143.21)	(111.24)
$MarketCap_i$	-0.16***		
	(45.10)		
$TradesQ1_i$		-0.97***	
		(7.67)	
$TradesQ2_i$		1.32***	
		(33.71)	
$TradesQ3_i$		0.86***	
		(13.11)	
$VolumeQ1_i$			0.00
			(0.00)
$VolumeQ2_i$			2.69***
			(55.96)
$VolumeQ3_i$			2.45***
			(46.09)
Pseudo-R^2	7.75%	6.85%	12.50%
Observations	610	1,307	1,307

Table 6
Characteristics 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 log of the difference between the highest and lowest prices for the coin on day t. The independent variable of interest is $PumpDay_{i,t}$, which is an indicator variable that 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. The sample includes all coins listed on the Binance and Yobit exchanges from December 2017 to June 2018. t-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable =								
	$Volume_{i,t}$			$Return_{i,t}$			$Volatility_{i,t}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$PumpDay_{i,t}$	3.56***	3.73***	3.60***	-0.03	0.01	0.02	1.86***	1.89***	2.04**
	(18.87)	(34.04)	(20.22)	(-0.75)	(0.22)	(0.61)	(14.79)	(22.19)	(16.77)
$Yobit_i$	-9.21***		-9.22***	0.03***		0.03***	-0.19***		-0.27***
	(-213.13)		(-218.84)	(3.81)		(3.12)	(-6.41)		(-9.08)
$MarketCap_i$	0.06***		0.06***	-0.00**		-0.00*	-0.04***		-0.03***
	(9.26)		(9.74)	(-2.01)		(-1.93)	(-7.27)		(-7.41)
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	79.31%	76.40%	82.31%	0.22%	1.93%	7.79%	1.25%	11.54%	11.19%
Observations	23,687	42,240	23,687	24,497	44,529	24,497	21,756	35,987	21,756

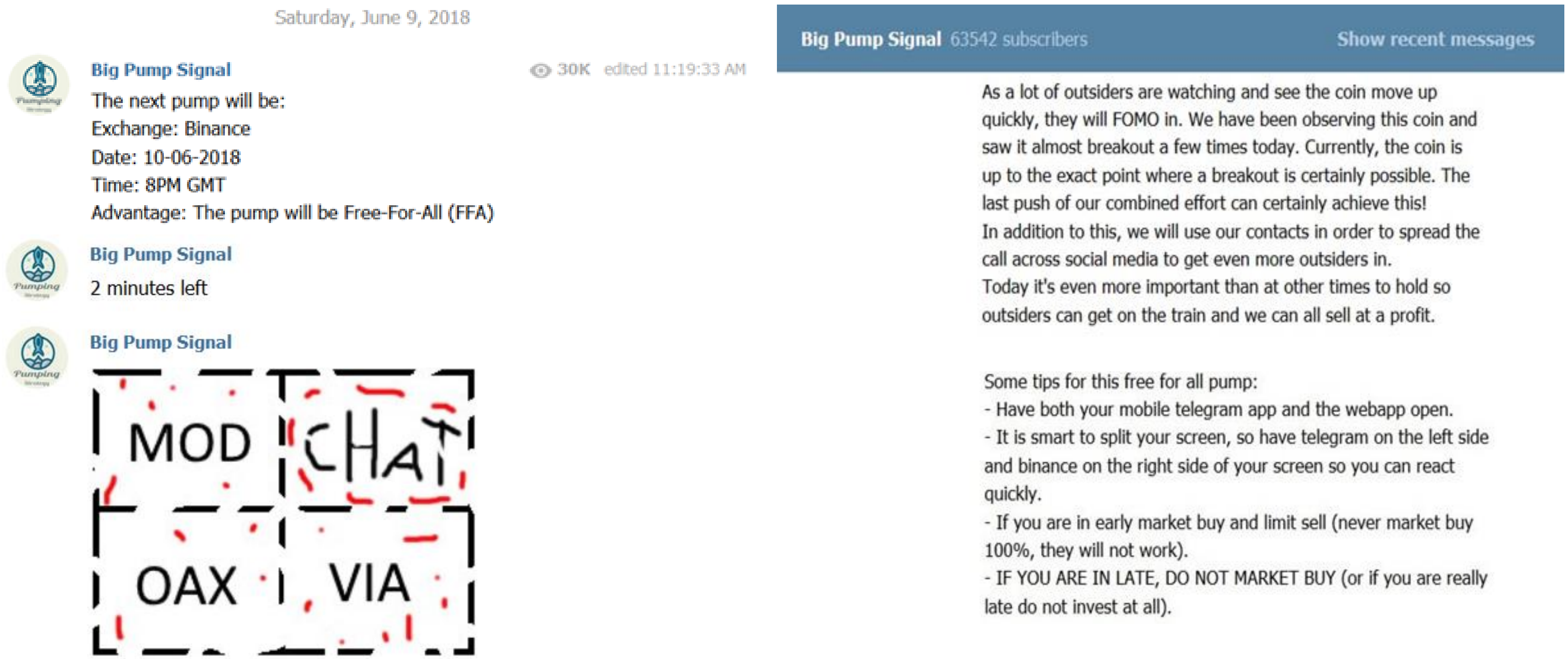
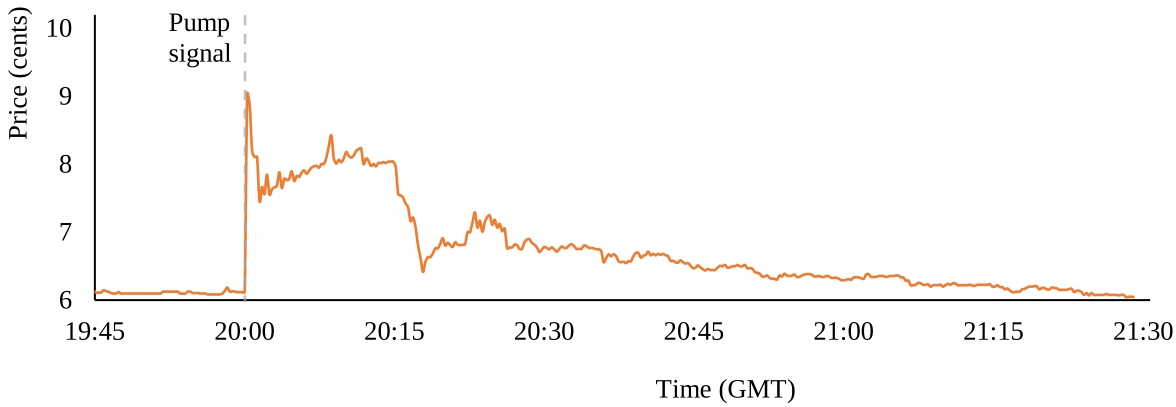
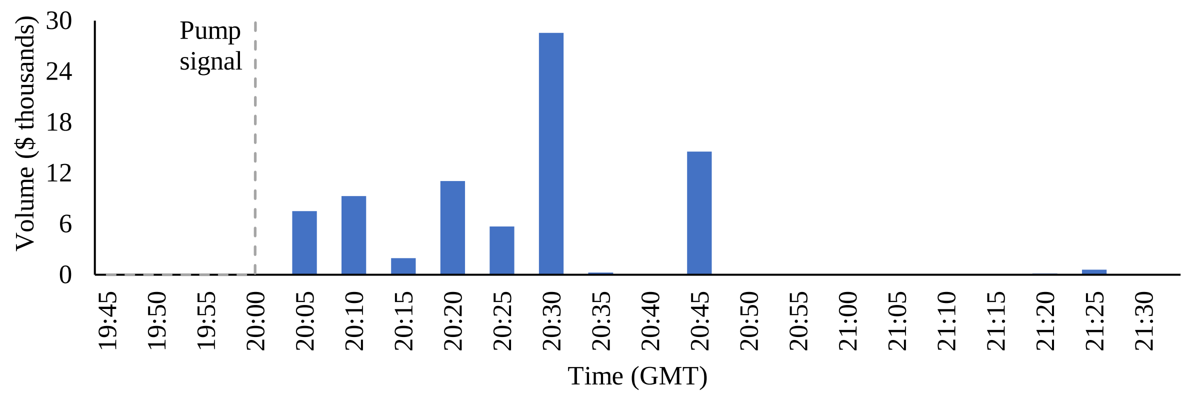


Figure 1. Sample messages sent on the 'Big Pump Signal' Telegram group.
This figure shows messages sent by the administrators of the Telegram group 'Big Pump Signal' to its members. In these messages, the administrators announce the date, time, and exchange for a pump in advance of the actual pump (top 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

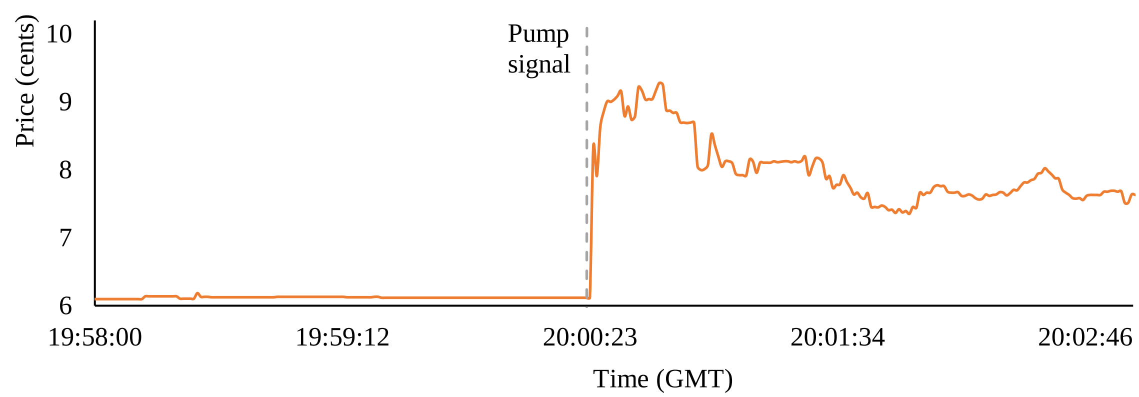


Figure 2. Price and volume for ChatCoin during the 'Big Pump Signal' pump.
The pump signal for the ChatCoin pump was sent by the administrators of the 'Big Pump Signal' group at 20:00:23 GMT on June 10, 2018. Panel A shows the prices (in cents) for ChatCoin in 15-second intervals between 19:45 GMT and 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.

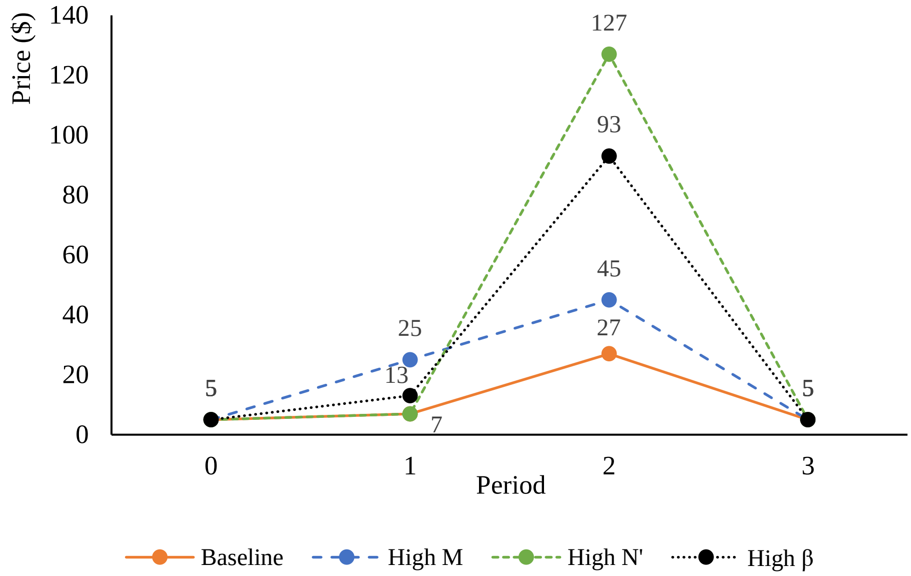


Figure 3. Price dynamics in the theoretical model.
The figure shows illustrative price paths from our theoretical model. For the baseline illustration, we set initial price $P_0 = \$5$, number of manipulators $m = 10$, number of participants $N' = 100$, and price impact parameter $\beta = 0.2$. In the 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.

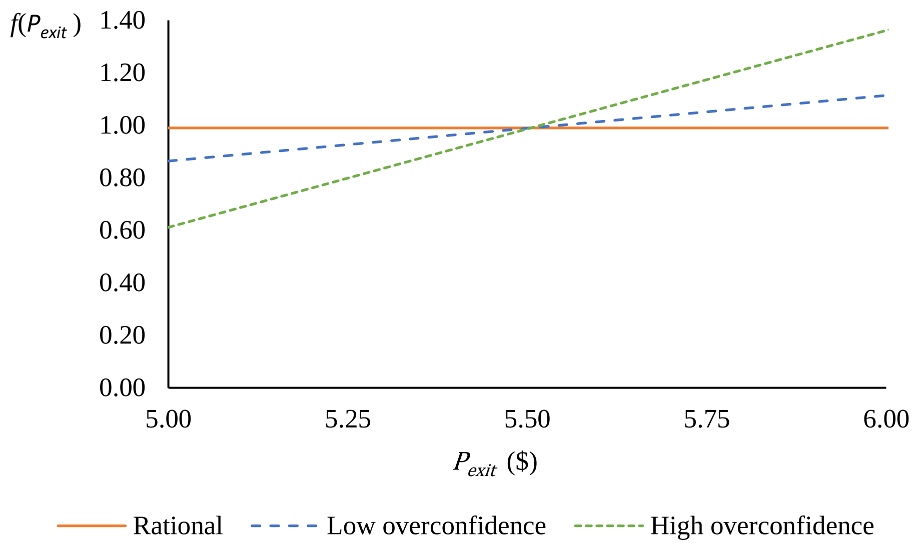
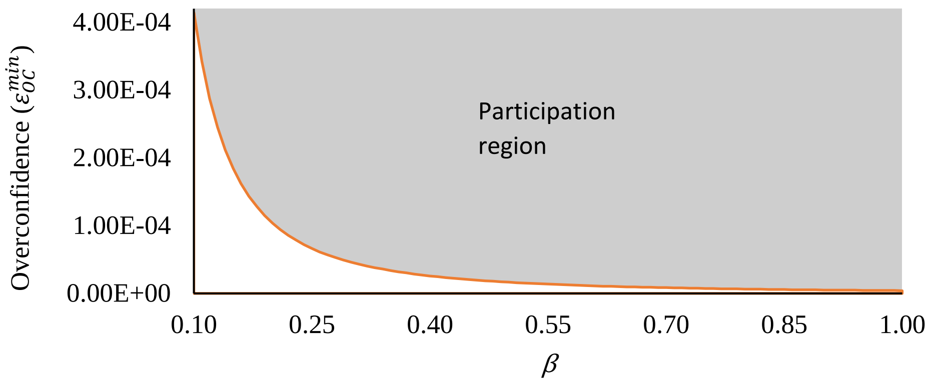
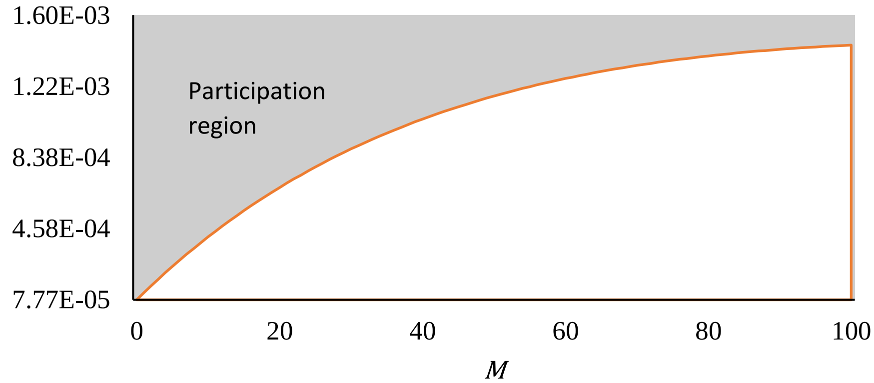


Figure 4. Exit price belief distributions for rational and overconfident individuals.
This graph plots the probability density functions (pdf) of exit price beliefs (the prices at which a pump participant expects to close their long position) for rational and overconfident individuals. In this illustration, we use the following parameter values: initial price $P_0 = \$5$, number of manipulators $M = 2$, number of participants $N' = 100$, and price impact $\beta = 0.01$. Rational individual beliefs are consistent with the true exit price distribution, which is uniform. In contrast, overconfident individuals overestimate the probability of receiving high exit prices and underestimate the probability of receiving low exit prices. The overconfidence parameter, ε_{OC}, is the slope of the transformed pdf. For a rational individual, $\varepsilon_{OC} = 0$, while for an overconfident individual, $\varepsilon_{OC} > 0$. In this illustration, low overconfidence individuals have $\varepsilon_{OC} = 0.25$ and high overconfidence individuals have $\varepsilon_{OC} = 0.75$.

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



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



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

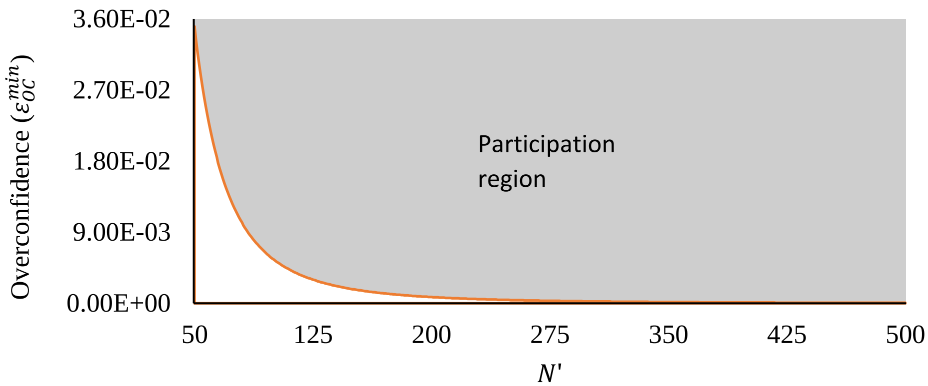
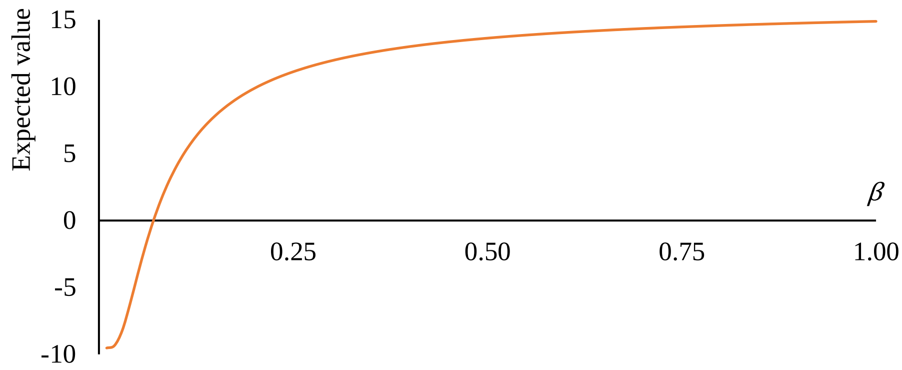
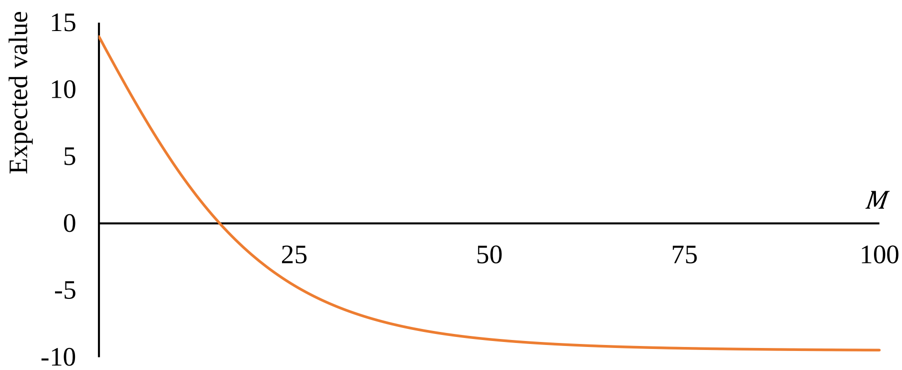


Figure 5. Pump-and-dump participation thresholds as a function of overconfidence and other parameters. This figure plots the minimum overconfidence level (ε_{OC}^{min}) above which individuals choose to participate in pump-and-dump manipulation games. Panel A plots this overconfidence threshold for different 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')

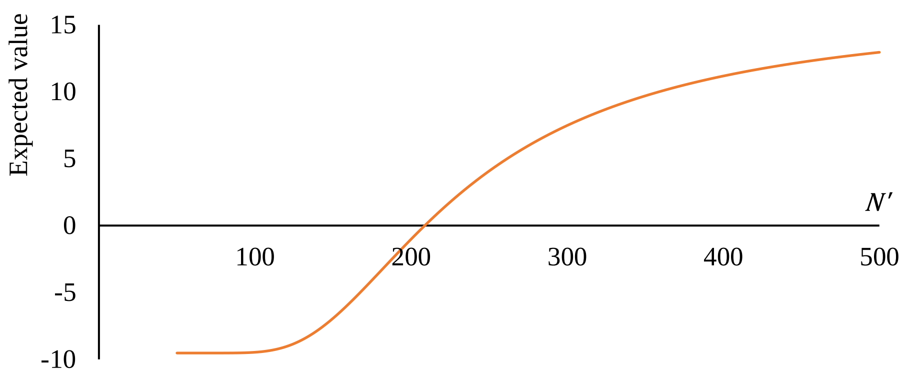
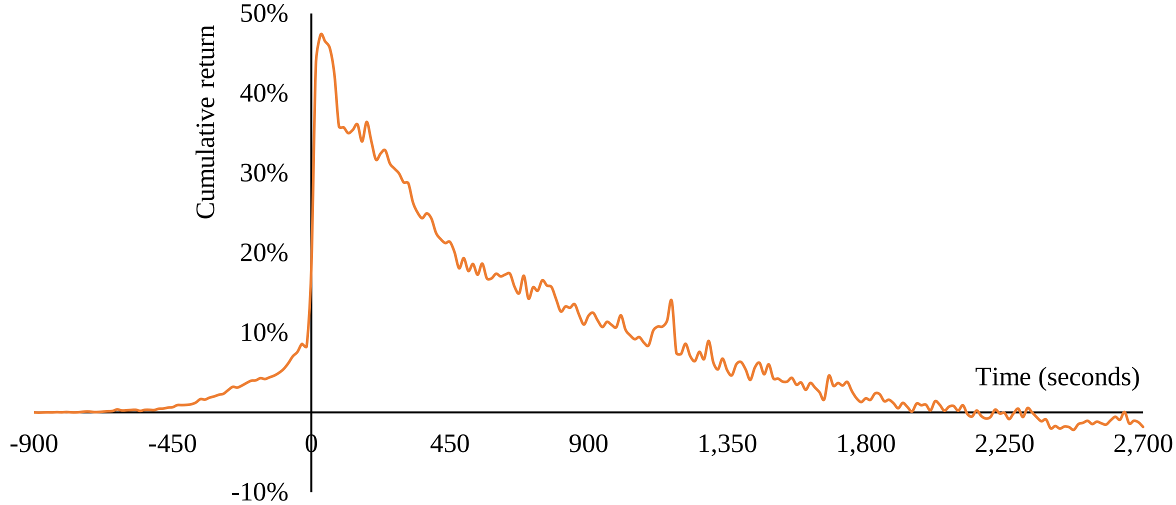


Figure 6. Gambler's expected value from pump-and-dumps for different values of the model parameters. The figure plots a gambler's expected value from participating in pumps (accounting for Cumulative Prospect Theory preferences) on the vertical axis against the price impact parameter (β) on the horizontal axis (Panel A), the manipulators' pre-pump long position (M) on the horizontal axis (Panel B) and the number of non-manipulators (N') on the horizontal axis (Panel C). To plot the graphs, 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 $a = \$6$. Additionally, we set the following values for the Cumulative Prospect Theory parameters: value adjusting parameter $\alpha = 0.95$, probability weight adjusting parameter $\delta = 0.5$, and loss aversion parameter $\lambda = 1.5$. Lastly, 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

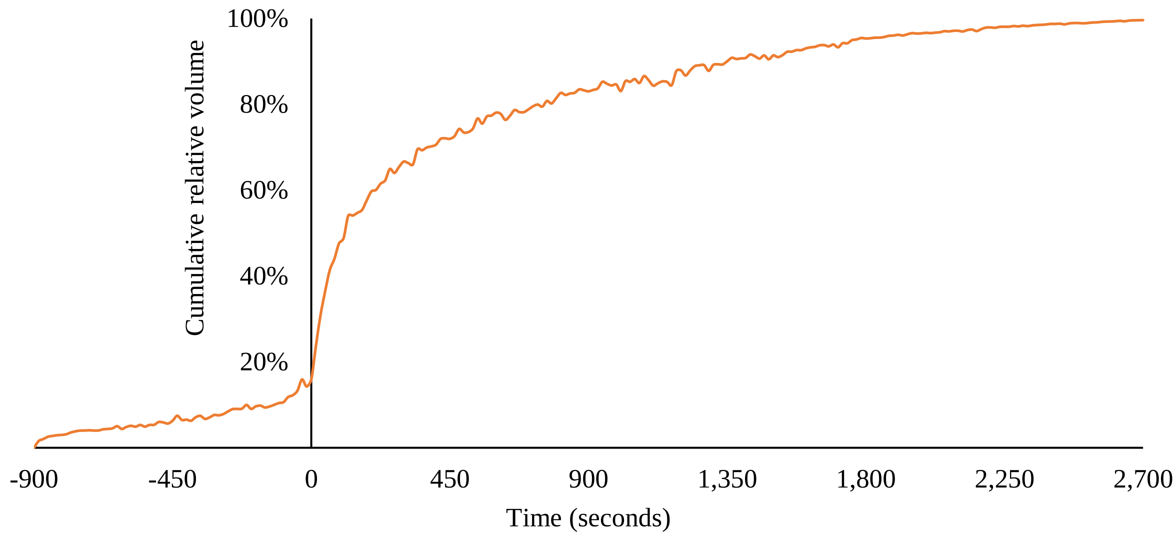
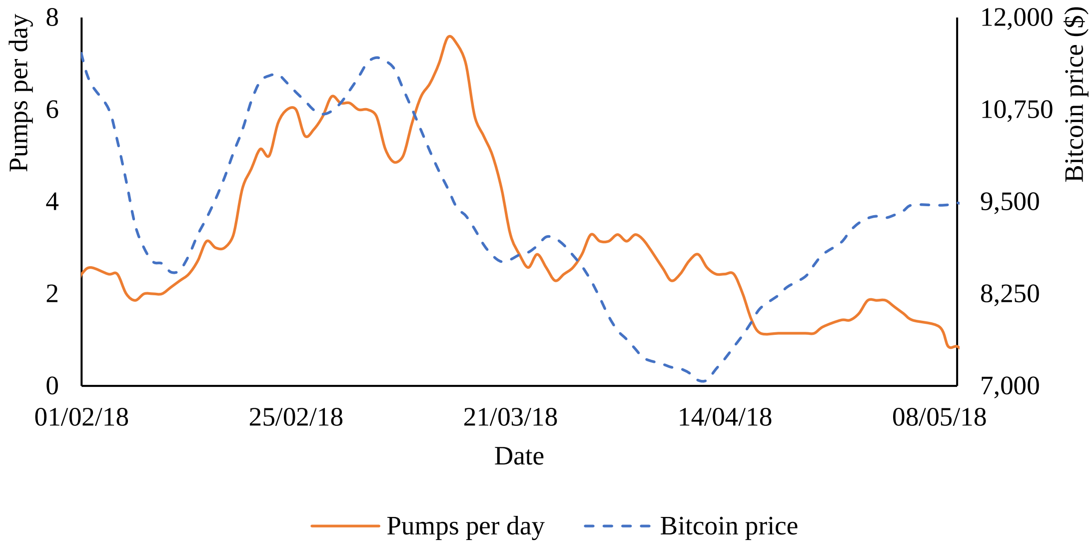


Figure 7. Return and volume dynamics during pump-and-dump manipulations.
The figure plots average cumulative returns (Panel A) and average cumulative volumes (Panel B) before, during, and after a pump signal ($t = 0$) is sent. The cumulative returns and volumes are measured in 15-second intervals from 15 minutes (900 seconds) before the pump signal until 45 minutes (2,700 seconds) after the pump signal, starting at zero at $t = -900$ seconds. 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

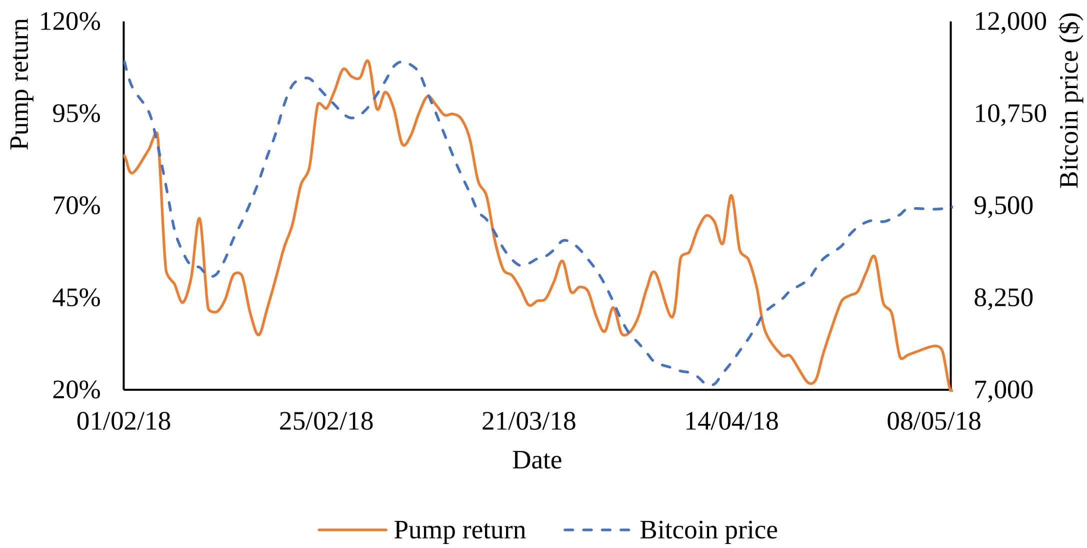


Figure 8. Number of pumps, pump returns, and Bitcoin price through time.
Panel A plots the daily number of pumps and the volume-weighted average Bitcoin price. Panel B plots the average return on pumps (from pump start to peak) in a given day and the volume-weighted average Bitcoin price. All variables are smoothed using a seven-day moving average. The sample includes 355 pumps on the Binance and Yobit exchanges between December 2017 and June 2018.