

Pump, Dump, and then What? The Long-Term Impact of Cryptocurrency Pump-and-Dump Schemes

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Abstract—The pump and dump scheme is a form of market manipulation attack in which coordinated actors drive up the price of an asset in order to sell at a higher price. Due in part to a lack of enforcement, these schemes are widespread within the cryptocurrency marketplace, but the negative impact of these events on the coins they target is not yet fully understood. Drawing upon a novel dataset of pump events extracted from Telegram channels, an order of magnitude larger than the nearest comparable dataset in the literature, we explore the differing tactics of pumping channels and the long-term impact of pump and dump schemes across 765 coins. We find that, despite a short-term positive impact in some cases, the long-term impact of pump and dump schemes on the targeted assets is negative, amounting to an average 30% drop relative to market prices a year after the pump event.

Index Terms—market manipulation, cryptocurrency, telegram, exchanges, fraud

I. INTRODUCTION

Pump and dump schemes are a type of investment fraud where asset prices are artificially inflated by a group of market participants in order for them to sell the assets at a higher price. Once the instigators sell off the asset and stop promoting it, the price falls significantly and any remaining investors in that particular asset end up losing money [29]. Figure 1 shows an example of typical behaviour of a cryptocurrency pump and dump event where the price rapidly rises as participants buy into the coin, peaks for around two minutes, then rapidly falls as some participants sell their holdings in the coin [32], [34].

This type of scheme is not in itself a new phenomenon, with examples littering stock market history back to the South Sea Bubble of 1720. However, the unregulated and decentralised nature of cryptocurrencies and the widespread adoption of encrypted messaging applications such as Telegram have made executing such schemes possible on a scale never seen before. This near-industrial scale of such schemes means that they have had an increasingly significant impact on the cryptocurrency market as a whole, as such events can be organised on a daily basis and across multiple different exchanges. The current state of regulation with respect to cryptocurrencies is



Fig. 1: Example of a pump and dump event on the cryptocurrency ARKER.

sparse or non-existent [8] and in effect this allows operators to get away with organising such events with no legal consequences or accountability, despite similar schemes in traditional stock markets being illegal with organisers actively prosecuted by the SEC¹ [30].

The aims and contributions of this paper are:

- **New and enlarged cryptocurrency pump event dataset.** This paper introduces and analyses a new enlarged dataset of pump events, which includes pump events collected directly from Telegram to build upon an existing dataset [23]. Our new dataset expands this existing dataset from 1, 111 events to 10, 687. The dataset is made publicly available for future research² along with

¹See Appendix C for the definition of acronyms.

²<https://gitlab.com/bristol-university-work/crypto-pump-and-dump>

the code used to collect it, enabling future updates and expansions.

- **Pump strategy analysis.** A full breakdown and analysis of the dataset was performed with respect to the organising channel, exchange and market capitalisation, revealing two strategies taken by pump organisers, referred to as the *quantity vs quality tradeoff*. A successful analysis of the performance of the pumps in the dataset further exhibits differences between these two strategies.
- **Long-term impact.** Whilst it has been suggested by Li et al. [24] that a higher concentration of pump events occurring on a given exchange are detrimental to the price of cryptocurrencies in the long-term, no study has focused on concretely quantifying and analysing the pricing of pumped coins in the long-term fallout from such events. In our analysis of the pricing impact after the pumps within our dataset, it is revealed that prices of pumped coins fell by 30% after 365 days relative to the wider market, indicating that such schemes have a strongly negative impact on cryptocurrency value.

II. RELATED WORK

Huang and Cheng [19] investigate the impact of pump and dump events in the Taiwanese stock market, a regulated market, by analysing market data on manipulations prosecuted by authorities from 1990 to 2010. They examine the cumulative abnormal returns (CAS) from day -100 to $+100$ relative to events and find that the peak CAS is 28% but by day $+100$ the CAS returns to 0%, suggesting that such events increase the volatility of returns during both pump and post-pump periods. Analysing the effects on market prices they find that the temporary price increases prices by over 24% but overall longer term price impacts are negligible. They further show that there is also a large temporary price impact associated with such events and suggest that this means events have a damaging effect on price accuracy and market efficiency.

One of the first papers describing pump and dumps in the cryptocurrency sphere, Harmick et al. [14] provide a description for pump and dump schemes and identify factors that affect the success of a pump. They collected data over a 7 month period from Telegram and Discord and broadly categorised the channels into 3 groups: **Obvious pumps** that clearly promote pump and dump schemes and provide countdown signals hours and days before the occurrence of the pumps; **Target pumps**, that avoid directly marketing themselves as a pump and dump channel but instead posted coin names without any prior announcement and **copied pumps** that copied other channels' posts, typically several hours after the original post. They found that coins with lower trading volume (and therefore lower market capitalisation and liquidity) were more likely to produce a successful pump, and also established that the number of exchanges a coin is listed on correlates negatively with the success of a pump.

Klamps and Kleinberg [21] propose an unsupervised anomaly detection algorithm to help identify pump and dump

events. They found that certain exchanges, specifically Binance and Bittrex, accounted for more pumps than the relative percentage of symbols explored on each whereas for Kraken, Kucoin and LBank the converse was true. On a coin-pair level, they found that most were targeted 0 – 3 times but there were coins that were targeted up to 13 times, implying that pump and dump groups target specific coins multiple times.

Xu and Livshits [34] provide an in depth analysis of the anatomy of pump and dump schemes and real-world case study of such an event. They note that participation levels in a group are at a fraction of the total membership. They go on to identify 412 pump events in 358 channels over an 8 month period on 4 exchanges.. After these pumps were matched to OHLCV market data using CryptoCompare, they develop a RF model and investment strategy for predicting pump events. They estimate that they only obtain half of the gain in value caused by the pump and find even with this caution, returns of 60% can be achieved.

Li et al. [24] investigated pump events using hand-collected data from Telegram across both CEXs (Binance, Bittrex and Yobit) and DEXs (PancakeSwap)³, from an economic perspective. They explain that these CEXs are not randomly chosen, and display common features such as having little if any “know your customer” requirements⁴ and a large number of listed cryptocurrencies to use as targets. After analysing market data around the collected events, they found that cryptocurrencies targeted are far more likely to have been pumped before and that effects on traded volumes disappear in one to two days, when viewed in the context on a week long window after events. Further analysis on cryptocurrencies with a relatively high market capitalisation pumped on CEXs reveals that the effects of pump events are not restricted to only small coins and on average most pump events increase trading volumes and prices. They conclude by analysing the effects of two opposing policy changes with respect to pump and dumps by Bittrex and Yobit. In the case of Bittrex, which started banning accounts suspected of market manipulation in November 2017, the number of pump events sharply decreased. Yobit, however, announced in October 2018 that it would randomly pump listed cryptocurrencies on its exchange, which generated a negative reaction from investors and reduced the overall prices and volumes of cryptocurrencies listed. They suggest that these opposing effects mean that pump and dump events are damaging to the price and liquidity of cryptocurrencies.

Morgia et al. [23] collected a publicly available dataset of pump events⁵ and proposed a real-time detection model that represented a significant improvement on existing models with respect to speed and accuracy. They also investigated “crowd pumps”; pumps that result from actions by a group of market participants that are not directly organised. They present pumps of GameStop and DogeCoin as examples of

³Not used in this project due to the difficulty in obtaining historical pricing data for DEXs.

⁴Binance and Bittrex have since introduced such requirements.

⁵<https://github.com/SystemsLab-Sapienza/pump-and-dump-dataset>, which forms part of the dataset used in this project.

such events, and compare “crowd pumps” to traditional pump and dump events, explaining that there are three key differences between the two: (1) crowd pumps aim to inflate prices and keep them high, whereas traditional schemes quickly sell at inflated prices for a profit; (2) the target of crowd pumps is known well in advance so any uptick in its price can trigger the start of a large price increase and (3) crowd pumps can last extended periods of time whereas traditional schemes typically last minutes.

In other work, Victor and Hagermann [32] analyse pumps on Binance over the period of a year and find that, on average, a pumped coin performs around 10% better in the 100 days after a pump event compared to its peers. They also use an XGBoost classifier, which uses tree boosting, to detect pump events and find 612 pump like events across 172 coins. Corbet et al. [8] find that cryptocurrencies do not fit into existing regulations. This makes applying any existing market manipulation regulations to cryptocurrencies nigh on impossible. Dhawan and Putniņš [11] postulate that no rational market participant would knowingly take part in a pump and dump scheme as they show them to be a negative-sum game. They further explain that their evidence suggests participants treat such events as a game where the goal is to outsell others.

There are numerous other papers focussed on building machine learning models to detect pump and dump events. Nilsen [26] used a LSTM network to create a real-time pump event detector with over 97% accuracy, Tsuchiya [31] used Bayesian linear regression to classify pumps before they occur with a 75% accuracy rate and Hu et al. [18] created a sequence-based neural network to identify pumps within Telegram channels.

Whilst this is clearly an active field, much previous work has focused on data collected during a specific period and for a specific exchange. By collecting data going back multiple years and leveraging existing datasets, we produce a more comprehensive and extensive dataset that allows us to develop a novel long-term analysis, and which can be updated and adapted for future use.

III. DATA COLLECTION AND PREPARATION

Our methodology is split into three distinct phases.

- **Pump Event Collection (Section III-A).** Identifying Telegram channels organising pump and dump events and collecting information about such events from them.
- **Market Data Collection (Section III-B).** Aggregating market OHLCV data for identified pump events.
- **Price and Data Analysis (Section III-C).** Using collected market data to analyse the impact of pump events.

A. Pump Event Collection

There are few large-scale existing datasets on pump events, the lone exception being the one produced by Morgia et al. [23], which spans multiple years (2017 to 2021), but covers only 1,111 pump events. We take this dataset as a basis, and update and extend it through our own process described below.

1) *Identifying Telegram Channels:* We used PumpOlymp⁶ to retrieve a list of 800 Telegram channels for investigation (as used by Xu and Livshits [34]). Further investigation on a subset of this list found that many of these channels were inactive or provided “signals” rather than organising pump and dump events. We filtered the list to find channel names that contained the word “pump”, which yielded around 130 channels for investigation.

2) *Finding and Collecting Pump Events:* Identifying pump events from channels was automated using the Telethon Python library. The main challenge was the different formats used to announce coins being pumped. As shown in Figure 2, the announcements generally took one of two forms: text containing keywords (e.g., “coin” and “pumping today”, as in Figure 2b), or text embedded in an image (as in Figure 2a). We extracted text from images using pytesseract⁷ and iterated through images checking for predefined regex patterns (e.g., #) matching identifiable patterns of announcement. These extracted coins were combined with the date and time of the message, also extracted via Telethon, to give a list of per-channel pump events.

#FLUX (Binance)
Buy zone [3255-3534](#)
Sell zone 3674-3989-4234-4689+

By @crypto_pump_island (@APGLOBALS)

(a) Pump announcement using an image.



(b) Pump announcement using text.

Fig. 2: Different styles of pump announcements.

Out of the 130 channels investigated, 34 of them had pump events that could be systematically identified using the methods described above. There were multiple reasons for this large number of unusable channels, chief among them was channels either no longer existing or having broken links. Issues also included channels organising pumps on DEXs, such as PancakeSwap, which do not have APIs giving access to historical OHLCV information. Some channels no longer organised pumps, instead providing general cryptocurrency investment “advice” in vague terms.

3) *Aggregating and Cleaning Pump Events:* The final stage of pump event collection was to clean and aggregate pump

⁶<https://pumpolymp.com>.

⁷<https://pypi.org/project/pytesseract>, powered by Google’s Tesseract-OCR engine, <https://github.com/tesseract-ocr/tesseract>.

events collected from Telegram to ensure that individual pump events were attributable to their original channel and that market data for the coins used was retrievable. This was split into three stages, detailed below.

a) *Identifying Channels*: Identifying the individual channels and their respective pumps was done using two to four digit codes generated from the respective channel’s names. For example, the channel `Hit Pump Angels` is represented by the code `HPA`. The full reference for this can be found in Table XIV, in Appendix B. This was done to allow unique identification for pump events that were broadcast across multiple channels and to ensure compatibility with the system used by Morgia et al.’s dataset⁸.

b) *Checking the Status of Coins*: Once events were uniquely identified, they were merged into a main table containing 10,687 pump events. As there is a large amount of listing and delisting of cryptocurrencies on a weekly basis, the main table was then filtered to remove coins that were no longer listed on exchanges’ APIs. For example, in the week ending Sunday 19th March 2023, there were 27 new listings across Binance, Bitmart, Hotbit and Kucoin alone [10]. This high turnover of listed coins made these checks essential.

Coin checks were done by comparing pumped coins and their respective exchanges against lists of cryptocurrencies available via CCXT, and by extension, the exchanges’ APIs. These checks revealed 459 pump events with coins that were no longer listed, which were subsequently removed from the dataset.

c) *Dealing with Yobit*: Yobit is a popular exchange for executing pump events due to its lack of “know your customer” requirements, used by exchanges to verify the identity of customers [35]. It has also previously performed its own random pumps on coins listed on its exchange [24] which implies that the exchange wants to encourage pump and dump organisers to use their platform. Unfortunately, Yobit’s API only provides OHLCV data for the past 7 days which makes analysing events from several years ago impossible. As such the 364 pumps identified on Yobit were filtered out and excluded from the analysis.

Applying the above aggregation and cleaning steps gave 9,191 pump events that were used for analysis in Section IV.

B. Market Data Collection

The next phase of the project was to retrieve market data for the pumps via CCXT. This section explains the processes used to do this and reasoning behind their choice.

1) *Data Granularity*: Deciding on the amount of data to collect and its granularity was the key decision for this stage. CCXT, and the exchanges that it interfaces with, allow queries to OHLCV data at varying granularities, ranging from 1 minute intervals to 1 day and 1 month intervals⁹. In an ideal

world, all data collected would be at 1 minute granularity to allow for the highest level of detail in the analysis.

There are some drawbacks to the approach outlined above, chief among them being the sheer amount of data required to capture multiple years worth of OHLCV history. Furthermore, analysing volumes over periods longer than the minute (i.e., total volume over an entire day) requires additional calculation and overheads. The solution to this was to retrieve different granularities at different time periods, with higher granularities over time periods closer to pump events. Data was collected at 1 minute (1m) intervals for 1 day either side of a pump event, at 1 hour (1h) intervals for 1 week either side of the event, and at 1 day (1d) intervals from a coin’s listing to the current day which for the purpose of this project is 7th March 2023. This gives both the benefits of being able to analyse trends over a long time period whilst also being able to see the immediate impacts of events at a high level of granularity.

2) *Back to the Start*: Collecting data at 1d intervals from a coin’s listing date required this date to be found in an efficient way. A basic solution to this would be to send a query spanning a time period from a year before cryptocurrencies became widely traded, such as 2005, and taking the first date data is available for as the listing date. Due to limits on the number of values returned at once by CCXT (in order to satisfy limits imposed by the underlying exchanges’ APIs) it would be impossible to implement this effectively without a significant query overhead. To reduce the number of queries, we use a binary search¹⁰, which searches for listing dates by calculating and comparing a midpoint that is compared against the search value [2]. By retrieving single OHLCV queries at midpoints, it is possible to tell whether a coin was listed before or after that date since if the query returns values, the coin was listed before the date used in the query and if it returns no values, then the coin was listed after the date of the query. This method was applied to every entry in the pump dataset, giving every pumped coin a start date to collect data from.

3) *Market Data Collection*: Once the listing dates of coins had been established, collecting the data at the granularities discussed in Section III-B1 was a relatively straightforward process. Queries for the respective granularities were paginated to ensure that API request limits were not exceeded and multiple passes of the dataset were performed to ensure that no data was missed due to API rate limits. Data was collected for each unique coin in the dataset of pumped coins, a total of 765 coins, suggesting that coins were pumped on average around 12 times across the dataset (further explored in Section IV-A3).

4) *Inconsistent Base Pairings*: One issue with the price data was the variation in base cryptocurrencies for the pairs retrieved from the exchange. For example, all the coins in the dataset pumped on Binance are paired with a BTC base whereas all the coins pumped on Hotbit are paired with USDT, a stablecoin that is designed to be valued at \$1. The problem with this is that 1 BTC is worth around 26,900 USDT¹¹, hence

⁸See <https://github.com/SystemsLab-Sapienza/pump-and-dump-dataset/blob/master/groups.csv>.

⁹It is worth noting that many exchanges’ APIs purport to only have 1 minute data for a specific period of time (typically 90 days) but no such restriction was found when collecting via CCXT.

¹⁰Adapted from <https://gist.github.com/mr-easy/5185b1dcdd5f9f908ff196446f092e9b>.

¹¹As of the 28th March 2023, but this price obviously varies wildly.

making any coin with a BTC pairing seem 26,000x lower in price when compared to a similarly valued coin with a USDT pairing. A simple fix to this would be to multiply all the BTC paired prices by 26,000 in order to achieve parity with USDT paired coins. Unfortunately, due to the massive fluctuations in the price between USDT and BTC, this would introduce a large margin of error, particularly as the price of BTC was as high as 60,000 USDT in 2021.

The solution was to collect OHLCV data for the BTC/USDT pairing for the same timeframes and periods discussed in Section III-B1 for all coins with BTC as their base pairing. These prices can then be combined with the original BTC base paired data to produce equivalent data in USDT. Combining the two sets of OHLCV was performed as follows

- **Open** – open price of the original BTC based pair multiplied by open price of BTC/USDT for the relevant date, timeframe and exchange.
- **High** – high price of the original BTC based pair multiplied by the typical price.
- **Low** – low price of the original BTC based pair multiplied by the typical price.
- **Volume** – volume figures of the original BTC based pair as this is quoted in the coin being pumped and is independent of any BTC/USDT conversion.

Typical price is calculated as follows

$$\text{Typical Price} = \frac{\text{High} + \text{Low} + \text{Close}}{3}$$

which provides an average price across the respective timeframe [13]. This is used to reflect that high and low prices of the original BTC based pairing and the BTC/USDT pairing are unlikely to ever line up perfectly (i.e. occur at exactly the same time), especially for longer timeframes. Therefore using an average of the BTC/USDT conversion price somewhat mitigates against this whilst still capturing differences between the high and low prices in the original BTC pairing data.

C. Price and Data Analysis

The final phase of the project was to analyse the collected market data for impacts and trends. Whilst the results of this analysis are contained in Section IV, we here explain certain measures used and their justification.

1) *Market Capitalisation Data*: Market capitalisation is a measurement of an asset's value, calculated as the multiplication of the current asset price by the amount of that asset in circulation. In the cryptocurrency sphere market capitalisation can be used as a relative measure of size and perceived levels of risk with respect to a cryptocurrency [3]. Cryptocurrencies with a high market capitalisation are perceived as less risky as they tend to have a history of growth and tend to be more liquid. Market capitalisation also plays a role in the success of pump and dump events, with pumps targeting coins with a lower market capitalisation more likely to be successful [14]. As such, our analysis used market capitalisation as a way to compare coins targeted across exchanges.

However, each exchange has different prices and volumes for coins, hence only capturing a snapshot of the asset's true market capitalisation. These price differentials are driven by the differences in trading volumes (and therefore liquidity), the fact that moving money across exchanges is inefficient and there is no accepted method for pricing such assets [28].

The solution was to use data from CoinMarketCap, a website that provides aggregated price and volume data for assets traded across multiple exchanges. Prices for a given asset are calculated from a volume-weighted average of all the traded market pairs (e.g. BTC/USDT) for that asset which in turn are calculated by converting the price of a pair into USD using reference prices [4]. Similarly, volumes are calculated as the sum of an asset's volume across all trading pairs where the volume of each trading pair is converted to USD using reference prices¹². This price and volume data, along with aggregated market capitalisation data, was retrieved via CoinMarketCap's API¹³ on the 27th March 2023.

2) *Calculating Pre-Pump Data*: Values for pre-pump prices were calculated using the average closing price of the coin for the 7 days prior to the pump event. The reason for this was to mitigate against the effects of any insiders such as channel admins or VIP members gaining knowledge of the coin about to be pumped before the specified start time and in effect pre-pumping the coin [14], [19].

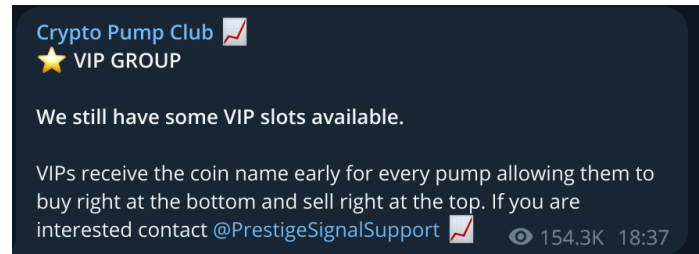


Fig. 3: Example of VIP early access to pumps.

Figure 3 shows a pump group advertising the VIP benefits of early access to coins being pumped, emphasising that prices of coins immediately prior to pumps have already been affected by such events. 7 days was chosen as the period to average over as it is long enough to smooth intraday market movements but short enough to not run into previous pump events. Pre-pump volume data was similarly calculated as an average over the 7 days prior to a pump for consistency.

3) *Measuring Maximum Price Increase*: The maximum percentage price increase ΔP used in our analysis is defined as

$$\Delta P = \frac{P_{\max} - P_{\text{before}}}{P_{\text{before}}} * 100$$

where

¹²For more detail on the methodology used to calculate these, see <https://support.coinmarketcap.com/hc/en-us/articles/360043395912-Volume-Market-Pair-Cryptoasset-Exchange-Aggregate->.

¹³<https://coinmarketcap.com/api>.

- P_{\max} is the maximum price in the 5 minutes after a pump announcement.
- P_{before} is the pre-pump price defined in Section III-C2.

We only use a 5 minute window to calculate this maximum increase because price peaks of pump events are typically found within the first minutes of pump event announcements [32], [34].

4) *Measuring Volume*: The volume within the pump window ΔV is calculated symmetrically to ΔP . Whilst the pre-pump and during pump volumes represent significantly different timescales, the relative nature of this metric means that pumps across coins with different liquidity characteristics can be directly compared. The volume moved during a pump event is taken as the amount of units of the coin being pumped within the 5 minute window immediately after the announcement of a pump event. As discussed above, price peaks, and therefore the highest levels of activity, are found within the first few minutes of such announcements [32], [34], meaning that a 5 minute window is a reasonable period to use for this calculation.

5) *Long-Term Timeframes*: One of our key goals was to study impact of pump events over the long-term by analysing price and volume data over multiple time periods after a pump event. The timeframes used for analysis were 7, 14, 30, 60, 90, 180, 270 and 365 days, to give a wide range of analysis that complements and extends existing research. An important caveat to note is that there are pumps that occurred less than a year before our market data was collected (e.g., pump events from January 2023 happened three months before our collection, hence there is only 3 months of data to analyse rather than a year). Another cause of censoring is that there are coins for which subsequent pumps occur, at which point, for our analyses, future data is considered to not be available for the original pump event, as effects would otherwise be confounded by the second pump.

6) *Relative Price Impacts*: In order to equally compare the price impacts across coins with massively different prices, a form of price indexing was used. This set the pre-pump price of a pump event to 100, with subsequent relative prices calculated as follows

$$R_n = \frac{P_n}{P_{\text{pre}}} * 100$$

where

- R_n is the relative price at day n.
- P_n is the absolute closing price at day n.
- P_{pre} is the absolute pre-pump price for the pump, as calculated in Section III-C2.

This means that subsequent absolute price rises above the pre-pump price cause the relative price to rise above 100 [12].

7) *Real World Adjustments*: We further compare the relative price indices of the pumps to the equivalent relative indices of the top 10 cryptocurrencies by market capitalisation¹⁴.

¹⁴As of 22nd April 2023. Excludes stablecoins that are meant to be pegged to a traditional currency.

These coins account for a large proportion of the total market capitalisation of all cryptocurrencies, meaning that their price movements represent the general sentiment of the market. The OHLCV data was retrieved at a daily granularity across the three most common exchanges in the dataset; Binance, Kucoin and Hotbit. The closing price was averaged to give a combined price across all the exchanges for a given day.

These individual average prices were then converted to give relative prices, for each of the top 10 coins, for the period after each pump event. Again, the closing price for the day of pump was set to 100, with subsequent prices calculated as detailed above. The prices were combined through the use of a weighted average, using the volumes of each coin as weights. This gave average relative market prices for the window after each pump, allowing a pumped coin's price changes to be compared relative to the wider market.

8) *Stitching These Impacts Together*: Once every pump event had a relative price index for both the coin being pumped and the top 10 cryptocurrencies, the next stage was to combine these to allow the impacts to be measured. This was calculated as follows

$$I_n = (R_n - M_n) + 100$$

where

- I_n is the resulting relative price adjusted for market price movements at day n.
- R_n is the relative price of the pumped coins at day n.
- M_n is the relative market prices of pumped coins at day n.
- 100 is a normalising factor to move the resulting price difference back to 100.

The result of this was relative prices adjusted for market movements for each pumped coin, allowing for a comparison of the price impacts independent of general market movements. For example, if a pumped coin is not affected at all and follows general market movements, its adjusted price would be close to or equal to 100 for the entire period. Adjusted relative prices were averaged across the entire dataset to give an average price change relative to the pre-pump price and general market movements. In order to do this, three different averages were used in order to capture the effect of outliers and view the overall data from different angles: the mean adjusted relative price for a given day, the median, and the mean of all values within the interquartile range.

9) *Quantifying the Effect of Subsequent Pumps*: The final part of investigating the long term impacts was exploring the price differentials between coins with varying numbers of pumps, which was achieved via an extension of the method discussed above. The first step required to achieve this was to put the pumps into a number of predetermined bins, where each bin contains a similar number of pumped coins. These are based on the number of times coins are pumped in the dataset. Since we found two groups in the dataset with significant differences in re-pumping behaviour, there are two separate sets of bins. These two groups are distinguished by the groups

organising them and are labelled as CPI organised and non-CPI organised pumps. A full breakdown of the differences between these groups can be found in Section IV-A2.

For CPI organised pumps, four bins were chosen, 1–10 pumps, 11–18 pumps, 19–30 pumps and 31+ pumps, with each bin containing a similar number of coins. For non-CPI organised pumps, for which re-pumping was rarer, two bins were chosen, 1 pump and 2+ pumps.

Following binning, an average adjusted relative price was calculated for the 365 days after pump events, similar to Section III-C8. One difference, however, was that data for the entire 365 day time period was used for every pump, instead of stopping if there was a subsequent pump. As with above, the mean, median and IQR mean were used as comparative averages. We also compared the performance of a coin’s first pump to subsequent ones. Again this analysis was split for CPI and non-CPI pump events in order to better differentiate between the two different organiser behaviours. For both groups, we compare performance ranging from the 1st to the 4th pump of a coin.

IV. ANALYSIS

A. Dataset Breakdown

The first section of analysis breaks down the pump event dataset and highlights some initial features and trends contained within it, including a natural split in the data which is used as a segregating feature in future sections.

1) *Distribution of Pumps*: Figure 4 visualises the spread of pumps across the time period covered by the dataset¹⁵. The date of FTX’s collapse is shown by the blue vertical line¹⁶. The plot indicates that there has been a shift in the exchange of choice for pump organisers from Binance to Hotbit and Kucoin, potentially caused by the introduction of mandatory KYC checks by Binance in 2021 [1], marked by the orange line. This change in policy meant that every user that wanted to trade or deposit funds had to pass some form of KYC, a feature that is not attractive to pump and dump groups [24]. On the other hand, Kucoin allows users to withdraw up to 1 BTC¹⁷ a day and perform unlimited amounts of trades without any KYC [22] and Hotbit only requires KYC if a user triggers a “higher risk control system” [17]. This lack of KYC requirements makes it easier for participants to take part in pump events on the respective exchanges, making them more attractive to groups organising pump events.

2) *Quality over Quantity?*: There is an outlier to this shift in the choice of exchange; a channel named Crypto Pump Island (CPI)¹⁸ which has continued to organise pumps on Binance at a very high intensity. Table I shows that CPI is responsible for over 86% of the pumps in the dataset and has the highest number of pumps per coin by a factor of 10, meaning that each unique coin has been pumped by

TABLE I: Number of pumps per channel in the dataset.

Code	Channel Name	Pumps	per Coin	
CPI	Crypto Pump Island	7920	86.17	22.06
HPA	Hit Pump Angels	145	1.58	2.20
BPF	Binance Pump Family	139	1.51	2.21
SP	Softex Pump	71	0.77	1.06
CPC	Crypto Pump Club	70	0.76	1.15
HTP	Hotbit Trading Pump	70	0.76	1.06
Others		776	8.45	1.16
Total		9191		

that channel on average 22 times across the time period of the dataset. This suggests that CPI is recycling coins when organising pumps, often multiple times a day, and is trying to achieve a high quantity of pumps rather than performance quality.

TABLE II: Number of pumps per coin in the dataset.

Number of Pumps	Coins	Percentage
1–10	480	64.26
11–20	104	13.92
21–30	60	8.03
31–40	42	5.62
41–50	21	2.81
51+	40	5.35

3) *Pumps per Coin*: There are only 765 unique coins in the dataset of 9,000 events, meaning coins were pumped multiple times. Table II shows the distribution of the number of pumps per coin across the dataset. Whilst most coins were targeted less than 10 times, there is a somewhat significant number of coins targeted over 30 times, likely for pumps organised by CPI. The most targeted coin has 98 pumps across a 4 year period. This means that there are coins that are frequently targeted by operators of pump and dump schemes, suggesting they have a track record of success and they have features that make them attractive to such schemes.

4) *Market Capitalisation*: One such attractive feature could be a low market capitalisation, which has been linked to a pump’s success [14]. Figure 5 shows the number of pumps per coin plotted against the coin’s respective market capitalisation which are further segregated by the exchange in which the highest number of pumps took place on. It also highlights whether the coin was pumped predominantly on CPI (x markers) or other channels (o markers).

Coins that are pumped more often in general have a higher market capitalisation, occur on Binance and are typically organised by CPI. As discussed in Section IV-A2, CPI runs multiple pumps a day which implies a preference for more liquid coins, as it is easier for participants to execute trades in the market [5] meaning buying into a pump is easier. Coins with higher liquidity tend to have a higher market capitalisation than less liquid ones which explains the behaviour in Figure 5. However, this higher liquidity and market capitalisation comes at the cost of lower returns on pumps [14], again highlighting the quality versus quantity tradeoff.

¹⁵Inspired by Morgia et al. [23], see page 7, Figure 3.

¹⁶The date FTX filed for bankruptcy: the 11th of November, 2022.

¹⁷Equivalent to around 26,900 USDT on the 28th March 2023.

¹⁸A full reference for channels and their respective channel codes can be found in Table XIV, in Appendix B



Fig. 4: Distribution of pumps categorised by channel and exchange.

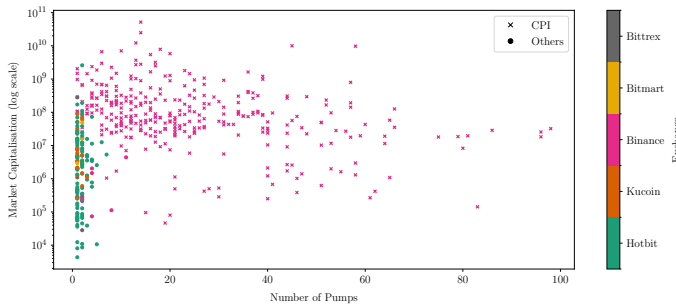


Fig. 5: Number of pumps against the coins' respective market capitalisation.

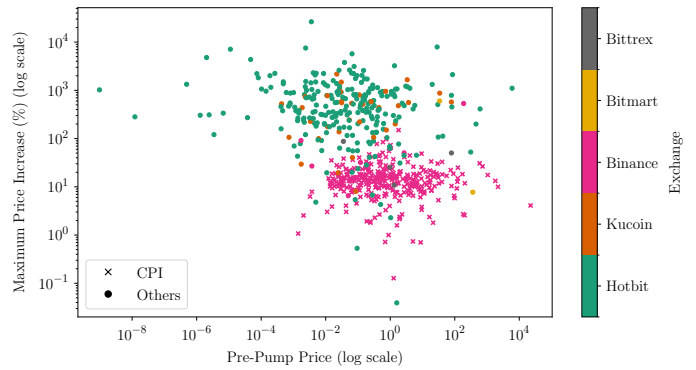


Fig. 6: Pre-price of coins against the average percentage price increase caused by pump events.

B. Pump Performance

The second section of analysis investigates the relationships between pre-pump characteristics and the immediate performance of pumps. It further highlights the quality vs quantity distinction defined in Section IV-A and explores the total amount of value moved.

1) *Pre-Pump Prices and Volumes*: Figure 6 plots the pre-pump price against the average maximum price increase of pumps for each unique coin. Once again there is clear separation between pumps organised by CPI and those organised by others. The maximum price increase, on average, is much lower (15.02% vs 790.54%) for pumps organised by CPI and therefore for those taking place on Binance. Conversely the pre-pump price, on average, is higher (92.19 USDT vs 41.01 USDT) for pumps organised by CPI.

The negative trade-off between pre-price and increase is in part explained by the fact that a higher pre-price means a coin's price has to increase more in absolute terms, in order to achieve the same percentage increase as a coin with a

lower pre-price. Also the effects of choosing coins with higher market capitalisation, and therefore higher liquidity, mean the proportion of market participants attempting to push the price up is lower. This means that it is harder to generate the volume required to massively increase prices.

2) *Volume Moved*: Figure 7 shows the average volume moved in the first 5 minutes after a pump event announcement, compared to the proportion of the pre-pump volume this represents. The amount of volume moved during a pump appears relatively similar for CPI and non-CPI pumps, although there is more variation and a higher standard deviation for non-CPI pumps (2.33×10^{10} vs 6.38×10^7). It also shows that the average proportion of the pre-pump volume this represents is significantly higher for non-CPI organised pumps (38703% vs 17.38%), although again the non-CPI pumps have a much higher standard deviation for this metric (25010 vs 27.67). Looking at the median values (1613% for non-CPI, 8.25%

for CPI) it is evident that pumps organised by CPI have a significantly lower impact on the increase in volumes. The choice of coins with higher trading pre-pump volumes and prices by CPI, as discussed earlier, means that more volume needs to be moved in order to reach the same values achieved by coins with very low pre-pump prices and volumes favoured by non-CPI organised pumps.

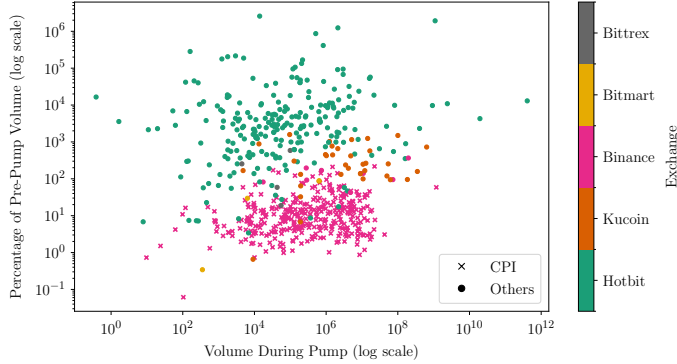


Fig. 7: Volume moved during a pump event against the proportion of this relative to the pre-pump volume.

3) *Total Value*: Up to this point this section has been exploring the relative impacts of pump events. Whilst this allows pump events to be compared on a like for like basis, it does not capture the total changes in value caused by pump events. For example, the total value of trades for 10 units on a coin worth 1 USDT is 10 USDT but for a coin worth 10 USDT the total trading value is 100 USDT for the same 10 units traded. To estimate the total value of a pump, we use the average maximum price achieved in the 5 minutes after a pump announcement. Whilst this is obviously not the price across the entire 5 minute period, it produces the best possible price, and therefore the best possible total value of trades across the 5 minute period, which can be compared across all pump events. The pre-pump total trading value is calculated as the pre-pump price multiplied by the pre-pump volume.

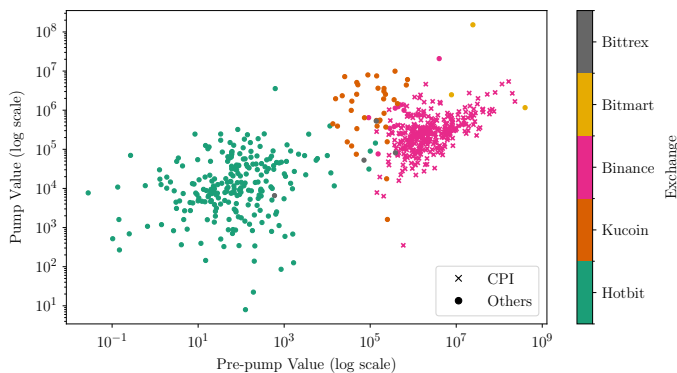


Fig. 8: Total value of trades during pump events against the average daily value of trades pre-pump.

Figure 8 shows the total value of trades in the 5 minutes after a pump announcement compared to the average daily

value of trades in the pre-pump period. This indicates that the average daily value of trades is higher for pumps organised by CPI and lower for those not, which is not surprising given the higher pre-pump prices and volumes for coins pumped by CPI discussed earlier. The value of trades in the 5 minutes after a pump announcement is also generally higher for pumps organised by CPI, particularly when compared to those organised by Hotbit. Interestingly, pumps on Kucoin have the highest average value of trades in the 5 minutes after a pump announcement. This is likely due to the Big Pump Signal group, one of the largest groups with some of the biggest price increases [23], using Kucoin as its primary exchange. The large number of participants in pumps organised by this group means a higher volume of a coin is traded which in turn allows the price to be pushed up higher, which increases the total value of trades after a pump announcement.

C. Long-Term Impacts

The third section of analysis focuses on the long-term impact of pump events on cryptocurrencies both overall and separated by pump organiser. It also investigates the notion of a relationship between the number of pumps and long-term price performance.

1) *Overall Relative Impact*: Figure 9 shows the mean prices of all pumped coins, relative to the pre-pump price, for the period spanning the year after a pump event. This is compared to the relative prices of the top 10 coins by market capitalisation, referred to as the market prices from this point onwards. This data is derived using the methodology outlined in Section III-C8 and it is worth noting that all relative prices for the coins are given with respect to the market prices. It also highlights the percentage difference between the pumped coins price and the market price at different timeframes throughout the year, shown via the vertical lines. Red lines indicate a percentage decrease relative to the market price and green lines indicate a percentage increase relative to the market price.

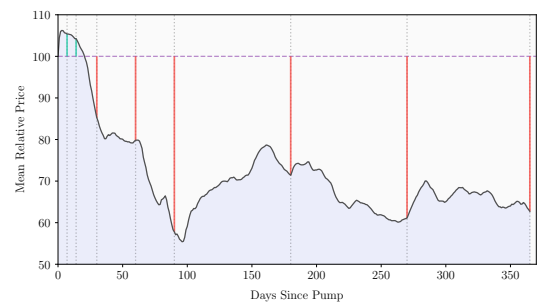


Fig. 9: Mean relative prices of pumped coins in the year after a pump, adjusted for general market movements.

In the short term Figure 9 shows that pumps have a positive pricing impact relative to the market and pre-pump pricing. This positive effect, however, is short-lived and the price is on average 11% lower than the pre-pump value, relative to market prices, 30 days after the event. Table III further shows the

TABLE III: Summary of the long-term price impact relative to a normalised pre-pump price of 100.

Day	7	14	30	60	90	180	270	365
Mean	104.04	100.01	79.73	82.15	62.87	69.32	60.83	59.23
Median	102.86	100.35	93.33	87.81	81.52	73.05	74.03	72.63
IQR Mean	103.16	100.44	94.96	89.36	82.86	77.33	78.32	79.84
Average	103.35	100.27	89.34	86.44	75.75	73.23	71.06	70.57

relative prices for each average at the timeframes highlighted in the figure. It further emphasises that there is a small positive increase in price performance relative to market prices in the first week after a pump, on average around 3%. Expanding the timeframe out gives a decrease of around 15% at 60 days and 30% at 365 days, implying a steady decline in the pumped coin’s value relative to market prices.

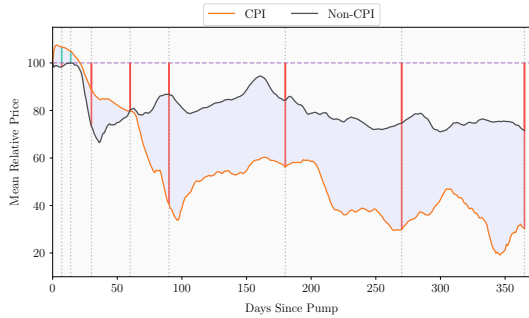


Fig. 10: Mean relative prices of pumped coins in the year after a pump, adjusted for general market movements and separated by organiser.

2) *Impact by Organiser*: Figure 10 separates impact for pumps organised by CPI and by others. For CPI-organised pumps, we see behaviour similar to Figure 9: a short-term positive effect followed by a negative long-term one. For non-CPI organised pumps there is no positive impact at all and in fact the price begins falling almost immediately relative to the market prices.

As explored in Section IV-A, CPI tend to choose coins that are more liquid, meaning they have higher volumes and are in general more visible to outside traders. This makes pump outsiders more likely to be attracted to these CPI pumped coins since these coins that have been pumped are higher ranked and therefore more visible. Since CPI organised pumps make up 86% of the dataset, the prices of these have the biggest impact on the overall relative prices for the dataset, meaning that the positive short-term impact of CPI-pumps on coins is reflected in the overall average of the dataset.

Table IV summarises the adjusted relative prices for CPI pumps at various timeframes. The results highlight the need for multiple averages, as the mean values for longer than 90 days are significantly different from the median value and the IQR mean, implying an influential outlier. From this it can be seen that coins pumped by CPI lose around 16% of their value in the year after a pump event, relative to market prices.

TABLE IV: Summary of long term impacts of CPI organised pumps.

Day	7	14	30	60	90	180	270	365
Mean	105.11	99.93	83.59	80.26	47.26	52.48	27.44	25.47
Median	103.86	100.77	94.13	89.15	83.30	76.81	75.71	72.13
IQR Mean	104.56	101.38	96.12	91.52	86.68	79.57	82.69	84.07
Average	104.51	100.70	91.28	86.98	72.41	69.62	61.95	60.55

Table V displays the same information for non-CPI organised pumps. The differences between the averages are much smaller than for the CPI-organised pumps, implying there are few if any big outliers in the data. Overall coins that are pumped by non-CPI groups lose just over 25% of their value in the year after a pump event, again relative to market prices.

TABLE V: Summary of long term impacts of non-CPI organised pumps.

	7	14	30	60	90	180	270	365
Mean	98.61	100.36	65.97	86.46	89.24	83.48	75.24	68.23
Median	97.33	97.07	86.92	81.97	78.81	70.47	72.97	74.22
IQR Mean	96.01	96.23	90.25	83.92	76.47	75.53	76.60	78.89
Average	97.32	97.88	81.05	84.12	81.51	76.49	74.93	73.78

Comparing the two groups highlights that in the long-term coins pumped by both groups experience a price decrease relative to general market prices. This makes it possible to conclude that, in general, pump events have a negative long-term impact on the value of cryptocurrencies.

3) *Impact By Number of Subsequent Pumps*: Figure 11 shows the market-adjusted long-term relative prices of coins for the 365 days after a pump event, grouped by the total number of pumps for unique coins in the dataset, for CPI and non-CPI organised pumps. Looking at the mean average displayed in Figure 11a, there appear to be outliers present with much better performance than expected, particularly in coins in the 19–30 bin. Conversely, the median average, displayed in Figure 11b, shows the potential presence of outliers that perform much worse expected. The fact that the IQR mean (Figure 11c) exhibits much more similar behaviour to that found in Section IV-C2 further reinforces the notion that the other two averages are affected by outliers, at both ends of the performance spectrum. The main pricing for non-CPI pumps also appears to be affected by outliers, since it is significantly higher for the 1 pump bin and significantly lower for the 2+ pump bin when compared to the other averages. One feature that all the graphs display is the worse long-term performance of coins pumped more than once.

Table VI shows a summary of the IQR mean of the market-adjusted relative prices for coins over our selected timeframes. This again highlights that pumps have a negative impact on the relative prices of the respective coins. With respect to the effect of the number of pumps, between the CPI bins there is no conclusive trend, since this varies in an inconsistent manner, implying that, at least for CPI-organised pumps, the number of

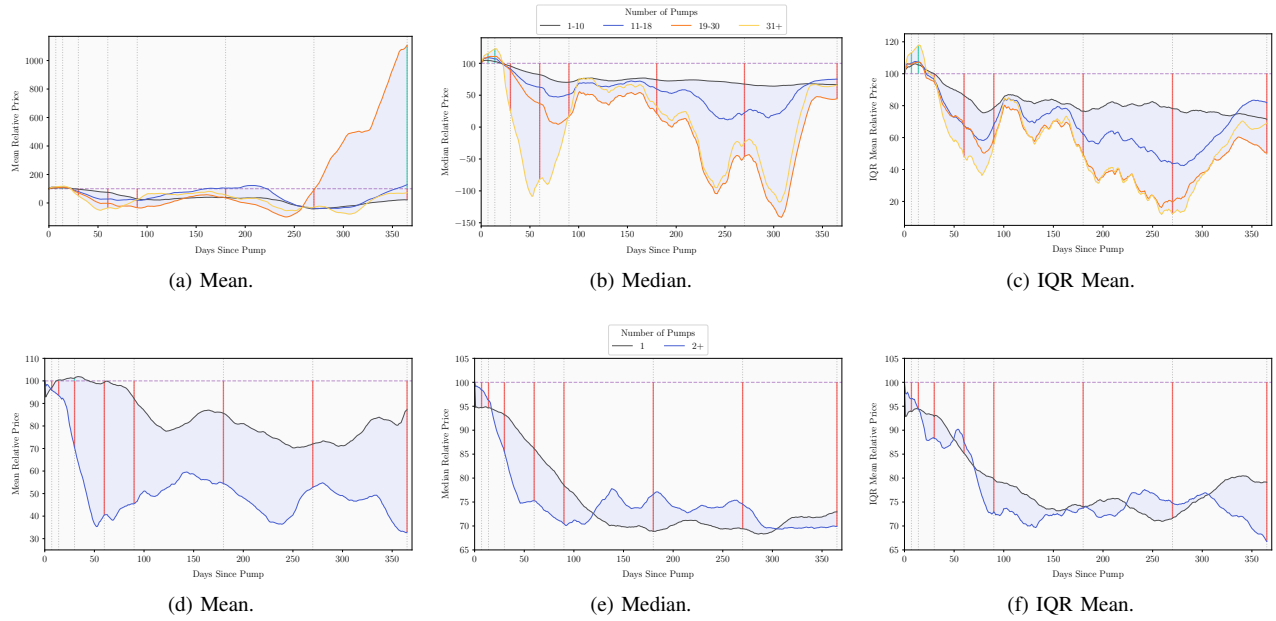


Fig. 11: Relative prices of coins pumped by CPI (top row) and groups other than CPI (bottom row) in the year after a pump, adjusted for general market movements and grouped by total number of pumps in the dataset.

TABLE VI: Summary of long-term impacts of CPI and non-CPI organised pumps, grouped by number of pumps and averaged using the IQR mean.

Day	7	14	30	60	90	180	270	365
CPI								
1-10	105.04	105.47	99.99	86.38	78.66	76.47	78.09	71.47
11-18	106.57	107.42	96.50	67.27	68.06	61.85	43.49	81.83
19-30	106.03	107.27	94.77	67.53	59.99	48.87	19.56	50.23
31+	113.19	117.77	97.44	48.08	55.94	48.09	12.22	69.08
non-CPI								
1	93.85	94.45	92.88	85.16	79.76	74.02	71.61	79.13
2+	96.55	94.45	88.27	87.50	73.00	73.67	74.78	66.76

pumps has no easily quantifiable bearing on the price impact in this dataset. There is divergent behaviour between the two different non-CPI bins with respect to shorter timeframes, with the 1 bin having a short-term relative price uptick whilst the 2+ bin immediately decreases. Both categories display a relative decrease in price over the course of a year, although as discussed above the 2+ has worse performance, 13% less than the 1 bin. Whilst these features could be indicative of more pumps meaning lower long-term prices, the large range of the 2+ pump bin and the lack of coins in it relative to the 1 pump bin, indicate that in reality more data is needed before any conclusive interpretations can be made on this relationship.

4) *First vs the Rest*: Table VII shows the average adjusted price impacts of the first and the subsequent three times a coin is pumped during CPI-organised pumps, as outlined at the end of Section III-C9. Again we see the a long-term negative

impact across all the coins pumped relative to the market. However, with regards to the variations between the groupings by pump number, a complex picture emerges. The impact of additional pumps, for both CPI and non-CPI organised pumps, is hard to discern across any of the timeframes, no matter the number of pumps or re-pumps. The only consistent trend across the pumps and re-pumps is the overall impact is negative in the long-term.

TABLE VII: Summary of long-term impacts of CPI and non-CPI organised pumps for coins on their 1st to 4th pumps, averaged using the IQR mean.

Days	7	14	30	60	90	180	270	365
CPI								
1	107.80	109.61	97.55	69.23	66.15	58.47	37.29	68.95
2	107.09	107.35	99.69	89.27	71.74	61.41	50.33	63.10
3	104.87	104.32	101.66	97.99	78.42	71.11	60.08	63.68
4	104.40	103.30	101.19	97.36	81.37	76.51	66.94	59.19
non-CPI								
1	94.76	94.45	91.33	85.84	77.36	73.88	72.93	73.38
2	98.08	98.43	94.42	89.12	77.76	86.19	73.63	75.64
3	100.05	101.08	95.25	85.29	64.68	89.07	73.95	73.90
4	97.58	98.84	95.53	94.28	65.98	95.21	90.43	92.17

From this we may conclude that at least when viewed from this perspective, the number of times a coin is pumped has no significant bearing on its long-term price. Furthermore, this analysis in particular does not adjust for whether subsequent pumps happen in the 365 day period after pump events, which could provide an explanation for the outlier discussed earlier.

V. DISCUSSION AND CONCLUSION

A. Contributions and Findings

We have contributed a new, enlarged dataset of cryptocurrency pump events based on existing sources, that contains around 10,000 events, representing a 10-fold increase compared to the largest comparable source [23]. As well as the dataset itself, we release the code used to collect the data, meaning the dataset can be maintained and updated.

Our main finding within this dataset was, relative to market prices, pump events have a long-term negative impact on the value of cryptocurrencies which represents a conclusive answer to the main hypothesis of this project. On average this impact is valued at a 27% price decrease relative to market prices 365 days after a pump event. These findings provide specific evidence for the notion proposed by Li et al. that pump events are, in general, detrimental to the price of cryptocurrencies [24]. Regarding the findings of Victor and Hagermann, that pump events provide a 10% positive price impact after 100 days [32], this project finds that, after 90 days, the prices of pumped coins are over 25% lower relative to the wider market.

Whilst we cannot be 100% sure that these effects are caused by the fact that the coins were pumped, other explanations for this long-term trend seem weak. This is emphasised by the fact we find this behaviour holds for different groups targeting different coins with various levels of market capitalisation with no obvious common factor or attributes between them, other than the fact that all the coins have been pumped.

Further, our investigations of the dataset reveal a *quality vs quantity tradeoff*, which exposes two different approaches to organising pumps. The quality approach involves choosing coins with lower liquidity, and therefore lower value, for pumps at lower frequencies which achieve a high percentage price increase. The quantity approach, on the other hand, focuses on coins with higher liquidity, and therefore higher value, for pumps at higher frequencies which achieve lower percentage price increases. Further empirical evidence, in the form of price and volume separation, was found through analysing the market data for each grouping.

A significant event within our data was the collapse of the cryptocurrency exchange FTX. An additional analysis presented in Appendix A covers the impact of this event. We find the collapse had no material direct impact on the number of pumps organised. However, the collapse impacted the underlying prices and volumes of cryptocurrencies in general, this in turn impacted the value of coins traded during pump events, decreasing the amount of money that operators, and to a lesser extent participants, could potentially make.

These findings highlight the need for further regulation of pump and dumps in the cryptocurrency sphere, given that these schemes are in effect market manipulation and are found to have had a significant negative impact on the value of cryptocurrencies. Regulators and governments are beginning to accept that pump and dump schemes are a significant problem that should be addressed in any future cryptocurrency regu-

lation; a recent UK government consultation cited them as a target for potential market abuse regulation [27]. However, this lack of regulation with respect to pump and dump schemes, which was first highlighted as a regulatory issue in 2018 [14], coupled with the high frequency and relative anonymity of such events mean they will continue to pervade cryptocurrency markets until decisive action is taken.

B. Future Work

There is significant scope for future work, some suggestions for which are discussed below.

a) *Investigating more channels*: Only the 130 most suspicious out of 800 channels were investigated from the initial list from PumpOlymp. Whilst these channels still resulted in a dataset far larger than existing ones, there are still a significant number of channels which may fruitfully be monitored for more pumps. Future work could expand the dataset by investigating these sources.

b) *Pumps on DEX*: As the APIs used to retrieve the market OHLCV data are for centralised exchanges, any pumps found taking place on decentralised exchanges could not be analysed and were therefore ignored. Additional work could focus on probing pump events on DEXs by analysing on-chain exchange transactions, using a method such as that described by Li et al. [24].

c) *Yobit and further data*: As discussed in Section III-A3, pumps organised on Yobit could not be analysed due to its API only providing 7 days of OHLCV data, which excluded around 350 pumps from further analysis. Subsequent research could investigate these by using data from source such as Kaiko, which provides over 10 years of historical data for over 100 exchanges including Yobit [20]. Furthermore, a limitation of the methodology used for this project was the OHLCV data was not checked for missing dates, due to time constraints, which again could be solved through the use of Kaiko data.

d) *General market data calculations*: The method used to calculate the relative market prices relied on the top 10 cryptocurrencies by market capitalisations as of 22nd April 2023. Whilst this provided a way of easily measuring the performance of pumped coins relative to the wider cryptocurrency market, it does not take into account previous changes to this top 10 ranking, meaning they may not represent the general market movements for earlier pump events. A solution to this would be to use historic CoinMarketCap market capitalisation to retrieve the top 10 coins at the time of each pump event and then use this to calculate adjusted relative prices.

C. Conclusion

In summary, our work has produced a new and extended dataset of pump events and provided a detailed breakdown and analysis of the performance of these pump events. Exploring the long-term impacts of pump events on cryptocurrencies reveals an overall negative impact over a 365 day period with respect to general market prices. The analysis also highlighted different tactics in the form of a *quality vs quantity tradeoff*, with different targets and different forms of market impact.

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APPENDIX A THE COLLAPSE OF FTX

The collapse of FTX had a material impact on both pump and dump operations and cryptocurrencies markets in general. Whilst this collapse is too recent¹⁹ to apply the long-term analysis used in Section IV-C, it offers an opportunity to explore the direct impact of this major event on pump events.

1) *Number of Pump Events*: The first impact explored is the number of pump events organised. As evidenced by Figure 12, the collapse of FTX caused some channel admins to pause the organisation of pumps whilst the market “recovered”²⁰.

Table VIII shows the proportion of pumps that happened before and after the collapse of FTX as well as the proportion of time each period represents. These proportions indicate that the spread of pumps before and after the collapse of FTX is roughly the same, implying that the collapse had little impact on the number of pumps.

Separating out by exchanges, shown in Figure IX, reveals that the proportion of pumps organised on Binance, and therefore those organised by CPI²¹, decreased relative to the time periods before and after. Bitmart and Bittrex have been

¹⁹FTX filed for bankruptcy on the 11th November 2022.

²⁰Quote taken from Figure 12.

²¹Since this is the dominant channel organising pumps on Binance.

Mega Signals Group

Hello everyone, we are aware of how big of an impact FTX's recent collapse has had on the cryptocurrency industry as a whole. We would like to sympathize with any of our members that have been affected by this FTX ordeal and we hope you can manage to recover from it soon enough. Our network has gone through multiple bear and bull markets over the last couple years and we can definitely confirm that this bear market has been one of the toughest ones to endure yet. Despite that, we've still been able to provide our members with constant profit over the last few weeks and we will continue to do so when the markets recover. Our network is still growing rapidly through one of the roughest periods in crypto history, with thousands of members joining every single day. As a group that has a big influence over the markets, we are constantly looking for better ways to help our members make profits. As of now, the only logical thing to do is to wait until the market can recover before scheduling our next pump and you can be sure that our team will do everything in their power to make sure all our members make a massive profit on our next one. As a good gesture to help our community recover from the FTX and FTT recent events, we will be dedicating all of our resources to make sure our members come out on top with a massive profit on the next one, stay tuned.

36.1K 14:17

Fig. 12: An attempt by a pump organiser to reassure participants after the collapse of FTX.

TABLE VIII: Proportion of pumps before and after the collapse of FTX.

	Number	Proportion	of Time	Pumps per Week
Before	8725	94.93	94.32	33.12
After	466	5.07	5.68	29.39

TABLE IX: Pumps separated by exchange before and after the collapse of FTX.

	Binance	Hotbit	Kucoin
Before	96.45	72.05	77.94
After	3.55	27.95	22.06

excluded as there are no pumps organised on these exchanges post-collapse. In reality, this means that there were fewer pumps performed per unit of time after the collapse of FTX than before, indicating a negative impact on the number of pumps on Binance after the collapse. This behaviour perhaps reflects the scrutiny directed towards Binance after the collapse of FTX, particularly when the auditor Mazars stopped providing proof of reserve checks in December 2022 [25], which led to over \$6 billion of customer deposits being withdrawn in a week, severely affecting the confidence of both the market and users in the exchange.

Conversely, there were more pumps performed on Hotbit and Kucoin per unit of time after the collapse, suggesting that there was a positive impact on the number of pumps. Since cryptocurrency markets in general have recovered in 2023, for example the price of BTC is up over 80%²² compared to the start of 2023 [6], which indicates investor confidence in cryptocurrencies in general is returning. In turn, this means

²²As of the 12th April 2023.

that there are more potential participants for organisers of pump and dump schemes to recruit, making it attractive for them to run more pumps, causing the increase.

2) *Short Term Impacts:* As discussed above, there are other forces at play other than the collapse of FTX that have been affecting pump and dumps, particularly in the medium term since its collapse. Exploring the 5 weeks either side of the collapse offers a more direct and focused look at the immediate impacts. Figure 13 shows the number of pumps on Hotbit and Kucoin before and after the collapse of FTX, with the average number of pumps in the periods before and after indicated by the red lines. This line indicates that this average was the same before and after the collapse, but there is a clear drop in the immediate weeks either side of it. The impact of uncertainty surrounding FTX emerged around a week before it declared bankruptcy, explaining the drop in the week preceding its collapse, and the collapse itself explains the drop in the week after.

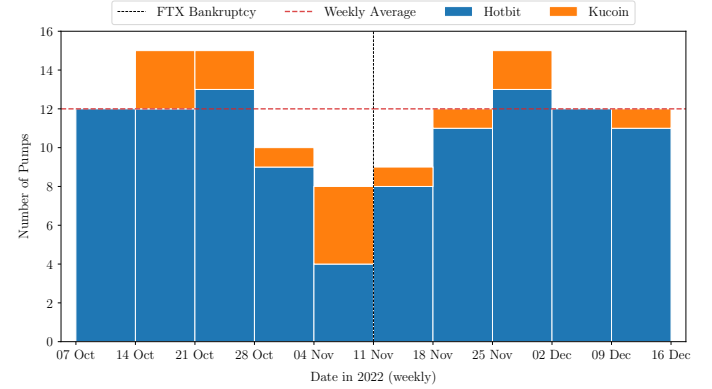


Fig. 13: Number of pumps around the collapse of FTX on Hotbit and Kucoin.

The recovery post-collapse was swift, with the number of pumps returning to the average number only a week after the collapse, particularly driven by pumps on Hotbit. Hotbit is a much smaller exchange than FTX was and operates in somewhat suspicious fashion²³ so participants in pumps organised on Hotbit had likely already experienced uncertainty around access to their assets. It could also be caused by the specific pump operators not caring about the collapse and trying to attract new participants with an alternative way to make money from cryptocurrencies.

In contrast Figure 14 shows the number of pumps on Binance around the collapse. This indicates that the number of pumps was higher in the week immediately prior to the collapse compared to those preceding it. Since all these pumps were organised by CPI, who target lower returns from a higher quantity of pumps, this could be potentially an attempt by the pump organisers to capitalise on the market uncertainty. The

²³For example the entire exchange had its assets frozen for over a month from August 2022 during an investigation by law enforcement, meaning customers could not deposit, withdraw or trade funds [15], [16] and it has virtually no KYC requirements [17].

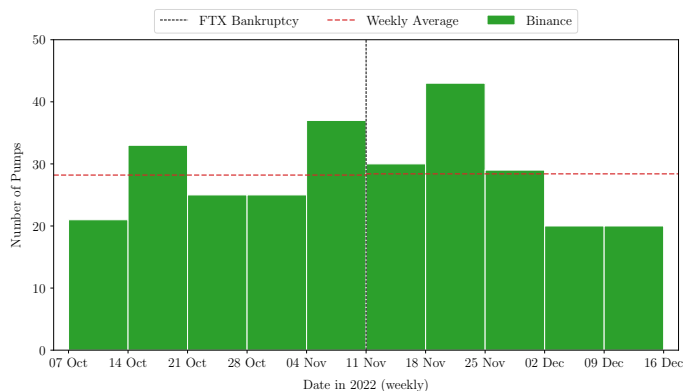


Fig. 14: Number of pumps around the collapse of FTX on Binance.

biggest drop for the Binance organised pumps comes at the start of December, when there was \$6 billion of withdrawals in a week due to the uncertainty around its proof of reserves report [33], since this directly affected the platform that participants were using.

Overall the collapse of FTX appeared to have varying levels of impact on the amount of pump and dump schemes organised around the collapse, from a short-term increase for CPI organised pumps and a very short-term drop for the others. The fact that none of the pumps were organised on FTX would have also meant that they were only affected indirectly by the fallout, potentially limiting the impact of the collapse.

3) *Performance of Pump Events*: Moving on to the performance of pump events before and after the collapse of FTX, Table X shows the difference between the maximum price increase and volume moved during pump events before and after the collapse. As established in Section IV-B, there are big differences between these values for CPI and non-CPI organised pumps, so the data is further separated by this.

TABLE X: Pump performance before and after the collapse of FTX.

	Price Increase		Relative Pump Volume	
	CPI	Non-CPI	CPI	Non-CPI
Before	6.72	434.22	-95.95	4284.40
After	25.92	688.16	-77.49	2006.64

Both the CPI and non-CPI organised pumps have higher average price increases post the collapse of FTX, however they differ on the proportion of the pre-pump volume and the volume moved during the pump represents.

Across 2022 the amount of trading volume across crypto exchanges reduced, particularly towards the end of year [9]. This would have significantly affected CPI organised pumps since they tend to target coins with higher liquidity, i.e. coins with more trading volume by non-participating market actors, which are likely to be those that have reduced their trading volume. These lower trading volumes by non-participating

market actors causes the pre-pump volume to be on average lower hence meaning that for a given pump volume the proportion of the pre-pump volume this represents increases. This is further shown in Table XI which displays that there is a much bigger fall in the pre-pump volume than in the during pump volume for CPI-organised pumps, meaning that the relative proportion of the during pump volume increases compared to the pre-pump volume, causing the behaviour in Table X.

TABLE XI: Relative difference of pre and during pump prices and volumes before and after the collapse.

	Pre-Pump		During Pump	
	CPI	Non-CPI	CPI	Non-CPI
Price	-43.65	-71.77	-33.51	-58.34
Volume	-86.02	-26.62	-22.39	-64.74

For non-CPI organised pumps the average pump volume fell by a significant amount, particularly relative to the pre-pump falls. Since this decrease in the during pump volume is greater than decrease in the pre-pump one, and this represents the decrease due to general market factors, this implies fewer participants or at least less volume per participant as this figure is far lower than the pre-pump figure.

Looking back at the relative price increases in Table X it appears that there is a higher relative maximum price increase post-collapse, which implies that pumps performed better. However, Table XI shows the reason for this is the maximum price of a pump fell less than the pre-price, which gives a bigger percentage return at a lower value. Furthermore it is easier to achieve a higher percentage increase on a lower price coin, further suggesting that much of this perceived increase in percentage returns is not valid.

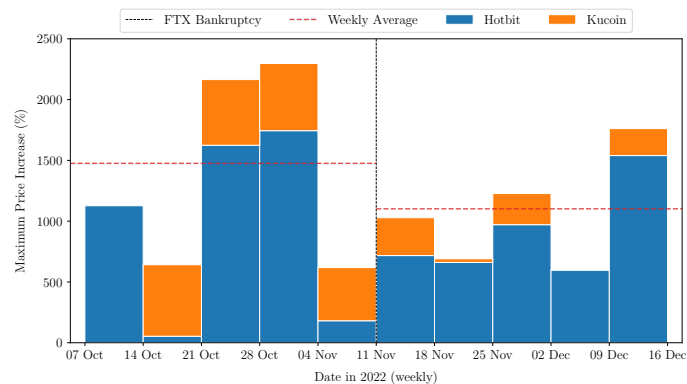


Fig. 15: Maximum price increase of pumps around the collapse of FTX on Hotbit and Kucoin.

Figure 15 displays the percentage price increases for pumps on Hobit and Kucoin for the weeks immediately surrounding the collapse of FTX. This shows that the average percentage price increase decreased after the collapse, although there is significant variation in the weeks prior to it, suggesting this could be driven by factors other than just the collapse.

APPENDIX B DATA SOURCES

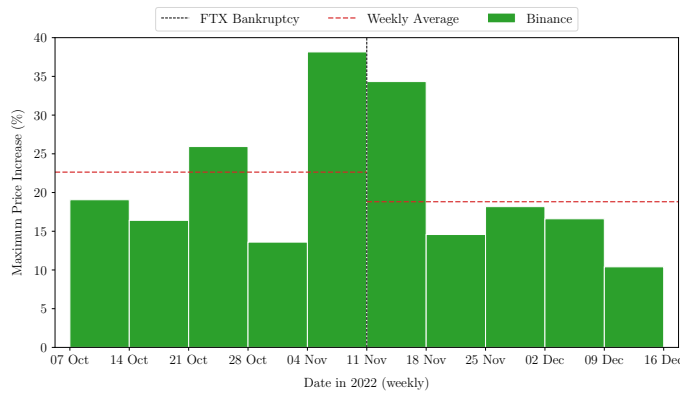


Fig. 16: Maximum price increase of pumps around the collapse of FTX on Binance.

Figure 16 shows the same again for pumps on Binance. Whilst the average is again lower post-collapse, there is a significant uptick in performance in the week immediately prior to and after the collapse, potentially caused by investors moving volume from FTX to Binance as its troubles became more apparent and investors moved their funds to other exchanges. Since Binance is by far the biggest exchange by volume [7], even before the collapse of FTX, it would be the main destination for such moves and as the coins chosen by CPI (and therefore the ones pumped on Binance), are more liquid, they would be more likely to receive volume from such trades.

4) *Total Value*: As established above, there were changes in both the price and volume of pump events after the collapse of FTX. The best way to establish the monetary impact of these effects is to look at the changes in value caused by pump events²⁴. Table XII shows the value of units moved in the pre-pump and during pump periods.

TABLE XII: Total value of cryptocurrency moved

	CPI		Non-CPI	
	Pre-Pump	During Pump	Pre-Pump	During Pump
Before	2.62×10^9	1.13×10^8	1.56×10^8	3.66×10^{10}
After	2.07×10^8	5.84×10^7	3.24×10^7	5.38×10^8
Change	-79.12	-85.31	-92.12	-48.40

Overall whilst the value of units moved during pumps shows some resilience with respect to the change in the general value of units moved in the pre-pump periods, it still represents a significant reduction compared to the pre-collapse values. Operators, and more broadly some participants, make money off these schemes based on the change in value of the coin. Hence, these decreases represent a large reduction in the amount of monetary value that can be made off these schemes, in turn reducing their performance in this respect.

TABLE XIII: List of exchanges used and their respective pump count and links.

Exchange	Pumps	Link
Binance	9129	https://www.binance.com
BitMart	15	https://www.bitmart.com
Bittrex	25	https://global.bittrex.com
Hotbit	852	https://www.hotbit.io
Kucoin	92	https://www.kucoin.com
YoBit	351	https://yobit.net/en

TABLE XIV: List of Telegram channels used and their respective channel codes, number of pump events and links.

Channel Code	Group Name	Telegram Link
ATW	Alt the Way	https://t.me/AltTheWay
BCP	Big Crypto Pump	https://t.me/bigcryptocurrencypump
BPG	Big Pump Group	https://t.me/bigpumpgroup_com
PBS	Big Pump Shitcoin	https://t.me/Bigpump_shitcoin
BPS	Big Pump Signal	https://t.me/bigpumpsignal
BPC	Biggest Pump Channel	https://t.me/Biggestcryptopumpchannel
BP2	Binance 24/7	https://t.me/binance247
BCS	Binance Crypto Signals	https://t.me/CryptoSignals_pump
BPF	Binance Pump Family	https://t.me/rocketpumptrader
BPD	Binance Pump and Dump	https://t.me/binance_pump_and_dump
BGW	Binance/GateIO/Kucoin Pump	Whales https://t.me/binacepumpswhales
CCS	Coin Coach Signals	https://t.me/CoinCoachSignals
CP	Cryptic Pumps	https://t.me/CrypticPumps
CCB	Crypto Coin B	https://t.me/CryptoCoinsCoach
CCPS	Crypto Coin Pump Signals	https://t.me/Cryptocoinpumpsignals
CP3	Crypto Pump 360	https://t.me/cryptopump360
CPC	Crypto Pump Club	https://t.me/cryptoclubpump
CPI	Crypto Pump Island	https://t.me/crypto_pump_island
CSP	Crypto Signal Pumps	https://t.me/crypto_pump07
CW	Crypto Waves	https://t.me/CryptoCoinsWaves
C4P	Crypto4Pumps	https://t.me/Crypto4Pumps
CPS	Cryptopia Pump Squad	https://t.me/cryptoflashsignals
FCS	Fast Crypto Signals	https://t.me/fastcrypt
HPA	Hit Pump Angels	https://t.me/hitpumpangels
HEP	Hotbit English Pump	https://t.me/hotbit_english_pump
HPF	Hotbit Pump Free	https://t.me/hotbitpumpfree
HPS	Hotbit Pump Signals	https://t.me/hotbit_pump_signal
HTP	Hotbit Trading Pump	https://t.me/binancepumpchannell
KCPT	Kucoin Crypto Pumps Trading	https://t.me/kucoin_crypto_pumps_trading
KPW	Kucoin Pump WSB	https://t.me/kucoinpumpswsb
LUX	Luxurious	https://t.me/LuxuriousCrypto
MPC	Magic Pumps Channel	https://t.me/magic_pump
MCP	Mega Crypto Pump	https://t.me/pump_and_dumpp
MPG	Mega Pump Group	https://t.me/mega_pump_group
PKG	Pump King Community	https://t.me/pumpingking
PL	Pump Leaks	https://t.me/pumpleaks
RPB	Rocket Pumps Binance	https://t.me/exclusivepumpanddumpbinance
SP	Softex Pump	https://t.me/softexpump
TWP	Today We Push	https://t.me/TodayWePush
TCC	Trading Crypto Coach	https://t.me/tradingcryptocoach
TCG	Trading Crypto Guide	https://t.me/TCGFORYOU
WSBP	WallStreetBet Pumps	https://t.me/wallstbetpumps
WCG	Whales Crypto Guide	https://t.me/Whalesguide
YP	Yobit Pumps	https://t.me/yobitpump_en

²⁴As established in Section IV-B3.

APPENDIX C
DEFINITIONS

The following acronyms and abbreviations are used throughout this paper:

CCXT	:	CryptoCurrency eXchange Trading library.
SEC	:	Securities and Exchange Commission.
U.S.	:	United States of America.
OHLCV	:	Open, High, Low, Close, Volume.
RF	:	Random Forest.
GLM	:	Generalised Linear Model.
CEX	:	Centralised Exchange.
DEX	:	Decentralised Exchange.
XGBoost	:	Extreme Gradient Boost.
LSTM	:	Long Short-Term Memory.
CAR	:	Cumulative Abnormal Returns.
regex	:	Regular Expressions.
API	:	Application Programming Interface.
KYC	:	Know Your Customer.
CPI	:	Crypto Pump Island.
IQR	:	Interquartile Range.