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An examination of the cryptocurrency pump-and-dump ecosystem

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ABSTRACT

The recent introduction of thousands of cryptocurrencies in an unregulated environment has created many opportunities for unscrupulous traders to profit from price manipulation. We quantify the scope of one widespread tactic, the "pump and dump", in which actors coordinate to bid up the price of coins before selling at a profit. We joined all relevant channels on two popular group-messaging platforms, Telegram and Discord, and identified thousands of different pumps targeting hundreds of coins. We find that pumps are modestly successful in driving short-term price rises, but that this effect has diminished over time. We also find that the most successful pumps are those that are most transparent about their intentions. Combined with evidence of concentration among a small number of channels, we conclude that regulators have an opportunity to effectively crack down on this illicit activity that threatens broader adoption of blockchain technologies.

1. Introduction

As mainstream finance invests in cryptocurrency assets and some countries take steps toward legitimizing bitcoin as a payment system, it is important to understand how susceptible cryptocurrency markets are to manipulation. This is especially true since cryptocurrency assets are no longer a niche market. The market capitalization of all cryptocurrencies exceeded $800 Billion at the end of 2017. Even after a huge fall in valuations, the market capitalization of these assets remains around $575 billion as of November 2020. For comparison, in the same time period, JPMorgan Chase, the largest U.S. commercial bank holding company, had a $370 billion valuation.

In this paper, we examine a particular type of price manipulation: the "pump-and-dump" scheme. These schemes inflate the price of an asset temporarily so a select few can sell at the artificially higher price. In the case of cryptocurrencies, at the beginning of a pump, a signal indicating the currency to buy is transmitted to insiders via a group messaging platform. Ideally, from the standpoint of the pumpers, the coordinated buying increases the trading activity and begins to drive up the price. When outside buyers are attracted and begin making purchases, the price rises further; then the pumpers sell the positions they acquired previously at lower prices.

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Pump-and-dump schemes are not a new phenomenon. In the case of stocks, pump-and-dump schemes primarily focus on penny stocks with low trading volume. Those involving stocks are typically isolated episodes conducted quietly away from the spotlight. So what is different about cryptocurrencies?

Several attributes have yielded a robust pump-and-dump ecosystem at unprecedented scale. First, the new social media technology platforms Telegram and Discord facilitate low-cost, private coordination through dedicated channels that are easy to form and free to join. Second, the explosion of thousands of cryptocurrencies has created myriad opportunities for exploitation. Most are thinly traded, creating favorable conditions for pumpers. Moreover, the proliferation of cryptocurrency exchanges has enabled unregulated trade between coins. Exchanges profit from the transaction fees resulting from pumps. Third, regulators (so far) have mostly taken a hands-off approach, creating an opening for abuse.

These conditions led to an explosion of cryptocurrency pump-and-dump schemes, which threatens to crowd out legitimate blockchain applications. We identified 952 pumps on Discord and 2469 on Telegram over six months in 2018, then connected this dataset with pricing data on nearly 2000 coins across 220 cryptocurrency trading exchanges tracked by coinmarketcap.com. This data collection enables us to provide the first measure of the scope of pump-and-dump schemes involving cryptocurrencies and indicates that the phenomenon is widespread.

1.1. Contributions of the paper

In the paper, we examine some of the properties of this ecosystem and its dynamics over time.

We first describe in detail how the pumps work in the cryptocurrency realm and quantify the extent of the phenomenon. We next measure the "success" (or profitability)[1] of the schemes, which we define to be the percentage increase in the price following a pump. We find that the median percentage price rise is 2.4–2.6% for the top 75 most popular coins, compared to 14%–16% for the least popular coins ranked below 1000 in terms of trading volume.

We then examine what happened to the profitability or "success" over time. For reasons we discuss in the paper, economic theory suggests that the cryptocurrency pump-and-dump ecosystem would not succeed over time. Our dynamic data over time allows us to examine this thesis empirically, that is, to examine whether profitability declined over time.

The dynamic data also enables us to examine other key questions about the ecosystem: (I) Was the ecosystem dominated by a few channels (running a lot of pumps) or were there many active channels? (II) Did pumps occur on many exchanges or just a few? (III) Were coins pumped repeatedly? (IV) Did regulators take any actions over time? If so, were these actions effective?

We find that even after controlling for other factors, success falls over time, with a steep drop-off near the end of the period for which we have data. This provides support for the thesis that these schemes would become less profitable over time. It would be desirable to test whether the trend of declining profitability can be observed over a longer time horizon. We concluded our own study due to the significant time commitments required to collect and verify the signals gathered, as well as the increasing difficulty to remain members of pump groups now that outside investigations by researchers and regulators are widely known about in the community.

By coincidence, we gathered data on pumps during the first half of 2018, which happens to be the time period immediately after the Bitcoin price reached its all-time high.[2] While one might expect a decline in the Bitcoin (BTC) to coincide with declining pump success, we actually observe the opposite. There is a negative relationship between changes in the Bitcoin (BTC) price and the success of the pump-and-dump schemes. That is when Bitcoin fell more, the pumps were more successful.[3] Indeed, the most profitable month for pump-and dump schemes was January. During that month the BTC price decline was the second largest, yet the pump and dumps were the most profitable. Hence, clearly it is not that pump-and-dump schemes were more successful when the price of Bitcoin was rising.

We then examined the ecosystem in detail and (perhaps surprisingly) found high levels of concentration in both exchanges employed for pumps and channels involved in running the pumps. Binance and Bittrex were by far the most popular exchanges for pump-and-dump schemes, together accounting for 86% of the pumps that listed or recommended an exchange. Moreover, we found that even though we tracked pumps on 25 Telegram channels and 47 Discord groups, it turns out that, like exchanges, this aspect of the ecosystem was highly concentrated, too.

We observed two very different approaches to pumping coins. One type was quite open and transparent about the pumps, issuing countdowns to the agreed-upon purchase time, while the other type took steps to obscure their coordinated activities to evade detection. Strikingly, we found that the transparent pumps were much more successful. They typically pumped a coin only once and advertised the chosen trading platform, typically a less-popular exchange. The transparent pump-and-dump schemes achieved a 7.7% median rate of return, while the obscured pump-and-dump schemes achieved a 4.1% median return. Strikingly, the returns earned by the transparent pumps did not decline at all over time, while the returns earned by the obscured pump and dumps declined significantly over time.

Our findings suggest that regulators could perhaps diminish the pump-and-dump ecosystem by focusing on the small number of exchanges and pump channels where activity is most prevalent and readily observed. It is not necessary to examine hundreds of

[1] Obviously, this measure does not capture total profits made by those involved. We do not have data on individual trades. The measure does, however, capture the maximum potential profit to insiders.

[2] In December 2017 the Bitcoin price peaked at 19,665.39 USD. The price dropped steadily in 2018, though it has recovered to over 18,000 USD as of this November 2020 writing.

[3] Overall the negative correlation is very small in absolute value (−0.20) and is not statistically different from zero (p-value = 0.71).

channels and exchanges. Indeed, the regulatory focus on the main channels whose activities are most brazen could undermine the most egregiously successful schemes.

The road map for the paper is as follows. In the next section, we provide background information and review the literature. Section 3 provides a detailed description of the methodology and how we collected the data. In Section 4, we describe the ecosystem and present descriptive findings. Section 5 describes the results of our regression analysis. Section 6 briefly concludes with thoughts about regulatory policy.

2. Background

History of the cryptocurrency market. Bitcoin (BTC), the first cryptocurrency, was founded in 2009. While the market took off slowly, a massive spike in the price of bitcoin in late 2013 led to wider interest in what had been until then a niche industry. The value of Bitcoin increased from around $150 in mid 2013 to over $1000 in late 2013. The fall was dramatic as well and bitcoin fell to $400 in a very short period of time. Despite the dramatic fall, cryptocurrencies were on the map and massive entry (as well as non-trivial exit) has occurred in the industry during the last five years.

While Bitcoin dominated the market through most of the 2009–2016 period, in 2013, a few other cryptocurrencies competed with Bitcoin. These coins began appreciating much more quickly than Bitcoin during the price rise. Gandal et al. analyzed how network effects affected competition in the cryptocurrency market during the price spike and subsequent fall in the price of Bitcoin (Gandal & Halaburda, 2016). Their analysis suggests that there were strong network effects and winner-take-all dynamics following the fall in the price of Bitcoin in early 2014. From July 2014 to February 2016, Bitcoin's value was essentially constant against the USD, while the other currencies depreciated dramatically against the USD. Litecoin, the number two coin in the market, declined by 70% in value, while other "main" coins declined by more than 90% in value. In early 2016, Bitcoin accounted for 94% of the total market capitalization, while Litecoin (the number two cryptocurrency) accounted for 2%. Despite its shortcomings, Bitcoin had emerged at that point as the clear winner and beneficiary of network effects.

In 2017, things changed dramatically. Bitcoin began rising again and by early 2017, the value of bitcoin was again more than $1000. It had taken more than three years for the value of bitcoin to return to the 2013 peak level, but that was only the beginning. Eventually, in December 2017, Bitcoin reached a peak of more than $19,000 before plummeting over the next few months to $6,000.

The market capitalization of cryptocurrency grew stunningly in the past few years. In February 2014, the market capitalization of all cryptocurrencies was approximately $14 Billion. In January 2018, near Bitcoin's peak, the total market capitalization reached $825 Billion. As of November 2020, total market capitalization was approximately $575 billion.

In February 2018, there were 715 cryptocurrencies with market capitalization between $1 million and $100 million.[4] January 2014, there were less than 30 coins with market capitalization between $1 million and $100 million. This sharp four year rise in high-valued coins raises concerns of an increased potential for price manipulation.

The larger picture. Cryptocurrency manipulations tie in to a concern over trading in unregulated financial exchanges. The potential for manipulation in over-the-counter (OTC) markets is a significant concern for financial regulators. OTC trading is conducted directly between two parties, without going through a stock exchange. In a recent white paper, the SEC noted that "OTC stocks are also frequent targets of market manipulation by fraudsters".[5] The U.S. Securities and Exchange Commission (SEC) report also documents that OTC trading has increased significantly over time.[6]

Pump-and-dump schemes were outlawed in the 1930s. Nevertheless, the practice has continued. In the early 1990s the brokerage Stratton Oakmont artificially increased the price of "penny" stocks it owned by creating a "hype" around the stock. Once the price rose, the firm sold its shares in the relevant holding. The founder of Stratton Oakmont, Jordan Belfort, was convicted for securities fraud.

The U.S. SEC actively prosecutes pump-and-dump cases using publicly traded stocks. Such schemes involving cryptocurrencies are not any different. However, regulators have yet to prosecute pump and dumps involving cryptocurrencies. With the exception of insuring that taxes are paid on cryptocurrency profits and individual state-based regulation, US regulatory policy towards cryptocurrencies and initial coin offerings (ICOs) has been generally been "hands-off". One problem in moving forward in the regulatory sphere is that – unlike stocks, commodities, or fiat currency – cryptocurrencies do not have a regulatory agency in charge of all cryptocurrency policy.

Technologies like Telegram and Discord allow people to easily coordinate such schemes. Telegram is a cloud-based instant messaging service. Users can send messages and exchange photos, videos, stickers, audio and files of any type. Messages can be sent to other users individually or to groups of up to 100,000 members. As of March 2018, Telegram had 200 million active users. Discord has similar capabilities and had 150 million users as of August 2018.

Discord and Telegram are primary sources for cryptocurrency pumps and have been used for pump-and-dump schemes on a large scale. Perhaps because of the regulatory vacuum, some of the pump groups do not hide their goals.

[4] As of February 2019, there are 751 such coins.

[5] Outcomes of Investing in OTC Stocks, by Joshua White, December 16, 2016, U.S. Securities and Exchange Commission Division of Economic and Risk Analysis (DERA).

[6] In 2008 around 16 percent of U.S. stock trades were of the OTC type. By 2014, OTC trades accounted for 40 percent of all stock trades in the US. Like cryptocurrency trading, OTC trades are not transparent and not regulated, and there is concern that such trading is more harmful than high-frequency trading via regulated exchanges — See McCrank (2014).

2.1. Literature review

The role of information in cryptocurrency trading. Researchers, regulators and the general public have tried to understand what explains the price of cryptocurrencies since Bitcoin's introduction in 2009. As a novel digital asset, information has been recognized to play a significant role. The network structure of on-chain Bitcoin transactions has been shown to evolve in accordance with the rise and fall of influential actors (Fire & Guestrin, 2020). When it comes to the price itself, Cheah and Fry presented empirical evidence that Bitcoin's early price rises exhibited hallmarks of speculative bubbles (Cheah & Fry, 2015). They followed up by developing econophysics models for these pricing bubbles based on data from Bitcoin and Ripple (Fry & Cheah, 2016). Urquhart compiled additional econometric evidence identifying inefficiencies in early Bitcoin returns that diminished and became more efficient over time (Urquhart, 2016). More recently, Yu et al. studied how market information availability in Bitcoin affected the volatility of returns. They found a positive relationship between day trading volume and market volatility, as well as between user awareness surmised from Google Trends data and the volatility of returns (Yu, Kang, & Park, 2019). Our paper builds on this literature by empirically examining deliberate attempts to game prices in cryptocurrencies, which may help explain volatility in returns.

More broadly, our work is related to papers in finance that examine how investors of different sophistication trade. For example, Brunnermeir and Nagel (2005) examined the behavior of hedge funds during the "Tech Bubble" in 2000. In their paper, there was discussion about different types of traders. Their paper cannot, however, identify specific traders. However given our data, we can identify trader (i.e., pumper) types and examine how the organizations and results differed among the types of pumpers.

Moreover, just as scholars examined whether Bitcoin prices were stoked by irrational investors, many scholars also argued that the tech bubble was driven by irrational individual investors. An interesting question is whether rational traders are able to neutralize the price impact of irrational traders. If so, then markets are still efficient despite the presence of irrational traders. Our analysis does not address the presence of irrational traders, but it does examine how differences in coordination measured by the transparency of signals can affect returns, and that these differences can persist over time. Our paper focuses on illicit trading activities affecting cryptocurrencies, which rely on blockchains to verify transactions. There is a much broader literature on using blockchains to solve security and privacy problems (Berdik, Otoum, Schmidt, Porter, & Jararweh, 2021; Chen, Srivastava, Parizi, Aloqaily, & Ridhawi, 2020; Li, Wu, Jiang, & Srikanthan, 2020; Putz, Dietz, Empl, & Pernul, 2021; Salman, Zolanvari, Erbad, Jain, & Samaka, 2019). The pump-and-dump schemes studied here take place on exchanges and so are typically not recorded on the affected currency's blockchain.

Stock price manipulation. The academic literature on price manipulation and pump-and-dump schemes involving stocks includes Aggarwal and Wu (2006). They examined SEC litigation against market manipulators in OTC markets. They find stocks with low volume are subject to manipulation. They find that stock prices, volume, and volatility increase during the pump-and-dump scheme, but end quickly once it is over. They write that while manipulative activities have declined on main exchanges, it is still a serious issue in the over-the-counter (OTC) market in the United States.

Massoud, Ullah, and Scholnick (2016) studied OTC companies that hire promoters to engage in secret stock promotions to increase their stock price and trading volume. They find that the "promotions", or informal pump-and-dump schemes, coincide with trading by insiders. Brüggemann, Kaul, Leuz, and Werner (2017) show that OTC stocks have lower levels of liquidity than a matched sample of similar NASDAQ listed stocks.

Cryptocurrency price manipulation. There has been quite a bit of work thus far both experimentally and analytically on broader issues around price manipulation around cryptocurrencies. Krafft, Della Penna, and Pentland (2018) created bots that executed penny trades in 217 different cryptocurrency markets. While their intent was not to incite bubble-type behavior, their bots created large price swings in the individual currencies after very small purchases.

Gandal, Hamrick, Moore, and Obermann (2018) identify and analyze the impact of suspicious trading activity on the Mt. Gox Bitcoin currency exchange, in which approximately 600,000 bitcoins (BTC) valued at $188 million were fraudulently acquired. They find that the USD-BTC exchange rate rose by an average of four percent on days when suspicious trades took place, compared to a slight decline on days without suspicious activity. They conclude that the suspicious trading activity by the Mt. Gox exchange itself likely caused the unprecedented spike in the USD-BTC exchange rate in late 2013, when the rate jumped from around $150 to more than $1000 in two months.

Griffin and Shams examined whether Tether, a digital cryptocurrency that is pegged to USD, affected the price of Bitcoin and other cryptocurrency prices during the huge increase in cryptocurrency valuations in 2017 (Griffen & Shams, 2020). Since they do not have data on which accounts initiated trades, they use algorithms to analyze blockchain data. They find that purchases with Tether occur following falls in Bitcoin prices and that the Tether purchases led to subsequent price rises in Bitcoin (and other cryptocurrency) prices. In particular, they find that short periods with especially heavy Tether trading volume are associated with "50 percent of the meteoric rise in Bitcoin and 64 percent of other top cryptocurrencies". They conclude that these purchases cannot be explained by investor demand, but that they are consistent with the hypothesis that Tether was used to provide price support and manipulate cryptocurrency prices.

Other researchers have studied financial fraud using cryptocurrencies. In two separate studies, Vasek and Moore (2015, 2018) researched online Ponzi schemes using cryptocurrencies. They measured millions of dollars reaped in by Ponzi scheme runners. Furthermore, they found that the most successful scams depend on large contributions from a very small number of victims. They then investigated Ponzi schemes advertised on the Bitcoin forum and the ecosystem that perpetuates them. Similar to our work, they mine information from the large social ecosystem around the cryptocurrency fraud they investigated.

Our work is quite different from the existing research on price manipulations; to the best of our knowledge, this is the first study to assess the scope of pump-and-dump schemes involving cryptocurrencies. We are also the first to examine which factors affect the "success" of pumps, where success means a large percentage increase in price.

Cryptocurrency pump and dump. Four other (essentially) concurrent papers also examine pump-and-dump schemes on cryptocurrencies, but with a different emphasis. Kamps and Kleinberg (2018) use market data to identify suspected pump and dumps based on sudden price and volume spikes (and the following sharp decreases). They evaluate the accuracy of their predictions using a small sample of manually identified pump signals and show that their methodology works well. Employing a similar approach with a different dataset, Mirtaheri, Abu-El-Haija, Morstatter, Steeg, and Galstyan (2019) use data collected from Twitter on cryptocurrencies cross-referenced with pump signal data from Telegram and market data. They note that a lot of the tweets are automated and attempt to predict pumps using only the Twitter traffic. These two papers show that academics have developed methodologies to predict pump and dump schemes.[7]

Xu and Livshits (2019) use data on just over 200 pump signals to build a model to predict which coins will be pumped. Their model distinguishes between highly successful pumps and all other trading activity on the exchange. Li, Shin, and Wang (2018) use a difference-in-difference model to show that pump and dumps lower the trading price of affected coins.[8]

Our work is different from these papers in several important ways. First, we have collected many more pump signals from channels on Discord and Telegram and evaluate them all, without restricting ourselves to the successful pumps. Our goal was to the extent possible to reach all schemes on Discord and Telegram. Second, we investigate reported pumps for all coins with public trading data, not only those taking place at selected exchanges. This enables us to incorporate ecosystem-wide explanatory variables such as the number of exchanges on which a coin is traded on, the rank of the coin, etc., in order to assess what makes a scheme successful.

3. Methodology

In this section, we discuss the methodology we used to collect the data on pump signals from public messaging sources, as well as how we gathered pricing data and measured pump success.

3.1. Pump signals data from discord and telegram

Our objective was to collect as many pump signals as possible from all channels in these platforms. These platforms are the main outlets for pump and dump schemes.

A pump signal is an announcement to encourage people to buy a cryptocurrency and then take advantage of the price increase created by the surge in purchasing. The first step in collecting this data was to become familiar with the platforms hosting these signals, Discord and Telegram.

We started our collection with URLs from a bitcointalk page on Discord pump groups: https://bitcointalk.org/index.php?topic=2887116.0. This is an authoritative place that pump and dump investors send others to when they ask about where to look for pump and dump signals. We inspected all Telegram channels[9] with over 4,000 users from an Android app that tracks the popularity of pump and dump groups (https://padl.mine.nu/). We programmatically scraped these Discord groups and Telegram channels about pump and dumps using their respective APIs, starting with the origin groups and spidering out to groups that were referenced in pump signals by our collected groups. In total, we collected data from 25 Telegram channels and 47 Discord servers.

One significant challenge is that the only way to join many groups is by invitation. After joining, we retrieved the entire available history of the identified channels using the respective APIs. Not all messages were pump signals, of course, so we followed a process to extract signals from the broader set of communications. We filtered the data based on keywords chosen specifically for each channel based on their posting patterns. This required a huge effort because communications/language on the channels were not uniform. We then manually inspected the filtered data and verified whether the post actually described an attempted pump or not, recording those that appeared to be pump signals. Finally, whenever we identified additional channels being discussed in existing ones, we added the new source to our database. We are confident that we managed to join most of the relevant channels during the period we examine: January to June 2018.

We systematically discarded some posts, judging them to not be pump signals. We excluded posts where users simply predicted the future prices of the coins. We also ignored signals coins to "hodl" coins, which is a cryptocurrency meme for holding on to coins for a long period of time. Since "hodl"-ing is antithetical to the short term pump and dumps, we excluded these.

One technical distinction between Telegram and Discord bears mentioning. With Discord, people join the servers. Individual channels/groups are associated with servers. The main purpose of the channels is to organize data, and any member of a server has access to all channels in that server. Thus, in the case of Discord, we were able to collect data on the number of members that belong to a specific server. It is not specific to a particular pump, since servers contain many channels; it essentially measures the potential market for participating on pump schemes promoted on channels on that server.

Telegram is a cloud-based service where individual channels are set up by individual operators and hosted on Telegram's infrastructure. Hence, there is no analogous variable to number of members that belong to a specific server in the Telegram data.

[7] It is clear that traders learned to recognize pump-and-dump schemes as well. Indeed, one of the authors was informed by a trader that they specifically developed trading strategies to take advantage of the typical fall in prices after the pump-and-dump schemes end. Regulators could have reacted as well, but they have typically preferred a "hands-off" approach to cryptocurrency regulation.

[8] There have been media articles about the phenomenon as well. Mac reported on pump-and-dump schemes in a Buzzfeed article published in January 2018 (Mac, 2018). This was followed by work by Shifflett and Vigna (2018) in a Wall Street Journal article published in August 2018.

[9] Telegram refers to its groups as channels; Discord calls them groups. Throughout the paper, we use the terms channel and group interchangeably.

3.2. Distinguishing pump types

While gathering the data, we observed two broad categories of pump promotion. *transparent pump groups* used the words “pump” and “dump” everywhere, including in the name of their channels. By contrast, *Obscure pump groups* usually avoided the words “pump” and “dump”. The main concern that was reflected in their discussions was that members were not sure if pump and dump was legal, so they avoided explicitly using the terminology. We also discovered that there were significant differences between the way the pump signals operated across the group types. We describe the key characteristics of the groups below.

Transparent pump groups. Pump signals in transparent channels typically follow a “countdown" strategy. They first announce that a pump will be happening between 24 to 48 h before the scheduled time. They follow up by posting many other announcements about timing and, optionally, the cryptocurrency exchange where the coin purchases should occur. When the announced time comes, they finally posted the name of the coin. They usually posted the pump results a few hours afterward, along with the date of the next scheduled pump.

These channels usually had premium membership, whose price was based on how many people a person had recruited to the channel. Users could also buy premium membership plans. Based on the type of plans, premium members would receive the pump signals a certain amount of time before others. Finally, these channels did not typically pump the same coins over and over.

Obscured pump groups. Since broadcasting a countdown clearly demonstrates coordinated pumping, the obscured pump groups designed their signals differently. Instead of a countdown, they typically announced target prices along with the coins, exhorting channel members not to sell below the target price. We termed this a “price target" strategy.

Whether caused by a lack of sophistication or a desire to avoid detection, the obscured pumps lacked many of the hallmarks of coordination. These channels typically did not a have premium membership option. Unlike the first group, they did not make multiple announcements about a particular pump. They typically simply posted the name of the coin and its current price, without making any advance announcement. Importantly, unlike the transparent pumps, they often pumped the same coins many times.

Verifying pump group strategies. To verify that the pump groups followed differentiated strategies (“countdown" vs. “price target"), we randomly inspected 125 Telegram signals in detail. Three coders qualitatively inspected the signals independently and came to a consensus. 105 of the 125 pump signals included either a countdown or a price target. Of the 53 signals from transparent groups, 32 included a countdown but no target, 13 had both a countdown and target, and 8 had a target but no countdown. 50 of the 52 inspected signals from obscured pump groups only had a target, with the remaining 2 including a target and countdown. Thus we can conclude that transparent pumps mostly use countdowns while obscured pumps almost exclusively set price targets.

Copied pumps. There were some Discord groups where the signals were entirely copied from other sources. Although they usually posted the signals hours after the pump, they included the actual time that a pump was published. They also included the source of that pump. We preferred not to use these signals, because we wanted to collect our data from primary sources. We used these channels to ensure complete coverage, i.e., to find the pump sources and follow them. We included them in the analysis when we could not get access to the source channels. Copied pumps accounted for 4 Discord groups with 514 associated pump signals not found elsewhere. There are no Telegram pumps in this category because of the complete overlap between these Telegram groups and other signals already collected.

We include the copied pumps for completeness, but our results are qualitatively unchanged if we remove the “copied pumps" from the analysis.

Pump group and data source. In the case of Telegram, 88 percent of the signals were obscured pumps and 12 percent were transparent. In the case of Discord, 42 percent of the signals were obscured, 40 percent of the signals were copied, and 11 percent transparent.

3.3. Pricing data on cryptocurrencies

We collected price data on nearly 2000 coins and tokens (henceforth referred to as coins) across 220 exchanges as reported to coinmarketcap.com, the leading website of aggregated data on cryptocurrency trading. We collected all price data for each of the coins listed on coinmarketcap.com from January through June 2018. This gave us a total of 316,244,976 collective volume and price data points across all of the coins listed. The data points collected are at the finest granularity presented by coinmarketcap.com at the time of collection, a 5-minute interval.

We realize there are limitations to this method of data collection. For instance, coinmarketcap.com does not list every coin or token available for purchase or trade. Further, this data is slightly different than what one would be able to collect from an exchange API. Since the website is collecting data from so many sources, it reports a volume weighted average of all of the prices reported at each exchange to calculate the price it reports. On the plus side, this approach is more comprehensive in the number of exchanges and coins covered.

We identified occasional gaps in the coin volume and pricing data reported by coinmarketcap.com. Such gaps are normal. They can be caused by exchanges not reporting data to coinmarketcap.com, by outages at coinmarketcap.com, or by errors in our data collection. To account for the last possibility, we identified any gaps exceeding 7.5 min (meaning that two consecutive data points were missing as the data is reported at 5-minute granularity). We attempted to refetch that data in case it was gathered by coinmarketcap but missed by our scripts. Fortunately, these gaps are quite rare. In total, 3.8 million volume and price data points are missing, which is approximately 1% of all such data.

Table 1
Pump (Median) Success/Profitability by month in percentage terms.

Month	Discord	Telegram
Jan 2018	5.4	6.4
Feb 2018	4.1	4.9
Mar 2018	3.9	5.2
Apr 2018	3.2	4.2
May 2018	2.9	2.8
Jun 2018	2.2	3.2

Matching discord/Telegram information with trading data. For the purpose of our study, it was essential to ensure a consistent mapping between what is announced in the pump signal to what is associated with the trading data. In particular, pump signals are by no means consistent when it comes to the coin names used in the messages. Some users refer only to the coin ticker such as DOGE, which is the ticker for Dogecoin. This can be a bad idea as several cryptocurrencies employ identical tickers (being decentralized, there is no equivalent to NYSE or NASDAQ to enforce the uniqueness of ticker symbols). Others use the full coin or token name, but that can be problematic because many coins have similar names. For instance, the cryptocurrency IOTA has the ticker MIOTA; the coin name is similar to the ticker for IoTex, which is IOTX. Still others use some combination of the ticker and full or partial name. For example, "Bitcoin (BCD)" refers to Bitcoin Diamond and not Bitcoin as the ticker for Bitcoin is BTC and not BCD.

We normalized reports to the name used by coinmarketcap.com. To do this, we created a name map that contains several variations of the actual cryptocurrency name based on our observations. We then removed special characters from the names reported in Discord and performed a case insensitive comparison to the map we created. If a match was found, we replaced the pump name with a clean version that matches the name elsewhere in our data. Some of the names required manual replacement since cryptocurrencies have the ability to rebrand. In this way, we were able to map 952 of the Discord pump signals and 2,649 of the Telegram pump signals to more than 300 cryptocurrencies.[10]

Identifying pump timing and success. Throughout the processes of aggregating, combining, and cleaning the data, it became increasingly apparent that we could not reliably use the time of a pump signal to mark the beginning of a period of anomalous trading activity.[11]

Hence, instead of taking the pump signal time as given, we treat it as the starting point to identify associated spikes in trading activity. We inspect 48 h before and after the time of the reported signal to find the maximum percentage jump between two consecutive price data points (typically spaced 5 min apart).

In the data analysis described in the next section, we use this maximum 5-minute percentage increase in this 96 h period in the coin's price relative to BTC as our measure of pump success.

3.4. Data summary

The Discord and Telegram data span the six month period from January to June 2018. A small number of observations were duplicates in the sense that they involved the same coin on the same day and roughly at the same time (within an hour) on the same exchanges. We eliminated the duplicates, but the results are qualitatively unchanged if we include them. Once we eliminate the duplicate observations and a few observations for which we did not have complete data, we are left with 952 observations with complete data on Discord and 2469 observations with complete data on Telegram. This gives a sense of the scope of the pump-and-dump phenomenon on these platforms.[12]

We find that ten percent of the pumps on Telegram (Discord) increased the price by 16.3 percent (15.6 percent) in just five minutes. Recall that the January–June 2018 period was a period in which cryptocurrency prices were falling significantly; hence "moderate" percentage increases were an achievement for the pump. Before we conduct the empirical analysis, the raw data in Table 1 shows that the profitability of the pump and dumps schemes declined over time.

4. Descriptive analysis

We first describe the variables to be used in the regressions in the next section and their summary values. Then we motivate the hypothesis that pump profitability might fall over time and provide summary measures. We next quantify the extent of concentration in the pump ecosystem, and then describe differences between transparent and obscure pumps. Finally, we consider what happens to coin prices after the pump is over.

[10] We have more total pumps than that, but approximately 5% do not have complete data and cannot be used in the analysis.

[11] This may be because "insiders", i.e., those running the pump, strategically purchase before the agreed upon time. This is consistent with the other work in this area. Kamps and Kleinberg (2018) noticed that pumps sometimes occurred exactly when a signal was put out and other times occurred afterwards. Li et al. (2018) collected more pump signal information than (Kamps & Kleinberg, 2018) and observed the same effect. Xu and Livshits (2019) collected *hourly* market data, and found that the markets move as much as 72 h before an announced pump.

[12] It is possible that there are a small number of pumps that occur both on Telegram and Discord, primarily in May 2018. This is not a problem since we analyze the Discord and Telegram data separately. (We do this because some of the variables are not available for both of the platforms.) Our results are robust to eliminating these potential duplicates.

Table 2
Descriptive statistics: Discord, N=952.

Variable	Obs	Mean	Std. Dev.	Min	Max
Max % Price inc.	952	6.78	17.34	0.64	221.90
Exchanges	952	21.11	26.50	1	182
Pair Count	952	24.74	89.05	1	759
Rank	952	257.64	309.30	2	1863
Server Member Count	952	5373	9467	141	49,415
January 2018	952	0.15	0.36	0	1
February 2018	952	0.12	0.33	0	1
March 2018	952	0.13	0.34	0	1
April 2018	952	0.12	0.33	0	1
May 2018	952	0.37	0.48	0	1
June 2018	952	0.11	0.31	0	1
Binance-only	952	0.22	0.41	0	1
Bittrex-only	952	0.20	0.40	0	1
Binance–Bittrex	952	0.08	0.27	0	1
Other exchange	952	0.04	0.20	0	1
No exchange	952	0.46	0.50	0	1

4.1. Variables for explaining pump success

We start by examining what factors explain the success of the pump-and-dump scheme, where success means that the pump increased the price significantly.

We employ the maximum % price increase (as described above) in the 48 h preceding and following the pump as the dependent variable. We denote this variable as % Price Increase. Most of the cryptocurrencies cannot be directly traded with USD, but they can be traded with bitcoin. Hence, we use coin prices in bitcoin.[13]

We have the following independent variables:

- Exchanges: the number of exchanges on which the coin can be traded. We measured this variable twice: once at the end of 2017 and once in September 2018. The correlations are above 0.99 and the results are unchanged regardless which date we choose. The 2018 variable has more observations, so we use that one.[14]
- Rank: the rank of the coin in terms of market capitalization. Bitcoin is #1. Coins with larger numerical rank have lower market capitalization.
- Pair Count: the number of other coins that the coin can be traded with.[15]
- Server-Member-Count (Discord Only): the number of members that belong to a server (which is not specific to a particular pump). This variable essentially measures the potential market for participating on pump schemes promoted on that server.
- Views: (Telegram only) Number of views per pump.[16]
- Dummy variables for February, March, April, May and June 2018.
- Dummy variables for Binance-only, Bittrex-only, and Binance–Bittrex. A non-trivial portion of the pumps were on both exchanges. In that case, Binance–Bittrex takes on the value one.
- other-exchange takes on the variable one when the pump lists an exchange other than Binance or Bittrex.
- no-exchange is a dummy variable that on the value one if no exchange was listed in the pump.

Descriptive statistics for all variables used in the analysis appear in Tables 2 and 3.

These table shows that in the case of Telegram (Discord), 45 percent (50 percent) of the pumps occurred on either Binance, Bittrex, or both and 48 percent (46 percent) occurred without an exchange listed.

Table 4 groups coins by rank (in terms of market capitalization.) In Table 4 shows that while many of the pumps involve coins with light trading and low market capitalization (similar to penny stocks), pumps are not limited to obscure coins. Coins with greater market caps experience smaller spikes in prices: the median price increase for the top 75 coins (in rank) is 2.4% for Discord and 2.6% for Telegram. The median return for coins ranked between 500 and 1000 was 5.8% for Discord and 7.1% for Telegram. See Table 4 for the full breakdown.

[13] Because of this, we cannot include the very small number of pumps using bitcoin itself.

[14] The 0.99 correlation is between the "number of exchanges" the coin is traded on at the end of 2017 and the same variable (the number of exchanges) observed in September 2018. Hence, it is the same variable (the number of exchanges) in two points in time. The key takeaway is that this variable did not change over time, so it does not matter whether we used the 2017 or 2018 observation.

[15] Similar to exchanges, we measured this variable twice, once at the end of 2017 and once in September 2018. The correlations are above 0.99 and the results are unchanged regardless which date we choose. The 2018 variable has more observations, so we use that one.

[16] With the possible exception of views, all of these variables are clearly exogenous to the pump. We think that views is essentially exogenous as well. Results are unchanged if we do not include views in the analysis

Table 3
Descriptive statistics: Telegram, N=2469.

Variable	Obs	Mean	Std. Dev.	Min	Max
Max % Price inc.	2469	9.57	22.93	0.42	341.99
Exchanges	2469	17.72	22.5	1	182
Pair Count	2469	16.89	64.17	1	759
Rank	2469	375	417	2	2036
Views	2469	9649	9815	0	77,266
January 2018	2469	0.16	0.37	0	1
February 2018	2469	0.12	0.32	0	1
March 2018	2469	0.13	0.34	0	1
April 2018	2469	0.27	0.45	0	1
May 2018	2469	0.19	0.39	0	1
June 2018	2469	0.13	0.40	0	1
Binance-only	2469	0.22	0.41	0	1
Bittrex-only	2469	0.18	0.39	0	1
Binance–Bittrex	2469	0.05	0.23	0	1
Other exchange	2469	0.07	0.25	0	1
No exchange	2469	0.48	0.50	0	1

Table 4
Median price increases by coin rankings.

Rank	Discord		Telegram	
	Pumps #	Price Inc %	Pumps #	Price Inc %
≤75	308	2.4	635	2.6
76–200	239	3.2	520	3.3
201–500	269	3.5	682	4.1
501–1000	99	5.8	393	7.1
> 1000	37	15.7	239	13.7

The pumping of more “mainstream" coins may be because it is not always easy to pump obscure coins that are traded on a small number of exchanges. Additionally, there is less volatility in mainstream coins, and some “investors" (pumpers) may have preferred a relatively lower risk level.

Overall, in the case of Discord data, the median (mean) percentage price increase was 3.5% (7.4%), while the 75th percentile of the distribution was 6.3%. In the case of Telegram data, the median (mean) percentage price increase was 5.1% (9.8%), while the 75th percentile of the distribution was 9.2%. Recall that the January–June 2018 period was a period in which cryptocurrency prices and trading volume were falling significantly; hence “moderate" percentage increases were an achievement for the pump.

It is not surprising that the coin rank is the independent variable that is most highly correlated with the percent price increase of the pump, both on Discord (0.48) and Telegram (0.35.) The correlations among the variables are shown in Tables 5 and 6. As Tables 5 and 6 show, the correlations are similar across the Discord and Telegram platforms.

4.2. Profitability over time

Economic theory suggests that the cryptocurrency pump-and-dump ecosystem would not succeed over time for several reasons. First, such schemes need outside investors to succeed. The idea is that the initial surge in volume attracts additional traders. Such (honest) traders in cryptocurrencies would learn how to recognize pump and dumps and adjust their strategies accordingly, so as not to fall prey to the schemes. It has been documented in the literature that it is fairly straightforward to adjust investment strategies to account for cryptocurrency pump and dumps.

Second, many insider members of the pump-and-dump schemes actually lose money. This is because, as has been documented, administrators/insiders of the schemes typically make purchases before the “beginning” time of the pump. This would make it less attractive to participate over time.

Third, regulators might begin to react if the phenomenon becomes prolific. A few isolated incidents might not justify a policy intervention, but hundreds or thousands of pumps might eventually lead regulators to act.

Our dynamic dataset allows us to examine whether profitability has in fact declined over time. From our data, the median profitability of the pumps go down over time for the six months we have data (January to June 2018.) This is true both for Telegram and for Discord.[17] See Table 1. The decline is steep on both platforms: On Telegram profitability was essentially 50% lower on average in June than in January. In the case of Discord, profitability was essentially 60% lower on average in June than in January.

[17] In the formal analysis, we run regressions. The regression results show that even after controlling for other factors that affect pump-and-dump success, success falls over time, with a steep drop-off near the end of the period for which we have data.

Table 5
Correlations among variables: Discord, N=952.

Variable	% Price inc.	Exchanges	Pair count	Rank	Server members
% Price inc.	1				
Exchanges	−0.15	1			
Pair Count	−0.053	0.72	1		
Rank	0.46	−0.42	−0.18	1	
Server Member	−0.035	−0.0031	0.021	0.000	1

Table 6
Correlations among variables: Telegram, N=2469.

Variable	% Price inc.	Exchanges	Pair count	Rank	Views
% Price inc.	1				
Exchanges	−0.14	1			
Pair Count	−0.06	0.64	1		
Rank	0.40	−0.44	−0.19	1	
Views	−0.10	0.09	0.04	−0.06	1

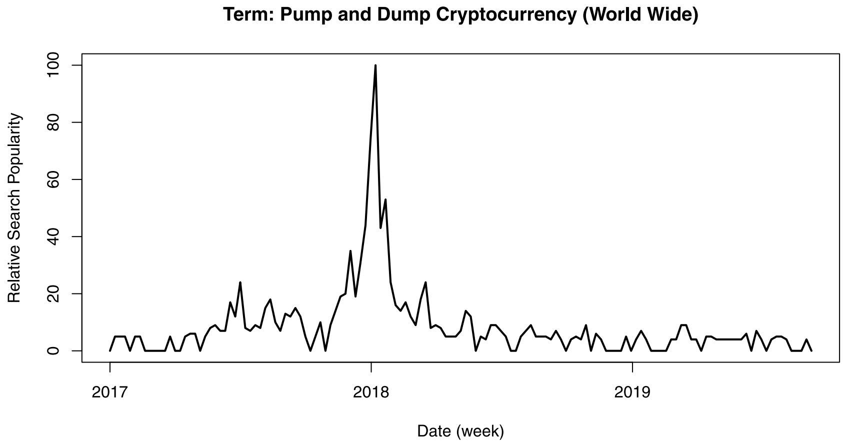

Fig. 1. Google Trends results from searching for pump and dump cryptocurrency.

While we cannot definitively answer the interesting question whether this decline in profitability reduced pumps over time,[18] it is interesting to note the following: Google Trends suggests that interest in pump-and-dump schemes took off during the increase in bitcoin's massive increase in price in late 2017 and declined sharply after June 2018. See Fig. 1.[19] While we do not want to push this point, it does provide some support for a decline in the cryptocurrency pump-and-dump phenomenon, which is consistent with declining profits over time.

4.3. Concentration in the ecosystem

The data also enable us to examine other key questions about the ecosystem: (I) Was the ecosystem dominated by a few channels (running a lot of pumps) or were there many active channels? (II) Did pumps occur on many exchanges or just a few? (III) Were coins pumped repeatedly? We (perhaps surprisingly) find high levels of concentration in both exchanges employed for pumps and channels involved in running the pumps.

- Cryptocurrency Exchanges: From our data, Binance and Bittrex were by far the most popular exchanges for pump-and-dump schemes. Binance and Bitfinex together accounted for 86% (87%) of the pumps for pumps that listed/recommended an exchange on Telegram (Discord). During this period and afterwards, Binance was the largest cryptocurrency exchange, by trading volume, and Bittrex had large trading volume as well. Both exchanges offer trading in hundreds of cryptocurrencies, which likely made them attractive to organizers of the pump and dumps.
- Channels: The perceived wisdom was that there were many channels running pumps. It turns out that, like exchanges, this aspect of the ecosystem was highly concentrated as well. In the case of Telegram for example, six channels accounted for more than 70 percent of the pumps.

[18] It was not possible to collect detailed information after the period for which we have data, since pump channels removed us from the groups.
[19] It is well known that interest in bitcoin in Google trends data is very highly correlated with the price of bitcoin.

- Coins: Additionally, twenty-three coins were pumped 18 or more times (thus on average, these coins were pumped at least three times a month during the six month period.). These twenty-three coins accounted for more than 20% of all pumps during that period on Telegram. Similarly on Discord, the top 20 coins accounted for 28 percent of the pumps. Again, this suggests a concentrated industry. This information should be helpful to regulators.

4.4. Comparing transparent and obscured pumps

The analysis comparing transparent and obscured pumps is only conducted for Telegram. This is because Discord only has 71 transparent pumps, while Telegram has 271. We found the following key differences:

- The transparent type of pump and dumps did not pump the same coin over and over. In particular, 167 different coins were used in the 271 transparent pumps. In the case of obscured pumps, just 276 different coins were used in 2198 pumps! Thus although the second category had roughly eight times as many pumps as the first category, they employed less than twice the number of coins.
- Transparent pumps were more likely to pick a particular trading platform (exchange) for the schemes, while the obscured type often did not specify an exchange. Transparent pumps were also more likely to stay away from the dominant exchanges.
- The transparent pump-and-dump schemes achieved a 7.7% median rate of return, while the obscured ones achieved a 4.1% median return.

Additionally, there is high concentration for both channels in terms of pump origin. In the case of the transparent traders, three channels accounted for more than 65 percent of the pumps. In the case of the obscured traders, six channels accounted for more than 75 percent of the pumps.

4.5. What happens after the pump is over

An interesting question is what happens after the pump is over. Do the pumped coins retain the price rise, or do they suffer a price "hangover"? To address this issue, we calculate two additional variables.

- **Starting price**: this is the starting price associated with the maximum five minute percentage increase in price. It can be interpreted as the "pre-pump" price.
- **End price**: This is the minimum price in the 48 h after pump.
- We then calculate the following variable: $\frac{\text{End price}-\text{Starting price}}{\text{Starting price}}$. This is the percentage change in price from the pre-pump period to the post-pump period.

We find the following: The median percentage change in price from the pre-pump period to the post pump period is -41% for Discord data and -38% for Telegram data. Overall, more than 60% of the coins have a lower "post-pump" price than the "pre-pump" price. Even though prices were generally falling during this period, a 40% fall in prices in 48 h is large.[20]

5. Formal regression results

We first study all pumps together, followed by examining obscured and transparent pumps separately on Telegram data.

5.1. All pump-and-dump schemes

In the regressions in Table 7, we use the percentage price increase as the dependent variable. Because the variables in the analysis are skewed, we run a log/log OLS regression using the natural logarithm of the variables, both the dependent variable and the independent variables.[21] We employ clustered standard errors at the level of the coin, since many of the coins appear more than once in the data set.[22] Our regression results when all pump-and-dump schemes are included together (see Table 7 are as follows:

- In the case of Telegram, the log/log regression has an adjusted R-squared of 0.32 versus 0.30 for Discord.[23]

[20] We ran regressions using the percentage change in price from the pre-pump period to the post-pump period as the dependent variable, and the right-hand-side variables as the independent variables. In these regressions, the adjusted R-squared was virtually zero.

[21] Not surprisingly, the log/log regression has much higher explanatory power (in the sense that it has a much higher adjusted R-squared) than either a log/linear or linear/linear specification. This is true both for Discord and Telegram.

[22] Descriptive statistics for the same variables used in the "unified" analysis are shown separately for the transparent and obscured pump types separately in Tables 8 and 9.

[23] In microeconomic studies like ours, an adjusted R-squared value of 0.30 is very high. We use the adjusted R-squared value because adding an independent variable to the model always increases R-squared (even if the estimated coefficient is not significant). The adjusted R-squared takes into account the number of variables included and it can decline if a variable that is not significant is added to the model.

Table 7
Examining what affects success of pump and dump schemes.

Independent variables	Telegram Dept. Var. % Price increase log/log	Discord Dept. Var. % Price increase log/log
Exchanges	−0.29***	−0.23***
	(0.057)	(0.067)
Pair Count	0.034	0.15**
	(0.05)	(0.066)
Rank	0.16***	0.24***
	(0.043)	(0.050)
Server Members		−0.007
		(0.020)
Views	−0.061***	
	(0.013)	
February 2018	−0.036	−0.24**
	(0.067)	(0.087)
March 2018	−0.046	−0.13
	(0.069)	(0.091)
April 2018	−0.20***	−0.40***
	(0.052)	(0.11)
May 2018	−0.43***	−0.49***
	(0.070)	(0.079)
June 2018	−0.26***	−0.66***
	(0.075)	(0.11)
Binance Only	−0.31***	−0.24***
	(0.055)	(0.062)
Bittrex Only	−0.17***	−0.23***
	(0.050)	(0.075)
Binance–Bittrex	−0.41***	−0.38***
	(0.086)	(0.080)
Observations	2649	952
Adjusted R^2	0.32	0.30

Standard errors in parentheses: They are clustered at the level of the coin.
* Significant at the 90% level.
** Significant at the 95% level.
*** Significant at the 99% level.

- The ranking of the coin is positively associated with success for both Discord and Telegram. This effect is highly significant in both cases.[24] Coins with lower market capitalization typically have lower average volume. Lower average volume gives the pump scheme a greater likelihood of success.
- The number of exchanges on which the coin can be traded is negatively associated with success and the effect is statistically significant for both Discord and Telegram. This makes intuitive sense, because with fewer exchanges, pump schemes have better control over the total volume of the coin.
- The number of other coins that the coin can be traded with is positive and statistically associated with success in the case of Discord. In the case of Telegram, the estimated coefficient is positive but is insignificant. One possibility is that more trading pairs allow greater flexibility for those involved in the pumps.
- In the case of Discord, the estimated coefficient on the variable "Server Member Count" is negative, but not significant. In the case of Telegram, the variable "Views" is negatively associated with success and the effect is statistically significant. Although we do not push this, one possible interpretation is that it is hard to coordinate if there are too many people potentially involved in the pump.[25]
- Pumps on Binance and Bittrex do worse than pumps not on those exchanges. It might be that, since these are dominant exchanges, more people are involved in the pumps — and coordination is more difficult.
- Perhaps most importantly, the declining "success" rate over time, as shown by the negative coefficients on the monthly dummy variables holds, even after controlling for the other factors. In both Telegram and Discord, the estimated coefficients associated with April, May and June are statistically significant, suggesting a deep decline in profitability over time.

5.2. Transparent and obscured analyzed separately: Telegram only

Our regression results when the pump-and-dump schemes are analyzed separately by category are shown in Table 10. The key results are as follows:

[24] Recall that higher rank means more obscure.
[25] It might also be because "Views" could be endogenous. All of the other results are robust to excluding "Views" from the analysis.

Table 8
Descriptive statistics: (Telegram) transparent pumps, N=271.

Variable	Obs	Mean	Std. Dev.	Min	Max
Max % Price inc.	271	29.44	53.4	0.49	341.99
Exchanges	271	13.5	20.3	1	163
Pair Count	271	14.56	71.25	1	759
Rank	271	699.53	613.43	3	2036
Views	271	3241.33	3021.19	0	14,498
January 2018	271	0.14	0.35	0	1
February 2018	271	0.13	0.34	0	1
March 2018	271	0.24	0.43	0	1
April 2018	271	0.23	0.42	0	1
May 2018	271	0.16	0.37	0	1
June 2018	271	0.1	0.3	0	1
Binance-only	271	0.18	0.38	0	1
Bittrex-only	271	0.11	0.32	0	1
Binance–Bittrex	271	0.06	0.24	0	1
Other exchange	271	0.42	0.5	0	1
No exchange	271	0.23	0.42	0	1

Table 9
Descriptive statistics: (Telegram) obscured pumps, N=2198.

Variable	Obs	Mean	Std. Dev.	Min	Max
Max % Price inc.	2198	7.12	13.64	0.42	309.09
Exchanges	2198	18.24	22.72	1	182
Pair Count	2198	17.18	63.25	1	759
Rank	2198	334.73	366.64	2	1935
Views	2198	10,438.91	10,070.62	0	77,266
January 2018	2198	0.16	0.37	0	1
February 2018	2198	0.11	0.32	0	1
March 2018	2198	0.12	0.32	0	1
April 2018	2198	0.28	0.45	0	1
May 2018	2198	0.2	0.4	0	1
June 2018	2198	0.13	0.34	0	1
Binance-only	2198	0.22	0.42	0	1
Bittrex-only	2198	0.19	0.4	0	1
Binance–Bittrex	2198	0.05	0.22	0	1
Other exchange	2198	0.02	0.15	0	1
No exchange	2198	0.51	0.5	0	1

- In the case of transparent traders (pumps), the log/log regression has an adjusted R-squared of 0.60 versus 0.26 for obscured traders.
- The ranking of the coin is positively associated with success for both types. This effect is highly significant for transparent traders and significant for obscured traders.
- The number of exchanges on which the coin can be traded is negatively associated with success and the effect is statistically significant for both groups.
- Again, pumps on Binance and Bittrex do worse than pumps not on those exchanges.
- Interestingly, the variable “Views" is positively associated with success and the effect is statistically significant for transparent traders. However, this variable is negatively associated with success and the effect is statistically significant for obscured traders . This may be because, in general, there are fewer “viewers" for the transparent pumps. Recall that the transparent pumpers typically restricted membership.
- For the obscured traders, the declining “success" rate over time, as shown by the negative coefficients on the monthly dummy variables holds, even after controlling for the other factors.
- Strikingly for the transparent traders, the “success" rate is virtually constant over time as shown by the very similar coefficients for the dummy variables on the months February through June 2018.[26]

6. Brief conclusions and thoughts on regulation

In this paper we examined the phenomenon of pump-and-dump schemes for cryptocurrencies. The proliferation of cryptocurrencies and changes in technology have made it relatively easy (and virtually costless) for individuals to coordinate their activities. In terms of scope, we found that these tactics are widespread on both Discord and Telegram.

[26] It appears that the success rate jumped from January to February, and stayed at that level over time.

Table 10
Examining what affects success of pump and dump schemes.

Independent variables	Transparent Max % Price inc.	Obscured Max % Price inc.
Exchanges	−0.38**	−0.21***
	(0.14)	(0.055)
Pair Count	0.11	−0.04
	(0.12)	(0.05)
Rank	0.39***	0.09*
	(0.11)	(0.039)
Views	0.11*	−0.04**
	(0.049)	(0.012)
February 2018	0.92***	−0.21**
	(0.23)	(0.061)
March 2018	0.75***	−0.17*
	(0.21)	(0.069)
April 2018	0.57*	−0.27***
	(0.25)	(0.054)
May 2018	0.77*	−0.55***
	(0.34)	(0.065)
June 2018	0.87*	−0.42***
	(0.33)	(0.072)
Binance Only	−0.88***	−0.2***
	(0.21)	(0.054)
Bittrex Only	−0.72***	−0.03
	(0.19)	(0.052)
Binance–Bittrex	−1.09**	−0.31***
	(0.32)	(0.084)
Constant	−0.67	2.33***
	(0.89)	(0.32)
Observations	271	2198
Adjusted R^2	0.60	0.26

Standard errors in parentheses: They are clustered at the level of the coin.
* Significant at the 90% level.
** Significant at the 95% level.
*** Significant at the 99% level.

We identified two distinct approaches to pumping cryptocurrencies: transparent pumps that openly promote coordinated purchases to raise prices and obscured pumps that set price targets instead. By making pump signals so obvious (e.g., pre-announcements, countdown messages, revealing the coin name at precisely the intended purchase time), the organizers of transparent pumps likely increased the chances of coordinated purchasing behavior to drive up prices. This is reflected in the superior returns to transparent pumps compared to obscure ones.[27]

Our analysis has implications for regulatory policy. Regulators could perhaps significantly disrupt future schemes by focusing their efforts on the most prolific exchanges and brazen pump channels. Far from insurmountable, a concentrated ecosystem makes enforcement tractable.

Pump-and-dump schemes historically involved stocks or securities. Hence, in the U.S., the Securities and Exchange Commission (SEC) had regulatory authority. However, the U.S. Commodity Futures Trading Commission (CFTC) defined cryptocurrencies as commodities. This interpretation gives them legitimacy to be involved in the regulation of cryptocurrencies.

During the period of our data, the CFTC (February 2018) issued a press release warning consumers to avoid pump-and-dump schemes. As they noted, this was the "First Pump-and-Dump Virtual Currency Customer Protection Advisory". The CFTC took an additional step by issuing a bounty shortly thereafter on cryptocurrency pump and dumps.

In February 2018, the same month as the first CFTC warning, interest in the CFTC shot up to a Google trends high that was never reached again. A comparison (using Google trends data) between interest in pump-and-dump schemes and interest in the CFTC showed that interest in pump-and-dumps peaked shortly before interest in the CFTC. Perhaps, more regulatory action at this stage might have dampened the phenomenon.

In general, U.S. regulatory policy towards cryptocurrencies can be characterized as hands-off. U.S. regulatory policy is inhibited in part because overlapping agencies have authority for regulating different aspects of the cryptocurrency ecosystem. The Internal Revenue Service (IRS), Financial Crimes Enforcement Network (FinCEN), the Commodity Futures Trading Commission (CFTC), and the Securities and Exchange Commission (SEC) are all involved in regulation related to the issuance, sale, and exchange of

[27] An interesting extension of this paper would be to conduct a case study by focusing on the few channels that repeatedly employed pump-and-dump schemes to see whether their strategy changed over time. But because this would be limited to just a few channels, such an investigation is better done as a case study, rather than an empirical paper employing econometric analysis.

cryptocurrencies. A recent paper notes that depending on the regulatory agency, according to U.S. Law, cryptocurrencies can be money, property, a commodity, and a security (Goforth, 2019). This causes confusion and creates a regulatory vacuum.[28]

While federal regulators have not been pursuing pump-and-dump schemes, state attorneys general have been active in investigating forms of price manipulation. The New York State Office of the Attorney General investigated cryptocurrency fraud at the cryptocurrency exchange level (New York State Office of the Attorney General, 2018). They found that while most trading platforms acknowledged that market manipulation and fraud were issues, they lacked controls to evade abusive behavior, such as pump and dumps. One currency exchange, Kraken, did not submit to their formal inquiry, but rather submitted a statement admitting that they did not believe market manipulation to be an issue.

In general, federal regulators should be very concerned by the vitality of the pump-and-dump ecosystem. Even though we have demonstrated a decline in pump profitability (primarily among obscured pumps), the scope of the phenomenon should raise red flags and trigger countermeasures.

CRediT authorship contribution statement

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[28] Nevertheless, market manipulation such as cryptocurrency-related pump-and-dump schemes could be viewed as illegal in the United States under the Securities Exchange Act of 1934 Rule 10-b5 which makes interstate commerce using manipulation or deceptive devices illegal. This is not a legal opinion, of course; it is simply an example of an existing law that could apply. Such clarification would be helpful since there is widespread belief spread by pump organizers that these schemes might be legal under US law.

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