What Goes Up Must Come Down: A Study About Pump-and-Dump Manipulation in the Cryptocurrency Market

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Abstract

Unlike in traditional stock market manipulation, manipulators in cryptocurrency pump-and-dumps openly declare their intentions to pump a coin. We investigate why individuals, despite earning negative expected returns, participate in these pumps. We extend the study "A New Wolf in Town? Pump-and-Dump Manipulation in Cryptocurrency Markets" by Dhawan and Putniņš (2022) through using their framework on a new timeframe to examine if gambling and overconfidence can explain pump-and-dump participation. Through analyzing a sample of 114 pumps during a six-month period, our study finds weak support for these behavioral explanations. However, we still observe that cryptocurrency manipulation results in economically meaningful wealth distortions and that participants face low returns with high volatility. Our findings could therefore be a basis for future research that could impact cryptocurrency regulation.

Keywords
Cryptocurrency, pump-and-dump, Telegram pump-and-dump, tokens, manipulators, Bitcoin

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1 Introduction

Pump-and-dump manipulation has appeared in conventional financial markets for years, and concern either trade-based or information-based manipulation. Information-based manipulation entails distributing false information about a security to provoke traders to act on it (Vila, 1989; Van Bommel, 2003). This kind of manipulation necessitates uncertainty about the security's fair value as well as information asymmetry; otherwise, uninformed traders will not act on manipulators' false information spread. Trade-based manipulation instead involves profiting from buying and selling through asymmetry in liquidity-motivated trading or price momentum (Allen and Gorton 1992; Jarrow, 1992).

In this study, we examine a new type of pump-and-dump manipulation with different underpinnings compared to manipulation on traditional markets. This new type of manipulation is characterized by Dhawan and Putniņš (2022) in the paper "A New Wolf in Town? Pump-and-Dump Manipulation in Cryptocurrency Markets". We to a large extent replicate their methods and extend their study by sampling a new time period from January to June 2021. We investigate the prevalence of pump-and-dump manipulation and show that it accounts for a significant amount of trading on cryptocurrency markets. Using hand-collected data over a six-month period, we identify 114 explicit cases on the cryptocurrency exchange Binance. From this, we observe that approximately $557.44 million are traded on average during our period and that manipulators generate a return of approximately 7.13%. We find that, out of Binance's 337 distinct coins, 68 experienced a pump during our 6-month period, which is approximately 20.17% of all coins on Binance. This rate is considerably higher than pump-and-dump manipulation in traditional stock markets (Aggarwal and Wu, 2006)[1].

While there are some similarities between cryptocurrency pump-and-dump and stock manipulation in that they aim to drive up securities' prices and returns before they crash, there are differences[2]. The most prominent one is that cryptocurrency manipulators generally do not claim to have private information or that a coin is undervalued, which is the case in typical stock manipulation (Leuz, Meyer, Muhn, Soltes and Hackethal, 2017). Instead, manipulators typically openly declare their intention of pumping a coin by releasing a pump signal in pump-and-dump groups. After the release of the pump signal, private investors rush to buy with the hope to purchase at a low entry price, whilst selling at a high closing price before the price collapses. While pumps are triggered through the release of pump signals, manipulators usually do not release false information about a coin's value. Rather, they reveal their intended manipulation. Also, manipulators do not exploit asymmetry in price impact that is otherwise underpinned in the trade-based manipulation's theoretical framework (Dhawan and Putniņš, 2022). This new type of pump-and-dump manipulation serves as the basis for our two research questions:

1. Can overconfidence and gambling preferences explain individuals' participation in cryptocurrency pump-and-dumps?

2. How do manipulators profit if they do not exploit the traditional underpinnings based upon trade-based or information-based market manipulation?

[1]They identified 142 pump-and-dump instances during an 11-year period (1990-2001), compared to our study which identified 114 instances during a 6-month period.

[2]Also, in relation to cryptocurrency pump-and-dumps, stock manipulation is usually directed towards penny stocks with low volume (Hamrick, Rouhi, Mukherjee, Feder, Gandal, Moore, and Vasek, 2021).

These questions are answered through the theoretical framework developed by Dhawan and Putniņš (2022). Cryptocurrency pump-and-dumps are zero-sum games where wealth is distributed between participators. Given that manipulators use their advantageous position to extract profits, pumps have a high likelihood of causing negative expected returns for non-manipulators. Although skills and speed can help individual investors profit, non-manipulators' negative return on the aggregate level makes it puzzling why rational investors participate.

We use two behavioral biases to explain this puzzle: overconfidence and gambling preferences. Overconfident individuals overestimate their ability to profit, and pumps appear as profitable games from their irrational forecasts. Individuals with gambling preferences find pump games attractive due to their belief of earning large gains with a right-skewed payoff distribution. Dhawan and Putniņš (2022) find both behavioral biases statistically significant in explaining individuals' pump-and-dump participation. The proxy for overconfidence is calculated through using the past successes or failures of the participating pump group(s). The gambling proxy is measured by using gambling activity from cryptocurrency gambling sites and normalizing it by the general cryptocurrency market activity. Through modelling the determinants against pump participation, we find weak empirical support for these behavioral explanations to pump-and-dump participation.

This study adds to the literature on behavioral biases in financial markets by assessing whether the findings by Dhawan and Putniņš (2022) hold in our replication and extension. We in large part test their methodology on our extended period, which from our research has been shown to have little coverage in literature. We also extend their study by investigating the impact of including pumps that have their price peak prior to their pump signal. This is because 33% of our recorded pumps had their price peaks prior to their pump signals, which contrasts Dhawan and Putniņš (2022) assumption that pumps start at the time of their official pump release.

Furthermore, we analyze the market impact of the pumps from our period and the welfare effects of cryptocurrency trading. We also contribute by documenting our methodology that can be used and replicated by future research and share our data through a GitHub link[3]. We collect a sample of 114 pumps and obtain granular information about those, such as start times through observing their pump signals. Our time period 2021 is interesting due to a sharp increase in public interest during the period, as seen in Figure 8. The risk of backfill bias is also decreased by taking a more recent dataset, January to June 2021, compared to 2018. Our sample is not affected by prosecution bias since we obtain data about pump-and-dumps regardless of whether they are prosecuted or not. We used a combination of an API from Tiingo.com and data from Binance to collect price and volume data for each pump. In contrast to the study by Dhawan and Putniņš (2022), we exclude the cryptocurrency exchange Yobit and only study pumps on Binance, due to finding too few pumps on the former.

The paper is structured as follows. First, we present a literature review in section 2. This is followed by an example of how pump-and-dumps prevail in section 3. Thereafter, we present data and methodology in section 4. Next, we describe pump-and-dump prevalence in section 5. We also explain participation in pumps through a theoretical framework developed by Dhawan and Putniņš (2022) in section 6. Section 7 considers an empirical analysis to examine drivers for pump participation. Section 8 describes the welfare implications of cryptocurrencies. Section 9 concludes.

[3]https://github.com/MejaochJulia/What-Goes-Up-Must$_Come - Down$

2 Literature Review

Currently, five contemporary papers explore cryptocurrency pump-and-dump manipulation. Li, Shin, and Wang (2021) characterize pump-and-dump impact on cryptocurrency markets and find that price peaks occur within minutes of the pump. They, in line with Dhawan and Putniņš (2022) find substantial wealth transfers between manipulators and participants and use individuals' gambling preferences and overconfidence as explanations for their participation. They find that participants who randomly profit from pump-and-dumps are more prone to participate in future pump-and-dumps and consequently lose money. This result is consistent with Dhawan and Putniņš (2022) framework on individuals' gambling preferences.

Xu and Livshits (2019) contribute to the literature by developing a predictive random forecast Model that delivers the probability of coins being pumped before the release of their pump signal. Their less behavioral focus when analyzing pump-and-dumps therefore differs from Dhawan and Putniņš (2022) and Li et al. (2021). Furthermore, Kamps and Kleinberg (2018) investigate pump-and-dump instances from classic economic literature to develop conditions applied for defining pump-and-dumps. They, in line with Xu and Livshits (2019) develop techniques for identifying pump-and-dump instances through detecting their abnormal trading patterns, although their techniques identify ex post cases whereas Xu and Livshits (2019) develop an approach to predict pumps ex ante. In line with Li et al. (2021) and Dhawan and Putniņš (2022), Hamrick et al. (2021) find that coins with low market capitalization acquire larger price jumps during the duration of a pump. Most listed contemporary papers investigate the market significance or frequency of pump-and-dump manipulation. However, Xu and Livshits (2022) characterize more structurally how further research can be built upon this field. Dhawan and Putniņš (2022) focus on reasons to pump-and-dump participation, and use more granular data compared to other contemporary papers.

This study contributes to the literature about market manipulation in the cryptocurrency market by using the framework developed by Dhawan and Putniņš (2022) to examine how our results vary during 2021. Our framework differs from papers that concern manipulation cases on traditional financial markets, for instance Aggarwal and Wu (2006), who contribute to the literature through examining stock market pump-and-dump analysis and its implications for stock market efficiency.

All papers mentioned in this section investigate pump-and-dump manipulation during 2018 or 2019. The most recent dataset is produced by Li et al. (2022) where pumps between September 2020 to December 2021 are collected, but the data is not as granular as ours. The cryptocurrency market has changed and grown, with increased public interest in pump-and-dump manipulation. It is especially interesting to investigate whether the behavioral biases used in the framework by Dhawan and Putniņš (2022) have significance in a recent time frame. We also contribute through examining price peaks that occur prior to pump signals. Most papers mentioned in this section note that price movements can occur prior to pump signals, possibly due to manipulators who pre-purchase. While Hamrick et al. (2021) and Kamps and Kleinberg (2018) consider price movements before pump signals, their data and methodology are less granular than our study's

3 Pump-and-Dump Manipulation in Cryptocurrency

Pumps of cryptocurrency coins often occur at chat forums, such as Telegram. The administrators who arrange the pump usually pre-announce it by declaring the point in time and exchange where the pump will take place. This information allows the participant members to move capital to the specified exchange and be ready to act on the upcoming pump signal. However, the pump-signal

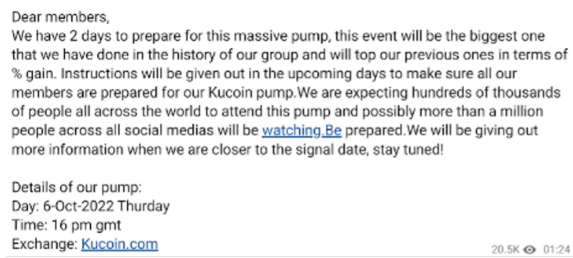

Figure 1: Pump-and-dump group Administrators Release the Pump Signal. In this figure, the manipulators first remind members of the pump and then count down to it. Administrators deliver the pump signal through announcing what coin is being pumped, which in this case is Bondly at 16:00:00 GMT.

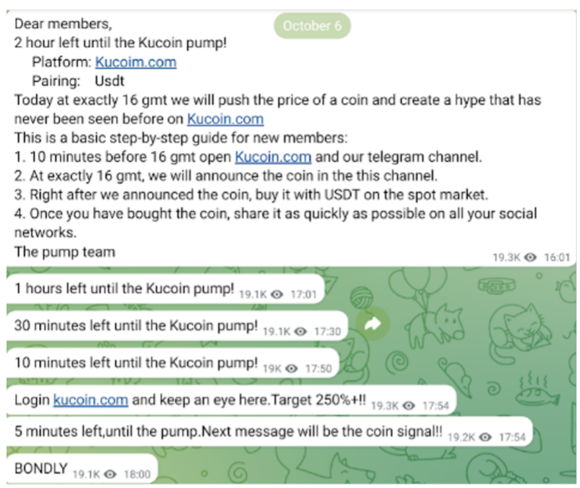

Figure 2: Price Movements of the Cryptocurrency Coin Bondly. This figure illustrates the price development of the pumped coin Bondly during the day it is pumped. The price peak occurs at about 16:00:00 GMT and the price starts to decrease to its initial level prior to the pump at about 17:00:00 GMT. In this case the price starts to increase about 1 hour prior to the price signal, which is likely due to manipulators' aim to buy the security at a low entry price before it increases due to the increased demand when announcing the price signal.

that presents the coin that will be pumped is normally specified at the chat forum only a few minutes to seconds before the actual pump occurs (Dhawan and Putniņš, 2022).

The pump of cryptocurrency coins can be illustrated through the pump of the Bondly coin that took place on the 6 October 2022 in the Telegram chat Big Pump Signal (BPS), which was one of the largest pump communities in 2022 measured by the number of subscribers (approximately 115,000 subscribers 2022). The BPS administrators began by declaring that the pump would take place at the Kucoin exchange at 16:00:00 PM GMT, seen in Figure 1. The pump signal in Figure 2 tells the name of the coin being pumped where the Bondly coin is illustrated by capital letters. The administrators communicated the signal for the Bondly pump at 16:00:00 GMT on October 6.

Figure 3 portrays the price movement of Bondly on October 6th. The trading level is relatively low until the day's 15th hour when the trading volume starts to increase. The fact that the trading level starts to increase before the release of the pump signal is likely because of the BPS

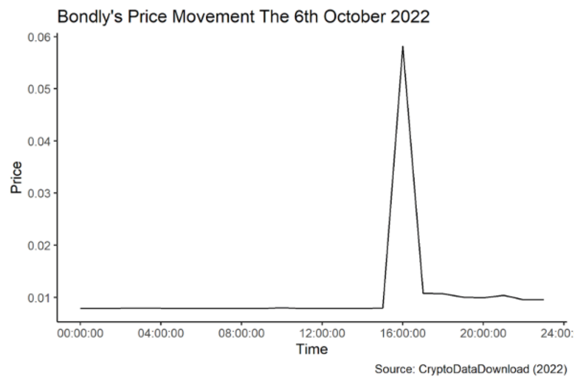

Figure 3: Pump-and-Dump Group Administrators in the Big Pump Signal Group Announce Information About the Upcoming Pump of a Coin.This shows a message by manipulators forwarded to its members in the Telegram pump-group: "Big Pump Signal" where the pump's date, time and exchange are displayed prior to the actual pump.

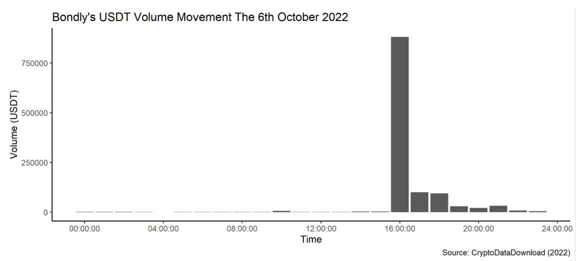

Figure 4: Volume Development of the Cryptocurrency Coin Bondly. This figure shows the increase in volume measured by USDT for the cryptocurrency coin Bondly during the day it was pumped. The peak volume was measured at approximately 16:00:00 GMT, which is the time when the coin's pump signal was released. In accordance with the price that starts to decrease to its initial level at 17:00:00 GMT in Figure 2, the graph shows that the trading volume starts to approach its initial level at 17:00:00 GMT. The peak volume was measured to 881,627 USDT.

administrators' pre-pump position. However, it peaks at 16:00:00 and starts to convert to the initial price level at around 17:00:00. The peak price is approximately 6.34 times as high as the pre-price level before 15:00:00. There is not only a considerable price movement as seen in Figure 3, but there is also a remarkable increase in trading volume at 16.00.00 as seen in Figure 4. The hour before the pump signal, the Volume was 4,011 USDT compared to the Volume at 16:00:00 which was 8,816,29 USDT, thus around 219 times as high.

4 Data and Methodology

4.1 Selecting a Time Period

The time period 1 January to 30 June 2021 was selected for our sample period. While it would be desirable to use a continuous dataset by starting where Dhawan and Putniņš (2022) left off, the choice to collect our sample in 2021 was made due to the following reasons. First, a majority of Telegram pump channels from 2018 had been deactivated, making it difficult to identify pumps from that time period. Second, our main reason for analyzing the prevalence of pumps-and-dumps during 2021 is because of the period's increased public interest in the phenomenon, viewed in Figure 8. This period is also acknowledged by Dhawan and Putniņš (2022) as especially interesting due to the high interest and volumes traded. For example, the largest cryptocurrency pump group on Telegram in 2021 had approximately 3 million participants compared to its 82,000 members in 2018 (Dhawan and Putniņš, 2022).

Using a more recent dataset from 2021 compared to 2018 also decreases the risk of backfill bias which could otherwise lead us to mostly observe successful pump-and-dump instances from Telegram groups as unsuccessful pump groups may be deleted. However, it is important to note that this risk cannot be eliminated unless we collect data in real time, which was not feasible for us because of time constraints. We did not find any similar contemporary study that collected pump data in real time.

4.2 Identifying Pumps

A sample of 114 pumps was hand collected from Telegram pump-and-dump chats during instances where manipulators had communicated pump signals to group members. Telegram channels were compiled from the Telegram chat by the pump-aggregator PumpOlymp.com which combines pump signals from the biggest cryptocurrency exchanges such as Binance, Yobit and Kucoin. We collected the names of all channels that had documented pumps on either Binance or Yobit in the year 2021, from which 54 pump channels were identified. Out of these, 36 still had chat history available during the period for our data collection[4].

115 instances of explicit pump-and-dump schemes between 1 January to 30 June 2021 were identified, out of which 114 pumps were on Binance and 1 from Yobit. Due to the low number of pumps identified on Yobit, we disregard pumps on Yobit in the empirical analysis. From the Telegram channels, coin, time, date, and exchange were documented for each pump signal.

4.3 Coin Data

Ancillary information was extracted from each pump through taking price and volume data for a 24-hour period using an API from the data provider Tiingo.com. From this, each pump's price peak, traded volume before and after the pump's start, price at the start of the pump, returns, as well as opening and closing price were collected.

The price peak was selected from the interval between the pump's start time and 23:59 during its day[5] - In the methodology used by Dhawan and Putniņš (2022), the choice of collecting the coins' price peaks after their pump signals implies the assumption that the price peak will occur after the signal, in line with the idea of an efficient market where participants act on market information at the time it is released.

However, in 33.33% of our pumps, the price peak occurred prior to the pump signal. This could be due to some investors obtaining information about the coin prior to others. For example, manipulators could potentially exploit pumps' information asymmetry and sell private information to participants beforehand.

[4]Data collection was conducted during October and November 2022.

[5]It is unclear how Dhawan and Putninš (2022) choose their price peak. However, it is reasonable to assume that they pick a price peak after the pump starts. This reasoning is elaborated more in the empirical analysis section.

4.4 Ancillary Data

Aggregate coin data including market return, market capitalization, amount of volume traded, number of coins from the Binance exchange and the exchange rate between Bitcoin and USD were extracted from CoinMarketCap.com and cryptocompare.com. Furthermore, we extracted transaction data from the gambling blockchain explorer website WalletExplorer.com. Global search volume index data was obtained from Google.com between 2018 and 2022 to analyze the development of public interest in cryptocurrency pump-and-dump.

4.5 Use of Alternative Data Sources

This study uses the same data sources as Dhawan and Putniņš (2022) to the highest extent possible. However, in some instances alternative sources were used. The website Pumpolymp.com was at the time of the data collection inactive, so the chat history on their Telegram channel was used instead when selecting the Telegram pump channels. Dhawan and Putniņš (2022) also collect ancillary coin data from Binance and via an API provided by Kaiko, while we use an API provided by the data supplier Tiingo.com. This is due to Binance only having coin data from March 2021 and onwards. Although the Kaiko API provides Yobit data, we excluded pumps on Yobit as it was irrelevant for our study. These differences in data sources may affect the results and weaken the comparability compared to the authors. However, substituting to comparable sources should not substantially affect our results, given that the other sources and methods are replicated.

5 Pump-and-Dump Prevalence

5.1 Descriptive Data

During our six-month period, we measured that 337 coins (Curry, 2022) were traded on Binance with a total trading volume amounting to \$557.44 million. The 114 pump cases in which we were able to collect the required data took place in 68 different coins. Therefore, 20.18% of the 337 coins from Binance were subject to at least one pump-and-dump manipulation during the period. The average number of pumps per coin was measured to 1.68 whilst the average number of pumps per pump day (i.e., a day where we identified at least one pump-and-dump instance) was assessed to be 1.52. These numbers are at the lower-bound since only instances where the necessary data was available are included, suggesting that pump-and-dump manipulation is more prevalent than explained by the data.

Volumes during pump-and-dump schemes are economically meaningful, with around \$557.44 million traded during pumps documented in our sample. The manipulators' profits were on average estimated to 7.13%, resulting in a profit of approximately \$14.43 million from a volume of \$202.32 million. Profits were calculated as the difference between the volume weighted average price from the price peak and the volume two hours preceding the pump.

From our observations, manipulators' profits are not as high as found by Dhawan and Putniņš (2022). They find that manipulators earn 24.77% in the time period December 2017 to June 2018, compared to the 7.13% profit measured in our sample. This number is also different from those reported by the working papers that we could find. Xu and Livshits (2019) report that large exchanges, such as the market leader Binance, in terms of trading volume (MarketCap, 2022) are not only more reliable than smaller exchanges, but also more difficult for cryptocurrency pump

Table 1: Aggregate Trading and Manipulation on Binance

Variable	Statistic
Panel A: Market activity	
Total coins	337
Total trading volume ($ million)	9,714,234
Panel B: Manipulation activity	
Total number of pumps	114
Number of pumped coins	68
Pumps with Average pumps per pumped coin	1.68
Number of pump days	75
Average pumps per pump-day	1.52
Total pump-day volume ($ million)	557.44
Total pre-pump volume ($ million)	202.32
Manipulators' total profit ($ million)	14.43
Manipulators' profit (% of pre-pump volume)	7.13%

administrators to manipulate. This is because smaller exchanges to a higher extent include low liquid coins that are easier to manipulate than higher liquid coins (Xu and Livshits, 2019). This could therefore be a reason for our lower measured profits for manipulators as we solely study cryptocurrency manipulation on Binance. However, we still find an increase in the number of pumps; Dhawan and Putniņš (2022) find 64 pumps on Binance over six months compared to our sample of 114 coins, an increase of 78.13%. From their sample, it can be concluded that 19.21% (29/151)[6] of all distinct coins on Binance have been subject to a pump-and-dump manipulation, lower than our number reported.

5.2 Manipulators' Profits Prior to Pump Signals

We further investigate the pumps that have price peaks prior to manipulators' official release of pump signals. Hamrick et al. (2021) note that pumps do not necessarily start at the time of the pump signal. This could be due to manipulators strategically purchasing the coin before the publicly announced time in order to obtain lower entry prices. This is consistent with other works – Kamps and Kleinberg (2018) and Li, Shin and Wang (2018) noticed that pumps both occur at the time when the signal is communicated and sometimes also after the pump signal. Xu and Livshits (2019) found that markets move as much as 72 hours before the pump.

Taking the price maximum, we find that 33.33% (39/117) of all pumps from our sample have price peaks prior to the official releases of pump announcements. Taking the price peaks that occur before the official release of the pump signals, we find that manipulators on average earn a 10.43% profit from administering pumps[7]. However, when analyzing the actual times for the price peaks and comparing them to the time of the pump announcements, we find that very few pumps occur close to the pump signal – out of 39 pumps, 13 have price peaks within 1 hour prior to the official pump signals. On average, coins were pumped 5 hours and 56 minutes prior to the official pump

[6] https://www.binance.com/en/blog/all/binance-2018-recap-286445971261435904

[7] The same methodology developed by Dhawan and Putninš (2022) is used here. However, since we are unable to use the start time of the pump, we instead use the time 2 minutes before the peak price as the starting point. It is derived from Dhawan and Putninš (2022) that pumps reach their peak prices within a median value of 1.54 minutes.

Table 2: Descriptive Statistics of Participants' and Manipulators' Pump Return

Variable	Mean	Standard Deviation	Median
Total number of pumps	114		
Pumps with price peaks before pump start	39		
Pumps with price peaks before pump start (within 1 hour before pump signal)	13		
Time before the pump that peak price is reached	5 hours 56 minutes	24.95%	4h hours 11 minutes
Manipulators' return (%), price peaks before pump signal exckluded	7.13%	60.08%	0.90%
Manipulators' return (%), price peaks before pump start included	10.43%	56.61%	1.47

announcements. This suggests one of two things: either that pumps could occur several hours before the official pump signal, or that pumps occur at the time of the signal but are ineffective in pumping up the price.

While this is interesting, the calculations onwards for the empirical analysis will be based on the assumption that price peaks occur after the release of pump signals, as this is closer to the methodology used by Dhawan and Putniņš (2022). We conduct a robustness test to examine the differences between both datasets[8].

5.3 Participants' and Manipulators' Profits

Table 3: Mean, Standard Deviation and Median of Participants' Pump Return

Variable	**Mean**	**Standard deviation**	**Median**
Participants' pump return	3.61%	26.85%	1.60%
Manipulators' pump return	7.13%	60.08%	0.90%

In table 3, we present descriptive statistics about manipulators' and participants' pump returns. To calculate returns, we used the price at the start of each price peak and the maximum price following these. If the coin's price reached its all-day peak prior to the pump's start, it was disregarded. This reflects how an external participant can make a profit, without insider information from manipulators. We find that on an aggregate level, participants earn 3.61% with a 26.85% standard deviation. Manipulators earn on average 7.13% with a standard deviation of 60.08%.

Figures 5, 6 and 7 plot findings from our data collection. Figures 5 and 6 show that most pumps generate a return between 1-10%. Figure 7 shows that pumps with a higher number of members generate lower returns. All pumps that involved more than 1,000,000 members either generated 0 or negative aggregate returns. As the returns for individual participants have higher volatility with

[8]See Appendix D and E

lower returns compared to manipulators, it is puzzling why people participate. Section 6 uses a framework developed by Dhawan and Putniņš (2022) to examine whether behavioral biases could explain this puzzle.

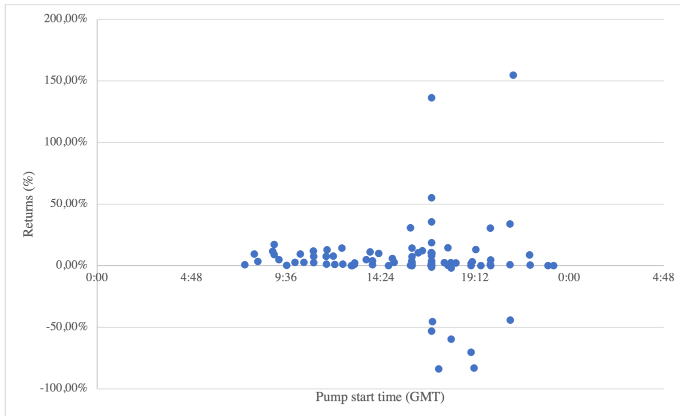

Figure 5: Scatterplot Over Participants' Return Per Pump. This figure shows a scatterplot of participants' return per pump during the time of the day (GMT).

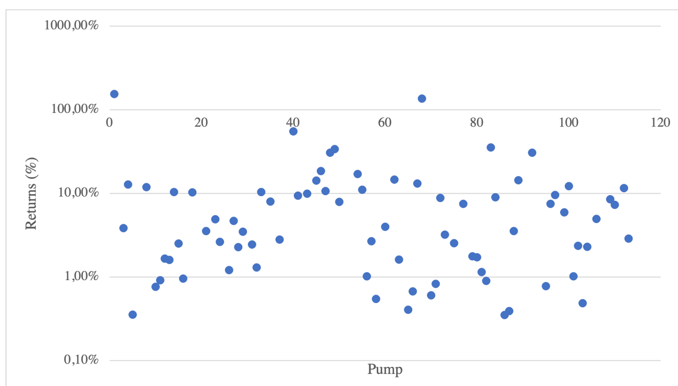

Figure 6: Scatterplot Over Participants' Return Per Pump. This figure shows the returns per pump on a logarithmic scale, negative returns removed.

5.4 Longer-term Trends During Pump Prevalence

To examine pump-and-dump manipulation from a long-term trend perspective, we use one proxy for pump activity. We primarily measure this long-trend perspective through Google search activity as it serves as an indicator of public interest and is a useful tool for analyzing how investor interest has varied through time. Figure 8, plots these proxies between November 2018 and November 2022. In line with Dhawan and Putniņš (2022), we find a significant increase in public interest and a more stable interest pattern during late 2020 and early 2021 whereas the frequency lowers

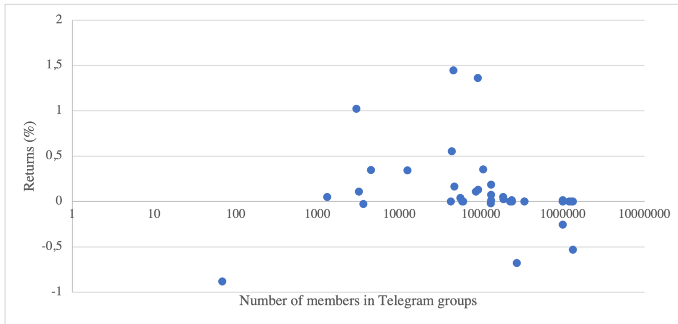

Figure 7: Scatterplot of participants' Return Against the Number of Participating Members. This figure shows the number of Telegram chat member that are involved in each pump, and the frequency of large returns that were generated.

between 2019 and 2022. Although we cannot give a certain report regarding how the public interest will vary during the next few years, the graph shows that it has increased more between 2021 and 2022 compared to between 2019 and 2020. Together with the increased trend of participating in pump-and-dump Telegram chats, also found by Dhawan and Putniņš (2022) and exemplified through the increased number of members in the BPS group (Dhawan and Putniņš, 2022), there are indicators that suggest a persisting trend with participating in pump-and-dump manipulation. The increased trend of participating in pump-and-dumps is likely to have several causes, but it is probable that high coverage in social media, press and regulatory debates are contributing factors to the spread of pump-and-dumps and that people invest in cryptocurrencies because of trends that create familiarity, heard behavior or bold events biases.

An example of social media's pump-and-dump influence is that Elon Musk's tweets have acted as a co-ordination instrument for pump-and-dumps similar to Telegram pump signals, where certain words from tweets have initiated pumps of securities (Levine, 2021). An additional example is the declared support for the token SafeMoon in a tweet by David Portnoy who is an influencer through his social media channels. This raised interest for the token on 17 May 2021, despite him admitting that "it could be a Ponzi scheme". Another important cryptocurrency event that makes the year 2021 interesting to study is the GameStop stock trading event during January 2021 where traders from the social media channel Reddit aligned their speculative acquiring of illiquid firms to cause substantial price increases. This event triggered a price increase of about 1,900% within a month and implied large losses for many households that held a short position in the security (Levine, 2021). Social media trends' effect on people's trading behavior in cryptocurrencies could therefore be a topic for further research. However, from Figure 8, it seems as if the trend during late 2022 starts to revert to the pattern observed during 2020 with more irregularities in public interest.

6 Explaining Participation in Pumps

We use the framework developed by Dhawan and Putniņš (2022) that demonstrate the process of pump-and-dump manipulation and why it is perplexing that individuals participate. This framework builds on the Cumulative Prospect Theory (CPT) by Tversky and Kahneman (1992) that describe reasons for why individuals find positively skewed payoffs attractive. A key assumption

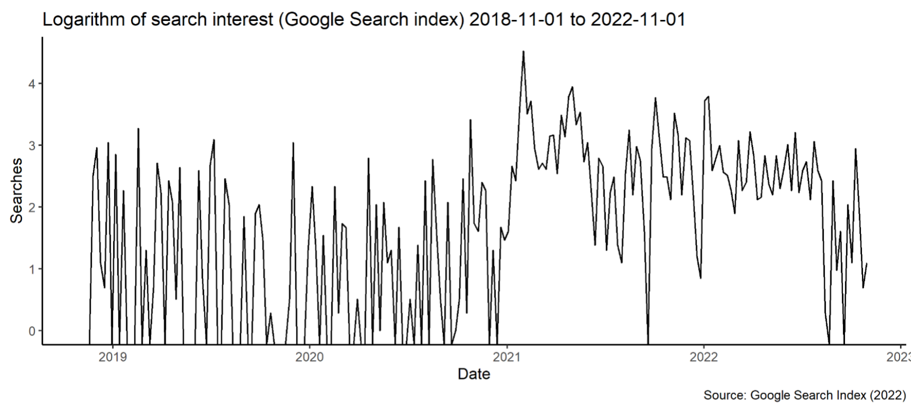

Figure 8: Development of Public Interest in Cryptocurrency Dump-and-Dumps Between November 2018 and November 2022. This figure plots the logarithm of the average number of searches documented worldwide concerning the three searches: "crypto pump and dump", "pump and dump group" and "crypto Telegram group". It shows how public interest in cryptocurrency pump-and-dumps has developed between November 2018 and November 2022.

in the CPT is that individuals are more concerned with avoiding losses than earning gains. This implies that individuals are keener to take risks to prevent losses than to make gains (loss aversion). Additionally, the CPT assumes that individuals have difficulty assessing probabilities of events, as they tend to underestimate the possibility of high-probability outcomes whilst overestimating the possibility of low-probability outcomes (Tversky and Kahneman, 1992). We start by explaining the framework's intuition and thereafter how behavioral biases, for example overconfidence, help solve the perplexity.

6.1 Describing Pump Participation

We use a four-stage period in our simultaneous moving exchange game. Three sorts of agents participate in this game: a market maker that enables trades, manipulators who manage the pumps, and traders who decide to join the pumps given that the manipulators announce a pump signal. In this game, we assume that trades' linear price impact holds, given that $P_t = P_{t-1} + \beta x_t$ is true, where P_t represents the price in period t, x_t is the net volume from the market at time t and β is the price impact factor ranging from zero and one. These assumptions build on the microstructure models of market making by Kyle (1985). Another reason for our assumption about the linear price impacts is that it excludes easy trade-centered manipulation tactics that could lead to infinite profits through merely buying and selling (Huberman and Stanzl, 2004).

This game begins at the start of period 0 at the time when the pump group administrators (manipulators) choose to pump a certain coin and where the coin's price equals P_0. During the first period when $t = 1$, the administrators decide to take a long position of $M > 1$ (M equals as many units as the number of manipulators where each manipulator purchases one unit or where a single manipulator acquires M units) of the security. Thereafter, manipulators inform pump group participants that a pump of a coin (where the coin's name is unannounced) will occur during $t = 2$ and communicates the exact time of the pump and its exchange. The higher the number of manipulators (M) is, the higher is the run-up during t = 1 prior to the release of the pump signal and the higher is the coin's peak price. Furthermore, the lower the liquidity of the coin and the higher the β, the higher is the run-up during $t = 1$ prior to the release of the pump signal. Consequently, the greater is the price increase following the pump signal since players purchase the security.

During $t = 2$, group administrators deliver a pump signal to pump group participators (N') where $N' > 1$ become informed of the name of the pumped coin. Concurrently to this, the participants decide whether to participate in the pump or not, in which they offer purchase orders to the market. These individual members purchase at the prices $(P_1 + 1\beta), (P_1 + 2\beta), \ldots$ where the price is dependent on their arbitrary latency. It in turn dictates their place in the queue as financial markets' matching devices usually manage incoming orders in order by arranging them in a queue. This thus means that latencies, such as the amount of time to construe the pump signal, when proposing orders determine traders' queue position and when the market executes these orders. The higher the number of participating players (N'), the higher is the price increase and price peak during $t = 2$.

During $t = 3$, those that participated in the game exit the pump simultaneously with the manipulators whilst at the same time proposing sell orders to the market. As explained with the market entry orders, factors such as the time taken to make the selling decision affect traders' execution prices.

6.2 Explaining Rational Agents

In this section that also builds on Dhawan and Putniņš (2022), we explain the categories of people who take part in cryptocurrency pump-and-dumps through describing the causes for participants' negative expected return. In addition, we describe how individuals' speed or other advantages could help describe why they take part in pumps. We thus investigate why group members with less skill or speed chose to participate.

Since the pumped coin's price will equal $P_1 = P_0 + M\beta$ prior to the announced pump signal when pump administrators purchase M units, participants will purchase the security when prices equal: $(P_0 + \beta(M + 1))$, $(P_0 + \beta(M + 2)), \ldots,$($\mathrm{P}_0 + \beta(M + N')$) if all N participants take part in the pump. This in turn depends on their arbitrary latency. This implies that the players' entry prices (P_{entry}) are evenly allocated from $(P_0 + \beta(M + 1)$ to $(P_0 + \beta(M + N')$. Likewise, participants' exit prices during $t = 3$ (P_{exit}) are evenly allocated from the first exit price after the peak price $(P_0 + \beta(M + N' - 1)$ to the final exit price (P_0). Although opening and closing prices follow a discrete uniform distribution (Corporate Finance Institute, 2022), because of the high number of pump members (usually thousands), we use the continuous distribution as our proxy. This gives us the following expected profit for individual i:

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

The individual i's expected profit is negative because of the positive sign of β and M. This expected loss entails the expected loss to the manipulator, consisting of 50% of the manipulator's opening price effect ($\beta M/2$) as well as the trade cost from the price impact factor (β). This stands in contrast to the pump administrators that can purchase before the pump signal is released, therefore at lower prices than other individuals. This means that given a high number of participants, manipulators can yield positive expected returns from pumps where the participants cover administrators' transaction costs. This is illustrated through the following statement where manipulators' expected profits are positive if and only if $N^{'} > 2M$:

$$\Sigma[\pi_m] = \frac{\beta M}{2}(N^{'} - 2M) \tag{2}$$

This means that although pump administrators could extract profits, the remaining group members in aggregate should be prepared to extract losses. This is because they as a group will lose manipulators' gross profit ($\beta MN^{'}/2$) as well as the transaction cost $\beta N^{'}$. The implication of this is that cryptocurrency pump-and-dumps is a zero-sum game for all players, involving manipulators given absent trading costs. This, in addition to the fact that capital transfers and positive trading costs to administrators will imply a negative-sum game for other players, should be recognized by rational individuals with accurate beliefs. Individuals should not want to join pump-and-dump games, assuming that they are risk-neutral and risk-averse with rational beliefs and without any benefits over other players.

Result 1: Individuals should not decide to join cryptocurrency pump-and-dump games given that they are rational with accurate beliefs.

If participants have more speed and skills than other players, they may be more skilled at selecting price peaks, sell the security when it starts approaching the dump phase and respond more rapidly than others. These individuals would therefore be capable of purchasing at a low entry price immediately after the pump signal's announcement and sell at a high exit price just after the pump peak. We continue with incorporating an additional parameter (S_i) in the framework that represents participants' skill and speed. It leans rapid (slow) participants' exit price distribution to higher (lower) exit prices. Identical ratios of rapid and slow players imply that $S_i < 0$ for slow participants whilst $S_i > 0$ for fast participants. These leaned distributions concerning exit prices benefit fast players who on average can reach higher exit prices, making them on average able to reach higher pump payoffs.

Thus, given that players are aware of their rapid or slow nature, it is reasonable for players with enough low risk aversion to take part in pumps. Although they might not reap positive returns from every pump, they on average reap positive expected returns. This therefore turns the dilemma to why slow players take part in pumps. However, the dilemma applies to all players except manipulators if participants are unaware of their pace or skill in relation to others. In that case, participants should expect an arbitrary part of all participants' combined outcomes, implying losses equivalent to pump administrators' gross profits and the aggregate trading costs. Thus, it constitutes a puzzle as to why participants that are unaware of their skills level or who have low skill take part in pumps, although participants' differences in speed could clarify why certain individuals join cryptocurrency pumps. See Appendix B for further explanations about fast and slow players' exit price impact and Appendix A for more information about pumps' price dynamics.

6.3 Overconfident Players

Another behavioral bias that could clarify individuals' pump participation is gambling preference as literature on behavioral biases explain how individuals prefer "lottery-like" holdings with a positively skewed payoff distribution where the losses and profits are nearly symmetrical. Barberis (2012) illustrate how gamblers see non-skewed payoffs as a sequence of gambles that together form a game. Gamblers also prefer repeated games compared to single games (Grinblatt and Keloharju, 2009; Dickerson, 1984). A game with symmetric payoffs turns into right skewed for a sequence of bets when a gambler performs a game repeatedly but ends it when their negative returns surpass a "walk away" level.

In line with what Dhawan and Putniņš (2022) propose, we assume that a gambler begins with capital \$$a$ where $a > 0$ when she contemplates whether to take part in a sequence of pump-and-dumps, up until they diminish her wealth to \$$b(b < a)$, leading to a loss of a − b or builds a wealth equivalent to \$$c(c > a)$ that establishes a profit of c–a. This approach diminishes the binary gamble (Barberis, 2012). As mentioned by Barberis (2012) and Dhawan and Putniņš (2022), by presuming that gamblers display preferences in line with the CPT, these yield positive expected returns which explains why individuals take part in cryptocurrency pump-and-dumps.

Result 2: Players that are sufficiently overconfident take part in cryptocurrency pump-and-dumps

6.4 Players With Gambling Preferences

In this section, we present behavioral motivations for individuals' participation in cryptocurrency pump-and-dumps to help resolve the dilemma of participation. We start by taking overconfidence into consideration. This bias could make individuals experience themselves to have an advantage over other participants. As shown in the behavioral finance literature, most individuals consider themselves to have higher capabilities than the average person, well known as the better-than-average effect (Alicke and Govorun, 2005; Deaves, Luders, and Luo, 2009; Gervais and Odean, 2001; Barber and Odean, 2000). Overconfident individuals who consider themselves more knowledgeable than other participants can expect themselves to enter and exit pumps more rapidly than remaining players, making them believe that they will reap higher rewards. In line with Dhawan and Putniņš (2022), we use the overconfidence parameter i which represents the overconfidence bias that makes individuals view themselves as more skilled at selecting pumps' price peaks and closing at higher prices than remaining participants. Individuals who expect themselves to reap positive returns from pump-and-dumps exceed the lowest overconfidence level of ϵ_{min}. Overconfidence bias is therefore our first explanation as to why people choose to engage in cryptocurrency pump-and-dumps. In addition, Dhawan and Putniņš (2022) find that overconfident individuals tend to select coins with low liquidity since low liquid coins usually have a higher spread of exit prices. This implies that only a minor bias is needed to turn a pump attractive for an overconfident individual and gives an explanation as to why pumps tend to arise in illiquid coins. Dhawan and Putniņš (2022) find that when pumps have high manipulation participation, they are inclined to have lower participation from overconfident participators, implying that min increases in M. This in turn happens as administrators enforce a cost on remaining participants, leading higher overconfidence to be necessary for making pumps attractive. Lastly, overconfident participants find pumps with a high number of players more attractive, where ϵ_{min} decreases in N'. This is because a high number of players cause higher and sharper price peaks and higher variation in exit prices where only a modest overconfidence bias in players' observed likelihood of selling their assets close to the peak is necessary for pumps' attractiveness. This means that overconfident players find few manipulators, a high number of participants and illiquid coins attractive in cryptocurrency pump-and-dumps.

Result 3: From the CPT, individuals choose to take part in cryptocurrency pump-and-dump as a type of gambling.

6.5 Additional Aspects Affecting Pump-and-Dump Involvement

In addition to overconfidence bias and gambling preferences that affect participation in pump-and-dumps, we know that the higher the trading by manipulators prior to the pump, the lower is the pump's attractiveness to all players, as shown by equation 2, since the expected return of taking part in pump-and-dumps diminishes in M. The higher M is, the higher degree of overconfidence is necessary to take part in pumps, and rational players anticipate greater expected losses to manipulators.

Result 4: The higher the number of manipulators in pumps, the less attractive is the pump perceived by the remaining players, resulting in their lower participation.

As Dhawan and Putniņš (2022) find, higher trading volumes are expected in dump-and-dumps over time during instances when the participation inflow level surpasses the participation outflow level. This state can be anticipated in situations with: (1) a higher tendency to gamble throughout the market where pump-and-dumps offer a channel for gamblers, (2) a general growing market-wide interest in the cryptocurrency market, (3) growing overconfidence bias, for instance because of past success in pumps that contribute to self-attribution bias, (4) higher earnings from prior pumps that increase the number of overconfident participants.

Result 5: More individuals take part in cryptocurrency pump-and-dumps over time when there is an increase in prior pump returns, when there is a higher degree of gambling interest throughout the market and when there is an increased market-broad degree of interest in the cryptocurrency market.

7 Empirical Analysis of our Framework

7.1 Modelling a Regression

We test our predictions from Results (2) and (3) through modelling a regression. While overconfidence and gambling preferences are preferably measured at an individual level, it is not feasible due to the nature of our data. We therefore create two proxies from the methodology developed by Dhawan and Putniņš (2022) and regress it on a dependent variable for pump participation.

The first proxy, overconfidence ($Overconfidence_{jit}$), tests result (2) from our framework. The proxy uses the past returns[9] of a pump group to measure success or failure. The returns are the average start-to-peak return of the group(s) on a specific pump j of coin i on day t obtained from the two most recent pumps. Statman, Throely and Vorking (2006) find a positive correlation between stock trading volumes and previous returns. They attribute this to inducing overconfidence, since investors tend to self-attribute positive returns with their own skills. Pump groups with previous successes should therefore be more overconfident, and the hypothesis is that we should see a higher pump participation from those groups.

The second proxy, gambling ($Gambling_t$), tests result (3) from Dhawan and Putniņš (2022) framework and is modelled by taking the revenue from Bitcoin gambling services. On these websites, individuals can bet Bitcoin and receive payoffs determined by random number generators. Dhawan and Putniņš (2022) hypothesize that individuals with gambling preferences use pump-and-dumps as another venue for gambling, and hence that there should be a positive correlation between pump-and-dump participation and cryptocurrency gambling. This proxy is modelled by using the daily Bitcoin gambling volumes from the database by WalletExplorer.com which collects cryptocurrency data from 86 exchanges. The effects of general market activity for cryptocurrency are removed

[9]Pump returns are calculated by taking the opening price at the time the pump starts against the maximum price after the pump starts. This is to reflect the maximum return an individual investor (who does not possess insider information like manipulators) can generate.

by regressing it on the current value and three lags of the average daily return and volume for cryptocurrencies. We then use the residuals from this as our proxy.

We regress these two proxies on pump participation ($Participation_{jit}$), which is the logarithmic trading volume for a coin i during pump j on day t. This trading volume is used from the start of the pump to three hours after the start for each of the 114 pumps.

We expect that fewer individuals will participate in pumps with more manipulators and control for the number of pump groups on Telegram as a proxy ($Manipulators_{jit}$). We also control for the number of members ($Members_{jit}$) in the participating Telegram groups, and expect that more members involved generates higher pump participation. Finally, we control for the liquidity of a coin by taking the logarithmic average of the trading volume ($Liquidity_i$)[10].

7.2 Empirical Results of Determinants for Pump-and-Dump Participation

The Results in table 4 show the results for our regressions. We see that all determinants have the same positive or negative direction as hypothesized.

Model 1 and Model 2 show that there is a positive correlation between overconfidence, gambling, and participation in pumps. However, we do not obtain statistically significant results for either of these proxies, and thus both Result 2 and Result 3 from our theoretical framework are difficult to confirm.

Model 3 shows a negative correlation between pump participation and the number of manipulators. This is consistent with Result 4 as more manipulators imply more difficulty for non-manipulators to make a profit, thus discouraging participation. However, we are unable to confirm this on a statistically significant level. We see a statistical significance at the 0.01 significance level for pump members and pump participation. This is expected as a higher number of pump group members should lead to higher trading volume. The last Model includes all regressors. We find that all variables retain their positive or negative signs and see no change in statistical significance.

One explanation to this is that the Model is imperfect and that the variables are not properly fitted to the data. We also consider an alternative regression (see Appendix C), where the participation measure ($Participation_{jit}$) instead uses pumps with price peaks that occur prior to their pump signals. For this regression, we use the volume traded for the duration of pumps that start before the official pump announcement and include it in our participation measure. We do not rely on this measure in our main tests (table 4) since we cannot certainly determine whether the pump occurs beforehand or if it is unsuccessful. One difference between our alternative and main regression is that our alternative regression indicated normality from a Jarque Bera test, which our main regression in table 4 does not. Nevertheless, the result from the regression in Appendix E is largely consistent with the main regression and both are robust[11].

Another explanation for why the Model inadequately fits the data is that the data tested by Dhawan and Putniņš (2022) was from 2018. The cryptocurrency market has undergone great change since 2018 (we elaborate on this in section 8), both in coins, volume traded and public interest. Factors that were relevant in 2018 may not be as relevant in 2021 and there may be external factors that were irrelevant during 2018 but that affect our model's applicability with data from 2021.

[10] Dhawan and Putninš (2022) use a dummy variable to see exchange-fixed effects between the exchanges Binance and Yobit. However, as our sample only included 1 pump on Yobit we have chosen to disregard this pump from our sample.

[11] Section C in Appendix shows robustness testing on both the main regression and the alternative regression.

	Dependent variable:			
	lgparticipation1			
	(1)	(2)	(3)	(4)
overconfidence	0.620			1.655
	(1.429)			(1.404)
gambling		0.025		0.046
		(0.116)		(0.111)
manipulators			-0.111	-0.091
			(0.171)	(0.172)
members1			0.00000***	0.00000***
			(0.00000)	(0.00000)
liquidity	0.009	0.028	0.039	0.016
	(0.161)	(0.159)	(0.150)	(0.156)
Constant	14.765***	14.652***	14.347***	14.410***
	(1.044)	(1.040)	(1.049)	(1.070)
Observations	114	114	114	114
R2	0.002	0.001	0.113	0.127
Adjusted R2	-0.016	-0.017	0.089	0.086
Note:	*p<0.1; **p<0.05; ***p<0.01			

Figure 9: Pump-and-Dump Participation Determinants. This table shows the results when testing determinants of our dependent variable, $Participation_{jit}$, in pump-and-dumps. Four Models are shown below, each incorporating different determinants for pump-and-dump participation.

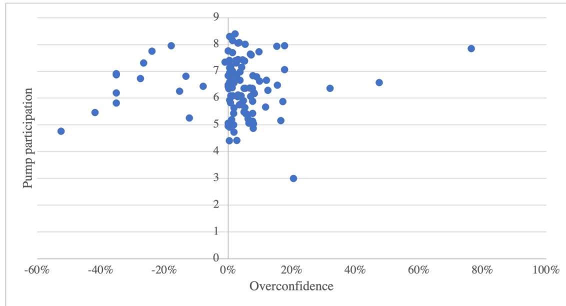

Figure 10: Scatterplot Between Pump Participation and Overconfidence. This figure shows a scatterplot between pump participation and our proxy for overconfidence.

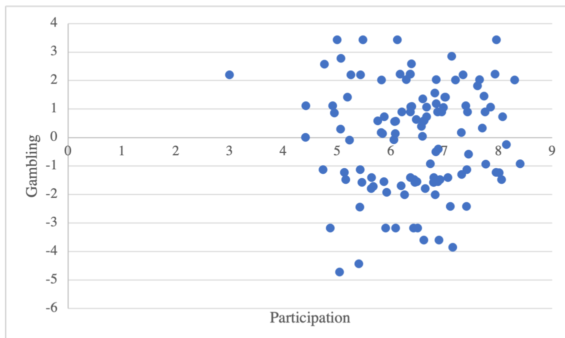

Figure 11: Scatterplot Between Pump Participation and Gambling. This figure shows a scatterplot between pump participation and our gambling proxy.

Our small sample size of 114 pumps compared to Dhawan and Putniņš' (2022) 335 pumps could be another reason for the statistical insignificance of our drivers for pump participation. We plot the variables ($Overconfidence_{jit}$) and ($Gambling_t$) against our participation measure ($Participation_{jit}$) in Figure 10 and Figure 11. Starting with Figure 10, we see a weak correlation between overconfidence and pump participation and that most datapoints cluster around the 0-10% overconfidence return interval. Figure 11 shows the plot of gambling against participation. Here, we see no relationship between these two variables.

Figure 10 suggests that we should derive statistical significance for our proxy for overconfidence, given a large enough sample size. However, we see no indication of a linear relationship between gambling preferences and participation in Figure 11 and thus conclude that our results do not align with Result 3 from our theoretical framework. This is not unreasonable given the set of data; we only test Binance as compared to Binance and Yobit tested by Dhawan and Putniņš (2022). Xu and Livshits (2019) note that Yobit tends to host illiquid coins that generate higher price distortions. Binance instead tends to generate larger trading volumes but smaller price distortions. One could reasonably suggest that risk tolerant individuals with a preference for gambling prefer Yobit or other exchanges with fewer trading controls compared to Binance. Therefore, our model for gambling preferences is potentially better suited for smaller or decentralized exchanges where illiquid coins are traded.

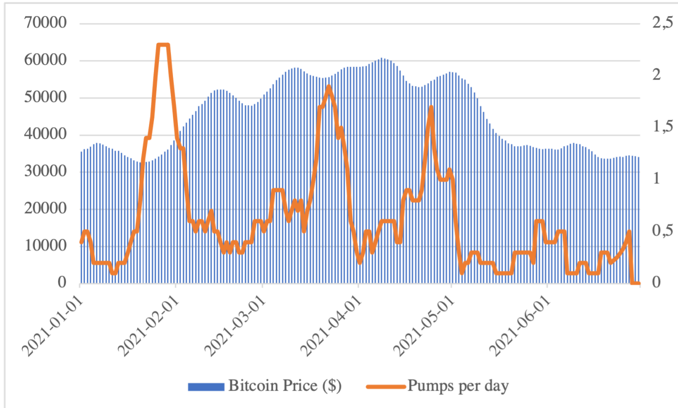

Figure 12: Plot of Number of Pumps Per Day Against Bitcoin Prices ($). This figure shows the number of pumps and Bitcoin prices over time by using our sample with pumps and the volume weighted average Bitcoin price, both smoothed using a 10-day variable

To closer investigate the proxy for overconfidence, we plot Bitcoin prices against a time series for the number of pumps per day in our sample in Figure 12. We also plot Bitcoin prices against the average pump returns in Figure 13. Pumps per day seem to follow a weak trend with the Bitcoin prices. This is consistent with Dhawan and Putniņš' (2022) findings that suggest that overconfidence leads to higher pump participation. However, we do not observe a lagged trend for the pump returns. This contrasts the findings by Dhawan and Putniņš (2022) that suggest a negative relationship between pump returns and Bitcoin prices. Furthermore, we observe a weaker trend for pumps per day compared to Dhawan and Putniņš (2022) seen in Figures 12 and 11[12].

To conclude, our Model does not derive significant results. It could be due to an imperfect Model that does not adequately explain the data from 2021. This is reasonable since we exclude one cryptocurrency exchange and test a new time period. However, our robustness test (see Appendix C) suggests a trend in the overconfidence variable. However, our sample size is too small to derive meaningful results.

8 Welfare Implications and Regulations

Compared to Dhawan and Putniņš (2022), we did not find significance for Models 2 to 4. As shown in table 1, cryptocurrency manipulation is economically important and has increased in frequency in 2021 compared to 2018 (Dhawan and Putniņš, 2022). Because of this, it is meaningful to consider a welfare perspective, for example because of individual traders' losses during the collapse of Terra (LUNA) in May 2022. Another example is the crash of Bitcoin in November 2022 where the coin's price was approximately 73.12% lower on 21 November 2022 compared to on 21 November 2021. This reflects that there may be a demand for regulation on the cryptocurrency market to protect individual investors.

Cryptocurrency pump-and-dumps primarily affect welfare from three perspectives (Dhawan and

[12]Section F in the Appendix plots a lagged correlation matrix and concludes that there is a weak negative lagged trend for pumps per day and no lag for pump returns.

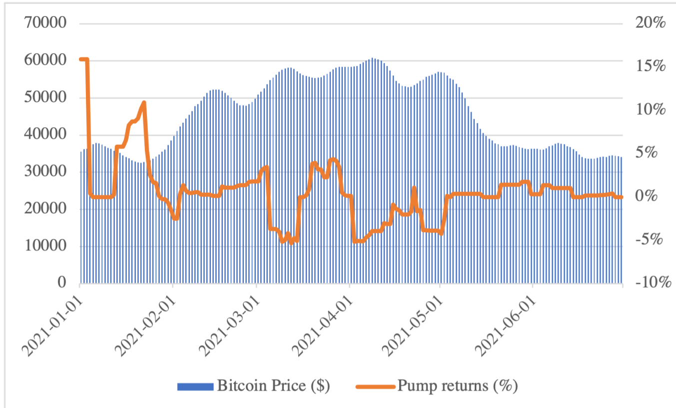

Figure 13: Plot of Pump Returns (%) Against Bitcoin Prices ($). This figure shows pump returns and Bitcoin prices over time which we obtain by using the average pump return (from start to price peak) and the volume weighted average Bitcoin price, both variables smoothed using a 10-day moving average.

Putniņš, 2022). First, pumps lead to wealth transfers as capital is moved from unsophisticated players, e.g. gamblers, overconfident and slow players, to more sophisticated players such as informed and rapid players, as well as manipulators. Gamblers' losses do not automatically lower their welfare since gamblers obtain utility from the gambling itself (Conlisk, 1993). However, their losses function as capital gains for pump-and-dump manipulators and more sophisticated participants. This means that the wealth reallocation from gamblers raises the total welfare through the amount of utility gained from gambling. However, if the unsophisticated players are less wealthy, thus having a higher marginal utility of wealth compared to the sophisticated participants, the wealth transfer from slow, less skilled, or behavioral biased participants to the pump-and-dump administrators is probable to lower the aggregate welfare. It is nonetheless important to consider the potential scope of damage to gamblers with regards to the scarcity of market regulations. Because of the lack of regulations that aim to protect investors during cryptocurrency pump-and-dump instances, there is a risk that gamblers are being significantly exploited by manipulators and more sophisticated players (Dhawan and Putniņš, 2022). Compared to other financial markets where wealth transfer from unsophisticated to sophisticated players in pump-and-dumps offsets the social value in knowledge creation and supply of sophisticated investors' price encounters, there is no comparable offsetting advantage in cryptocurrency pump-and-dump manipulation.

Second, as with other types of market manipulation, cryptocurrency pump-and-dumps trigger price distortions that could damage price informativeness and accuracy. These distortions could theoretically reduce the efficiency associated with resource transfers. Since pumps' price distortions tend to be short-lived, it is hard to envision that pump-and-dumps have a material outcome on resource transfer.

Third, extensive cryptocurrency manipulation could harm cryptocurrency markets' integrity and investor belief in tokens. This is because literature concerning manipulation in traditional financial markets finds that decreased confidence, less involvement and thus lowered liquidity are some of the effects of market manipulation (Dhawan and Putniņš, 2022). Organizations that worry about their reputation might decide to not associate themselves with cryptocurrency markets. Regulators view manipulation as a reason to limit the growth of cryptocurrency markets and cryptocurrency-related products. For instance, the US Securities and Exchange Commission (SEC) has denied many requests for Bitcoin exchange traded fund because of concerns about the Bitcoin market's market manipulation (Dhawan and Putniņš, 2022). However, regulators' lacking trust in cryptocurrency markets could potentially impact how cryptocurrency markets develop in the future and people's adoption of cryptocurrency coins. This may in turn have substantial welfare implications.

There is currently an absence of regulations and a lack of supervision from exchanges, leaving pump-and-dump manipulation to continue. Leaving the cryptocurrency market unexamined might lead consumers to lose confidence in these markets and in the technology of tokenization (Dhawan and Putniņš, 2022). Therefore, there may be a possibility for thoroughly constructed regulation that restricts the potential gains of manipulation. Nevertheless, regulating the cryptocurrency market implies costs linked to monitoring and compliance. Corbet, Hou, Hu, and Oxley (2022) also underline the complexity concerning prosecution as manipulators from internet forums could hide their identities that obscures identification. They question whether regulation could be used for cryptocurrencies considering the associated uncertainty regarding what financial product they denote. Fletcher, Larkin, and Corbet (2021) also highlight the complexity associated with classifying Bitcoin and finds that the coin does not effectively fit into any US regulatory framework. As cryptocurrencies are traded globally, a cryptocurrency regulation would likely require substantial global coordination among states. In addition, the cryptocurrency ecosystem currently possesses impactful innovation with possibilities for producing large economic benefits from its financial infrastructure. This means that if constructed poorly, regulations could destroy this innovation at a considerable welfare cost. If instituting regulations, it is thus important to carefully direct them towards diminishing harmful events without damaging the innovation or generating regulatory burdens on activities that do not associate with damaging behaviors.

There are other advantages associated with the cryptocurrency ecosystem. For instance, Cong, Li, and Wang (2018), Cong, Li, and Wang (2020) and Li and Mann (2020) highlight the advantages of digital tokens and the advantages of raising capital through initial coin offerings. Consequently, cryptocurrency manipulation is associated with benefits beyond their instant wealth transfers.

9 Conclusion

We investigate if overconfident bias and gambling preferences can explain why individuals participate in cryptocurrency pump-and-dumps and how manipulators profit by analyzing data from 114 pumps between January to June 2021. We do this to a high extent by replicating the methods by Dhawan and Putniņš (2022) for selecting price peaks and through studying individuals' behavior from 2021.

Compared to Dhawan and Putninš' (2022), we find a non-significant and weak relationship between individuals' pump participation and gambling preferences and overconfidence bias. Therefore, we cannot answer why individuals participate in pump-and-dumps with regards to behavioral explanations. This means that we do not support that behavioral biases explain pump participation. Our exclusion of the exchange Yobit compared to Dhawan and Putninš (2022) could impact these results. In addition, our small sample size compared to Dhawan and Putninš (2022) makes it difficult to produce meaningful results that can be reliably interpreted. As we see an increasing trend with participating in cryptocurrency pumps, for example through the increased number of members in the BPS group and an overall increased interest in cryptocurrency pump-and-dumps (Figure 8) during the previous years, social trends could explain increased participation.

In contrast to pump-and-dump manipulation in traditional financial markets, we find that cryptocurrency pump-and-dump manipulators profit from administrating pumps through the transaction costs paid by participants, where individuals' losses serve as manipulators' gross profit. According to equation 2, manipulators can earn positively expected returns from pumps when participants cover administrators' transaction costs, and their gross profits are positively affected by a high number of participants. From our results, we noticed that approximately 33% of all pumps had a price peak prior to their pump signal. This supports our framework that manipulators can earn revenue before the pump signal.

We used Dhawan and Putninš (2022) method of calculating manipulators' profit where we assumed that price peaks would occur after the price signals. We also examined price peaks that occurred prior to the pump start but encountered difficulties with correctly identifying the price peak. We therefore chose to continue with the methodology by Dhawan and Putninš (2022). From this method, we found that participants on average earn 3% return with a standard deviation of 27% which is lower than found by Dhawan and Putninš (2022). This implies a considerable risk associated with pump-and-dump participation which is not necessarily compensated by higher returns in contrast to what conventional finance theories with assumptions about rational investor behavior, such as the CAPM, advocates. This also raises the question of whether the cryptocurrency market and pump-and-dump manipulation should be regulated by public policy to protect individuals from being exploited by manipulators. We however find that there could be several difficulties associated to this regulation, for example related to destroying impactful innovation. Except from finding more pumps from Binance, another difference between our findings and those by Dhawan and Putninš (2022) is that they estimate that about 15% of the coins on their exchanges had been pumped compared to our estimate of 20%. Although we in line with Dhawan and Putninš (2022) found that cryptocurrency pump-and-dumps create significant price distortions and abnormal trading volumes, we did not find as high price and volume distortions as the authors.

To better understand the implications of these results, we leave room for future studies to address what behavioral biases that could impact pump participation. There is no granular methodology for finding price peaks that occur prior to pump signals. Developing a methodology for this on a granular level could better capture price peaks.

Our study not only contributes to the literature on pump-and-dumps by testing whether pump participation can be explained by behavioral biases but is also meaningful in relation to welfare and regulatory aspects concerned with individuals' vulnerability and risk towards manipulators when participating in pump-and-dump games. Our consideration of price peaks prior to pump signals on could be a basis for future research within this field.

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Appendices

A Explanation About Price Dynamics in Pumps

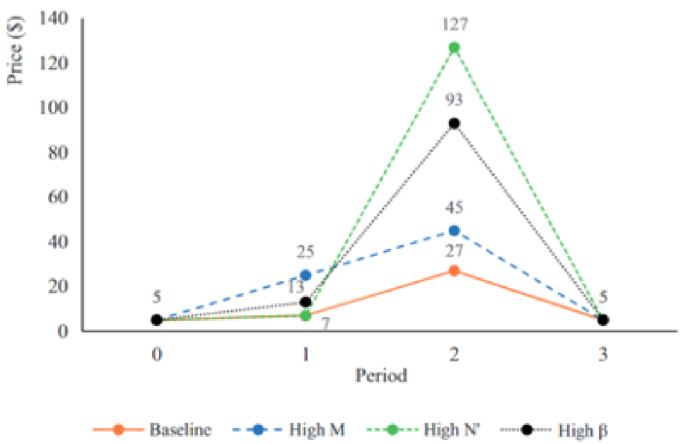

Figure A1: Price Dynamics in Pumps by Dhawan and Putninš (2022).

This figure, which is borrowed from "A New Wolf in Town? Pump-and-Dump Manipulation in Cryptocurrency Markets" by Dhawan and Putninš (2022) pictures pumps' price features from our theoretical framework in section 6. There are four different scenarios: a baseline, high number of manipulators, high number of participation and high β scenarios. Table A shows the price impact of different scenarios and how they compare to each other. A higher number of manipulators (M) implies a higher run-up during period 1 prior to the pump announcement. A higher number of pump participants (N') means a higher price peak and a quicker price increase during period 2. A higher impact value and lower liquidity (β) implies a sharper increase during period 1 prior to the pump announcement, as well as a larger price growth after the pump announcement. However, we refer to the paper by Dhawan and Putninš (2022) for the formulas and assumptions behind the calculation.

Figure A2: Price Impacts from Different Scenarios.

Scenarios	P_0	M	N'	β
Baseline	5	10	100	0.2
High M	5	100	100	0.2
High N'	5	10	600	0.2
High β	10	10	100	0.8

B Fast and Slow Individuals' Exit Price

This figure, which is borrowed from "A New Wolf in Town? Pump-and-Dump Manipulation in Cryptocurrency Markets" by Dhawan and Putninš (2022) illustrates fast and slow players' exit prices. Slow (fast) players have a low (high) likelihood of obtaining a high (low) exit price, whilst a high (low) likelihood of obtaining a low exit price. By setting the initial number of Manipulators (M)

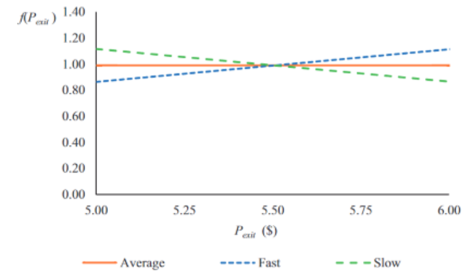

Figure B1: Distribution of Fast and Slow Individuals' Exit Price by Dhawan and Putninš (2022).

to 2, the number of individual players (N') to 100, price level (P_0) to \$5 and price impact parameter (β) to 0.01, exit prices for fast and slow players are calculated through using the probability density function. This price distribution is uniform given that there are equal ratios of fast and slow participants. Although participants still confront uncertainty concerning their exit prices, the price distribution of exit prices benefit fast participators as they on an aggregate level obtain higher exit prices, and therefore higher average returns. We refer to the paper by Dhawan and Putninš (2022) for the formulas and assumptions behind the calculation.

C Alternative Regression

	Dependent variable:			
	ParticipationAlt			
	(1)	(2)	(3)	(4)
OverconfidenceAlt	1.084			1.169
	(1.487)			(1.512)
GamblingAlt		0.060		0.099
		(0.121)		(0.121)
ManipulatorsAlt			-0.315*	-0.308*
			(0.181)	(0.184)
MembersAlt			0.252**	0.276**
			(0.110)	(0.112)
LiquidityAlt	-0.028	0.010	-0.013	-0.013
	(0.167)	(0.166)	(0.162)	(0.168)
Constant	14.844***	14.623***	12.807***	12.543***
	(1.086)	(1.083)	(1.458)	(1.502)
Observations	114	114	114	114
R2	0.005	0.002	0.048	0.060
Adjusted R2	-0.013	-0.016	0.022	0.017
Note:	*p<0.1; **p<0.05; ***p<0.01			

Figure C1: Regression Using the Alternative Data Including Price Peaks Occurring Prior to the Official Pump Starts.

D Robust Regression

These two figures show results for robust regressions for both our main and alternative regressions. This allows us to examine if price peaks prior to pump signals have a large impact on our results. We mainly test for outliers since we conduct a Breusch Pagan test where we do not reject homoscedasticity. From our output, we observe no significant differences compared to the normal regressions, suggesting that influential outliers are impacting our regression results.

```
Call:
lm_robust(formula = Participation ~ Gambling + Overconfidence +
    Manipulators + Members + Liquidity, data = regN, se_type = "HC1")

Standard error type:  HC1

Coefficients:
               Estimate Std. Error t value  Pr(>|t|)
(Intercept)    11.12930     1.3661  8.1469 7.129e-13
Gambling        0.08360     0.1100  0.7603 4.488e-01
Overconfidence  1.44276     1.6306  0.8848 3.782e-01
Manipulators   -0.06386     0.1288 -0.4958 6.211e-01
Members         0.34654     0.1099  3.1522 2.098e-03
Liquidity       0.05008     0.1258  0.3983 6.912e-01
               CI Lower CI Upper  DF
(Intercept)      8.4215  13.8371 108
Gambling        -0.1344   0.3016 108
Overconfidence  -1.7893   4.6748 108
Manipulators    -0.3192   0.1915 108
Members          0.1286   0.5644 108
Liquidity       -0.1992   0.2994 108

Multiple R-squared:  0.1172 ,	Adjusted R-squared:  0.0763
F-statistic: 2.452 on 5 and 108 DF,  p-value: 0.03806
```

Figure D1: Robust Regression on our Main Regression.

```
Call:
lm_robust(formula = ParticipationAlt ~ GamblingAlt + OverconfidenceAlt +
    ManipulatorsAlt + MembersAlt + LiquidityAlt, data = regAlt,
    se_type = "HC1")

Standard error type:  HC1

Coefficients:
                  Estimate Std. Error  t value
(Intercept)       12.54345     1.4200  8.83334
GamblingAlt        0.09918     0.1211  0.81892
OverconfidenceAlt  1.16888     1.5790  0.74025
ManipulatorsAlt   -0.30766     0.2039 -1.50891
MembersAlt         0.27577     0.1118  2.46587
LiquidityAlt      -0.01309     0.1464 -0.08941
                   Pr(>|t|) CI Lower CI Upper  DF
(Intercept)       2.067e-14  9.72874  15.3582 108
GamblingAlt       4.146e-01 -0.14089   0.3393 108
OverconfidenceAlt 4.608e-01 -1.96103   4.2988 108
ManipulatorsAlt   1.342e-01 -0.71181   0.0965 108
MembersAlt        1.524e-02  0.05409   0.4974 108
LiquidityAlt      9.289e-01 -0.30326   0.2771 108

Multiple R-squared:  0.06049 ,	Adjusted R-squared:  0.017
F-statistic: 1.353 on 5 and 108 DF,  p-value: 0.2479
```

Figure D2: Robust Regression on our Alternative Regression.

E Robustness Test

Figure E1 shows the output from a Jarque Bera Test conducted on both the main regression and the alternative regression, to test whether the error terms follow a normal distribution. For the main regression, we find a test statistic of 6.0909 and a p-value of 0.04757, and thus reject the

```
Jarque Bera Test

data:  Main Regression
X-squared = 6.0909, df = 2, p-value = 0.04757

data:  Alternative Regression
X-squared = 1.8653, df = 2, p-value = 0.3935
```

Figure E1: Jarque Bera Test – Testing for Normality.

```
Breusch-Pagan test

Data:  Main Regression
BP = 10.259, df = 5, p-value = 0.06822

Data:  Alternative Regression
BP = 4.2533, df = 5, p-value = 0.5135
```

Figure E2: Breusch Pagan Test – Testing for Heteroskedasticity.

```
Variance inflation factor
Main Regression
      Gambling Overconfidence   Manipulators
      1.067456       1.109523       1.520975
       Members      Liquidity
      1.523306       1.085949

Alternative Regression
      GamblingAlt OverconfidenceAlt   ManipulatorsAlt
         1.067456          1.109523          1.520975
       MembersAlt       LiquidityAlt
         1.523306          1.085949
```

Figure E3: Variance Inflation Factor (VIF) – Testing for Multicollinearity.

null hypothesis that the data is normally distributed. For the alternative regression, we observe a test-statistic of 1.8653 and p-value of 0.3935, and do not reject the null hypothesis. This finding is critical since predictions and confidence intervals are based on this assumption.

Figure E2 shows our results for a Breusch Pagan test for both the main regression and the alternative regression for heteroskedasticity. We find a higher p-value than 0.05 for both our main regression and alternative regression and do not reject the null hypothesis of homoskedasticity and therefore assume that homoskedasticity is present. We observe that the p-value is considerably higher for the alternative regression.

Figure E3 shows our results for the variation inflation factor (VIF) to measure how each coefficient variance is inflated due to the presence of multicollinearity. We observe that each VIF variable is between 1 and 2, suggesting that we are not faced with multicollinearity and do not need to remove any variable.

F Crosscorrelation Matrix

The figures show cross correlations for pumps per day (F1) and pump returns (F2) against Bitcoin prices. All variables are smoothed with a 10-day moving average. We find weak correlations for all variables. There is a 0.481 correlation measure for lag 13 in Figure F1 for pumps per day and a -0.484 correlation for lag 0 in Figure F2 for pump returns.

```
Autocorrelations of series ‘X’, by lag

  -19   -18   -17   -16   -15   -14   -13   -12   -11   -10 
0.405 0.429 0.448 0.464 0.474 0.480 0.481 0.476 0.467 0.456 
   -9    -8    -7    -6    -5    -4    -3    -2    -1     0 
0.443 0.425 0.405 0.380 0.353 0.322 0.289 0.263 0.236 0.212 
    1     2     3     4     5     6     7     8     9    10 
0.179 0.151 0.127 0.108 0.090 0.077 0.069 0.065 0.065 0.066 
   11    12    13    14    15    16    17    18    19 
0.067 0.067 0.067 0.066 0.063 0.059 0.053 0.045 0.034 
```

Figure F1: Cross correlation on Pumps per day Against Bitcoin Prices.

```
Autocorrelations of series ‘X’, by lag

   -19    -18    -17    -16    -15    -14    -13    -12    -11 
-0.193 -0.208 -0.223 -0.238 -0.253 -0.270 -0.288 -0.307 -0.328 
   -10     -9     -8     -7     -6     -5     -4     -3     -2 
-0.350 -0.372 -0.393 -0.412 -0.429 -0.443 -0.456 -0.468 -0.478 
    -1      0      1      2      3      4      5      6      7 
-0.483 -0.484 -0.456 -0.424 -0.387 -0.375 -0.362 -0.347 -0.332 
     8      9     10     11     12     13     14     15     16 
-0.317 -0.303 -0.292 -0.284 -0.280 -0.269 -0.262 -0.258 -0.257 
    17     18     19 
-0.255 -0.254 -0.252 
```

Figure F2: Cross correlation on Pump Returns Against Bitcoin Prices.