UNIVERSITY OF TARTU

School of Economics and Business Administration

Elchin Rahimov, Kamran Rahimov

MARKET MANIPULATION IN CRYPTOCURRENCIES THROUGH SOCIAL MEDIA: THE ROLE OF INFLUENCERS

Master's thesis

Supervisors: Darya Lapitskaya (MA), Mustafa Hakan Eratalay (PhD), Rajesh Sharma (PhD)

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We have written this master's thesis independently. All viewpoints of other authors, literary sources, and data from elsewhere used for writing this paper have been referenced.

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Abstract:

The thesis aims to determine social media influencers' roles and effects on cryptocurrency markets. In our study, we mainly focus on Telegram channels as the reason for pump-and-dump actions that have a massive influence on the market, and Twitter because there are discussion communities where people share their thoughts about cryptocurrencies.

Previous researchers have studied this topic with different social media platforms and methods and mainly focused on predicting future changes in cryptocurrency prices. However, we chose Telegram as our primary data source and analyzed it to determine if social media influencers are effective in market manipulation. Despite previous studies, we also increased the date range to about three years, choosing the most pumped and effective results to compare.

Our study focused on 72 unique coins from 5 different pump-and-dump Telegram channels within three years (2019-2021). Previous studies have established the potential for forecasting coin prices based on the analysis of pump-and-dump activities. We examined how successful and trustworthy social media influencers are by applying logistic regression. Our research also focused on which factors can affect choosing a coin to pump and become successful.

In addition, the study aimed to check the trend and interest on the social media platform Twitter during the two weeks of pump action. To analyze whether there is an organized fake creation of interest behind the specific coin they will pump, the study uses the daily number of posts with specific keywords related to the coin.

Based on our analysis results, Telegram channels are successful in their market manipulation, and they can achieve very high price differences in a short time interval. Results from Twitter data show that the day of the pump announcement and after one day is the main period where we can observe a maximum number of posts related to the coin.

CERCS research specification: S180, S181, S188

Keywords:

Cryptocurrency, market manipulation, logistic regression, pump, dump, bitcoin, coin

1 Introduction

The increasing popularity of cryptocurrency markets in the modern world is undoubted. Giving tremendous earnings in a short period is the main reason for the popularity of cryptocurrencies. Even non-experts have begun to trade in these assets, and cryptocurrency exchanges currently conduct transactions worth more than 100 billion US dollars every month. (La Morgia et al., 2020)

The research area of the crypto markets is new as cryptocurrency itself, but it is growing at a speedy pace. Cryptocurrencies, as virtual forms of currency, are a broad classification and can be considered as digital versions of traditional fiat currencies. Since cryptocurrencies are not known as a developed resource class, current global standards on virtual forms of money are pretty limited. (Tandon et al., 2021). Malherbe et al. (2019) mentioned that cryptocurrencies are part of the monetary economic landscape in theory. Using blockchain technology, cryptocurrency supporters attempted to construct a monetary system that would not rely on the customary trusted third parties, beginning with a fundamental critique of both nation-states and banks. Far from being "trustless," the cryptocurrency movement has been shown here as a monetary innovation in which trust does not vanish but evolves in various forms. (Malherbe et al., 2019)

Starting in 2016, the price of Bitcoin drastically changed. One notable example is that the price peaked at 19,345 US dollars, which was 4000 US dollars before (Hamrick et al., 2021). Over the COVID-19 pandemic in 2020, Bitcoin and other cryptocurrencies gained value due to subsequent government policy and fears of fed investors about the global economy. In 2021, the price of Bitcoin reached its all-time high value surpassing over 63000 US dollars in April. There are spillover effects in cryptocurrencies (Kumar & Anandarao, 2019) that calculate how cryptocurrency's price would be affected if a one-unit shock hits on specific cryptocurrency (Moratis, 2021), and the higher volatility in price is also applicable to other leading cryptocurrencies in the market and altcoins[1]. Several factors behind the volatility and price change include technology and economic determinants (Li & Wang, 2017) and the significant effects of one person or group of people (Gandal et al., 2018).

Powell (2019) mentioned in their research repeated buy actions that trigger people to buy more coins, and as a result, prices become sixfold. This case from the Powell (2019) study shows that market manipulation is the tool that operates with disinformation. Media actions conclude

[1]https://academy.binance.com/en/glossary/altcoin

with an impact on general people to buy coins more even though they are just the result of the pump-dump operation. It is also a fact that different manipulation techniques in the market can influence the prices of cryptocurrencies; however, many cryptocurrencies have minimal liquidity. These techniques are pump and dump, whale wall spoofing, wash trading, and stop hunting. These are the most common techniques, but we will research mainly pump and dump actions which are most famous among influencers. After gaining popularity in crypto markets, the number of papers and research has increased in parallel. Even though some previous articles describe crypto market changes, there is not enough focus on measuring influencers' role in these fluctuations. (Calo, 2013)

A noticeable exception can be observed in the paper by Mirtaheri et al. (2019), who analyses the influence of social media on the crypto market. Still, as a difference, the author focuses mainly on the pump and dump actions in that a group of people decides to buy or sell the crypto simultaneously, which causes changes in the market prices. However, no studies are dedicated to searching the influential effects of a group of people with extensive data. Also, current studies did not research the influence of different social media phenomenons over the price of cryptocurrency on the market. Research questions are as follows: How strong is the influence of one or a group of people on social media? Can social media influencers influence the prices of coins? Which coins were affected most during these price change activities?

We apply logistic regression to answer research questions. Our study examines potential pump actions from Telegram channels and analyzes them using logistic regression to see if they are successful.

With the continuously increasing popularity of crypto markets, people have more interest in investing money in these digital coins. However, people want to earn money fast in an easy way, which is why manipulators have enough chance to change the prices of currencies. (Beck et al., 2019) demonstrated that the regular publication of many news stories regarding cryptocurrencies could make it difficult for individuals or traders to sort out essential information and make informed decisions in this arena. Fortunately, individuals regularly exchange and discuss news on social media platforms, such as Twitter, which is the topic of this research. As a result, it has been demonstrated that social media can serve as an effective proxy for monitoring and tracking notable cryptocurrency related news.

This thesis aims to find differences in the prices of cryptocurrencies by checking the impact of social media influencers. Although this type of research currently exists, Telegram and Twitter's effects on price changes have yet to be extensively studied. In the research, we will identify the power of social media, how effective are posts of famous people on these social platforms are, and the fluctuations in cryptocurrency markets compared to financial data after posting information by influencers. Also, we will find out the role of social media communities in crypto prices. Compared to other papers, we do not try to predict market changes; we want to identify which influencers have a better impact and how they manipulate prices. We define a specific period and the most popular coins and altcoins for research; then, we get data on these coins from social platforms like Twitter and Telegram to see how influencers have consequences by social media on the market. In our research, we checked all the active channels from Telegram and then analysed the overall messages. We chose the pumped coins for analysis. In this way, we created a list of coins which have been used several times or at least once for pump and dump actions.

The structure of paper is organized as follows. Section 2 contains a literature review related to works and studies of cryptocurrencies. Section 3 describes the data and initial analysis of the significant effects of cryptocurrencies. Section 4 shows the methodology. After that, Section 5 gives empirical results, and the final section concludes.

2 Background

2.1 Cryptocurrency market research

Cryptocurrencies and markets are new sections in the modern finance sector, but nowadays, it is evident that these new financial sections are chart-topping. With Bitcoin in 2009 as the first cryptocurrency, it started to increase its popularity, and Bitcoin still keeps researchers' interest in it. Becoming the most successful digital currency makes Bitcoin so popular and expensive. After Bitcoin gained fame, several coins and altcoins appeared in the cryptocurrency markets. Li and Wang (2017) mentioned that crypto coins built on computer cryptology and decentralized network architecture are new digital currencies.

There are many crypto money with different specific methods and laws, so it takes work to specify them reasonably. Cryptocurrencies are one of the most famous developments in the world; this changes the meaning and process of traditional financial money (Antony, 2018). We can observe that some people can be excited, and others are disturbed about the popularity of digital coins. For instance, people can share, reshare, and comment on their thoughts, interests, and information about these money types on Twitter which provides a safe and comfortable platform (Tandon et al., 2021). Many people are attracted by new and exciting technology, such as blockchain and digital currencies. To forecast usage, Bitcoin can use a large consumer base, which follows future developments in parallel. Multiple uncertain Ethereum scenarios demonstrate the need for reevaluation of the theoretical portfolio to eliminate any potential discrepancies. Dogecoin is a new cryptocurrency with less diversity than Ethereum.

The legal status still needs to be defined in many countries, or time-dependent changes can be observed in legal status within the same country (Kumar & Anandarao, 2019). Cryptocurrencies are generally made regarding Bitcoin, which is the most used unit. Although some countries allow Bitcoin trading and transactions with Bitcoin, it is prohibited or restricted by stringent rules in some countries. Similarly, many countries' official institutions, organizations, and courts classify Bitcoin differently. Legal regulations on cryptocurrencies are far from regulating all areas related to virtual currencies due to the limited foresight capabilities of lawmakers. (Malherbe et al., 2019) This creates legal gray areas. However, it has been argued that the legal regulations to be made with cryptocurrencies in Bitcoin will positively impact the economic growth and development of cryptocurrencies because legal uncertainty hinders this development. In many developed countries, the use and trade of Bitcoin are regulated by current laws regulating money laundering and finance terrorism. According to the European Central Bank, traditional financial sector regulations do not apply to Bitcoin and its derivative cryptocurrencies because the system does not include traditional financial actors. (Gandal & Halaburda, 2016)

While this research does not focus on the technical aspects of Bitcoin supply, we aimed to provide a basic explanation of how the process works. Mining is an essential part of Bitcoin's "enterprise" structure. Bitcoin addresses the primary challenges of regulating the number of new bitcoins and confirming transactions through a "mining" process, as there is no central authority and, thus, no centralized accounting. With a few exceptions, most cryptocurrencies work the same way. In mining, miners collect all uploaded transactions and put them in a block. They compete to include transaction blocks in the network (the ledger of Bitcoin transactions). To be successful, a miner must be the first to solve a complex factorization problem involving prime numbers. While solving the problem is complicated, proving that a given valid solution is simple. Issue complexity is automatically changed so that, on average, a new issue is resolved every 10 minutes. The first miner to solve the mystery adds the transaction blocks and gets the reward of fresh bitcoins. A more powerful computer increases the chances of discovering the answer before other miners. (Gandal & Halaburda, 2016)

Although Bitcoin controlled most of the market in the 2009-2016 period, in 2013, several other cryptocurrencies fought Bitcoin. These currency units gained much faster value than Bitcoin during the price spike. Between the rise in the price of Bitcoin and the corresponding decline, Gandal and Halaburda (2016) looked at how network influences affect competition in the crypto money market. Following the decline in Bitcoin prices in early 2014, their work reveals that they have significant network effects and all the dynamics of winning. Between July 2014 and September 2016, the value of Bitcoin against the US dollar did not change in practice, although the value of other currencies fell significantly against the US dollar. Litecoin, the market's second most valuable currency, has lost 70% of its value, while other "major" currencies have lost more than 90%. Bitcoin accounted for 94% of global market value in early 2016, while Litecoin accounted for 2%. Despite its flaws, Bitcoin has emerged as the apparent winner and benefactor of network effects at that moment. Things changed substantially in 2017. Bitcoin's value continued to rise again, and by early 2017, it had above 1000 US dollars once more. Bitcoin's value has taken more than three years to return to its 2013 peak, but that was only the beginning.

Hamrick et al. (2021) in this research shows that Bitcoin eventually peaked at more than 19,000 US dollars in December 2017 before dropping below 6,000 US dollars in the following months. In the last few years, the market capitalization of cryptocurrency has hit a peak. The total market value of all cryptocurrencies was over 14 billion US dollars in February 2014. The overall market capitalization of Bitcoin surpassed 825 billion US dollars in January 2018, approaching its high. Total market capitalization was over 575 billion US dollars in November 2020. Seven hundred fifteen cryptocurrencies had a market value of between 1 million and 100 million US dollars in February 2018. Less than 30 coins with a market valuation of 1 million to 100 million US dollars on January 4, 2014. The dramatic four-year growth in the value of high-valued coins raises worries about the possibility of price manipulation.

2.2 The pump-dump manipulation technique and its effects

Market manipulation happens when individuals or groups of people attempt to influence the conduct of others in order to profit from their misfortune. The unfortunate reality is that market manipulators are frequently willing to manipulate or lie about prices, supply, demand, and other factors that influence the value of financial securities (Gantz, 2022). Schröder (2009) describes market manipulation as an attempt to gain profit from affecting market prices artificially by choosing investor profits as the primary goal.

Cryptocurrency markets keep their popularity and increase revenues day by day. However, some manipulation techniques have a negative effect on this market, and as a result, the risk factor impacts becoming trustable of these digital coins. (Güleç & Aktaş, 2019). The pump-dump action is a kind of fraud in which fraudsters share false signals to the market to increase prices. As a result, people who need to be more informed about this action start to lose money because of incorrect information about pumping. People react to false information, assuming prices would be higher before declining prices; they buy vast amounts of coins. Since information is false, prices begin to go down in a short period (Kamps & Kleinberg, 2018). Güleç and Aktaş (2019) describes the pump dump action administrators of the group who choose the least famous coin and have a minor operation on it. They post the exact date and time for pump action in the next step. However, until now, other members have yet to learn which coin has been chosen. All members start to buy this coin on the mentioned date and time, and then the pump-action starts. As a result of high demand, the price of the coin increases; after getting their target, all members sell the cryptocurrency simultaneously. Channel members sell all coins they have and gain some revenue, while other people who are not members of these channels lose all their money with an immediate decrease that is called dump action. This phenomenon is prevalent in the cryptocurrency field. (Powell, 2019)

To increase manipulation activities in social media, a group of people who are coin founders or collaborators promotes and spreads the wrong information, leading people to buy and increase the price of the coin in the market. While it is more prevalent in social media like Telegram and Discord, some cases directly include celebrity and influencer promotions. The reasons behind the popularity are different; one of them is that cryptocurrency markets, compared to stock markets, are less regulated. While it is illegal in the second one, cryptocurrency markets fall into a legal grey area. Recent numbers show that in 2021 crypto investors scammed around 1 billion US dollars worth of coins (Fletcher, 2022). People who invest in cryptocurrency can be affected and lose lots of money. The reason behind the loss is that this type of activity takes little time. We will discuss in the paper the amount of time needed to influence the market price to rise and fall again. According to Hamrick et al. (2021), the profitability and success fell over time; analyzed this argument by taking six months of data from January to June 2018. They also studied the pump and dump ecosystem and came up with the results, the most popular coins are not effective in the case of influence, and there is a higher percentage change in the price of less popular coins. Cryptocurrencies with lower market capitalization tend to have lower average trading volumes, making them more susceptible to pump-and-dump schemes. Therefore, these lower-ranked coins are more frequently targeted by social media influencers (Hamrick et al., 2021). In our thesis, we will consider the data range starting from 2019 to 2022, which will allow us to analyze a wide range of data and come up with more substantial evidence.

Kamps and Kleinberg (2018) is valuable research about cryptocurrency markets and wildly pump and dump actions. As a result of the study, they provide some criteria and anomaly detection techniques to define suspicious activity. They mentioned the limitations of their study, which is using public data that cause some accuracy problem in getting results.

Xu and Livshits (2019) is another study in this field, and they examined over 200 pump signals and highly successful pumps on the exchange. Cryptocurrency manipulation schemes differ and are restricted by pump-and-dump schemes. One of the first scandalous activities publicly revealed includes the Mt. Gox Bitcoin currency exchange, where around 600.000 Bitcoins were acquired in suspicious ways worth 188 million US dollars. Studies revealed that this action had affected the price of Bitcoin, which jumped from 150 US dollars to more than 1000 US dollars in two months period (Chen et al., 2019). The study analyzed manipulating activities in this period and revealed the percentage rise in the price when suspicious activities took place. Studies show there was around a four per cent rise in a day, leading to a significant price jump in late 2013.

The high number of people that trade in cryptocurrency market can affect the market in the mean volume of trading. One of the worthy studies in this field by Hamrick et al. (2021) focused on pump and dump activities in Telegram and Discord. They collected data from 25 Telegram channels and 47 Discord servers with over 4000 subscribers. Additionally, they had data covering the six-month range date period in 2018. They also analyzed the effectiveness of pump activities and post-pump actions on the market. They concluded that the interest in these activities decreases over time. However, it only includes six months of data.

Our study includes Twitter data to check its influence on the market. Twitter is one of the primary sources where influencers interact as Twitter users. It will allow Twitter users to follow the news on the market and the ideas of famous people. A person with a high number of followers can easily direct people the way and affect the market by spreading rumors to follow their decision. Users with many followers share their thoughts on this social media, including coin names or hashtags. This creates interest in the mentioned coin, and users believe the potential and buying the coin increase its price.

The study from Mirtaheri et al. (2019) includes Twitter data for checking pump activities. Mirtaheri et al. (2019) mainly focused on the pump activities and how to use Twitter to increase the interest around the coin. Our study includes specifically chosen coins from Telegram channels and posts about these coins from Twitter. We apply measures to identify this type of person and their possible influence in the market, allowing us to conclude whether this person is a cryptocurrency market influencer. A few cases happened on Twitter where famous people, using their popularity, affected the people and the market (Shead, 2021). Our study includes different exchange markets where people can have access and trade to analyze the effect on the price. We took main markets such as Binance, Kucoin and others, the most popular markets to trade cryptocurrencies. These are also considered the trusted ones. As of 2021, Binance had a 7.7 trillion US dollars turnover and is the leading platform in its segment (Maloney et al., 2022).

3 Data

This section describes how we get data and from which platforms. To measure the pump-dump promoted by influencers in the social media, we mainly focused on Twitter and Telegram. We use two different platforms to get our data and show both impact of famous people and the role of pump dump actions. These are some spaces where people gather quickly, share their thoughts, and interact socially. Firstly, both social media channels of communication work with the *follower principle*, which means the number of followers can detect a person's popularity or group. Many followers mean a more famous person, and in this case, influencers can reach out to more people to influence. Twitter is a source of data that is considerably renowned for plenty of research (Tandon et al., 2021). We get tweets that have been posted by famous influencers and related to cryptocurrencies.

We chose Twitter because it has proved content associated with the financial market, especially the cryptocurrency market (Tandon et al., 2021). Influencers mostly post crypto-related information on this platform, significantly impacting price changes. We add Telegram as another data source that is recognized to implement pump and dump actions (Nghiem et al., 2021). Telegram has two group chats: Telegram groups where people can share their thoughts and comments and admins; Telegram channels where only channel owners can share information (Mirtaheri et al., 2019). In our research, we get data from Telegram channels. We choose different groups where people gather and take actions to influence the markets in Telegram and the critical factor is the number of people.

As the third part of our data, we collect the market prices of chosen cryptocurrencies, including open, high, low and close. We choose the available market where we can find the prices and can download them. Influencers pump many different coins, so we choose the most pumped coins in our first and second part data.

We choose 1 minute frequency for the historical data since we want to see the price changes after posts.

3.1 Telegram Data Collection

In cryptocurrency markets, scammers post false signals on some platforms to increase prices, (Hamrick et al., 2021) and they prefer to use Telegram in many cases. The reason behind choosing

Telegram is that Telegram gives anonymity to them. To work with Telegram data, we need to identify how are the influencers in the Telegram data case. But because anonymity policy of Telegram, we cannot know the names of influencers. For instance, the owner of channels in Telegram can see the information of members in the channel. Still, members cannot see information about the channel's owner because of the Telegram policy. So in Telegram's case, we can accept channels as influencers, not people.

Firstly, we choose the most appropriate channels to get data from. We research popular blogs and websites where people can find much popular Telegram channels to join and attend pump-dump actions. Upon examination of these channels, it was observed that a significant number of them were either inactive with few subscribers, or failed to consistently share relevant content. These factors have the potential to introduce inaccuracies and bias in our research. To take better results, we joined these channels, which have members more that 5000, to make an impact and read some parts of the posts to make sure they are posting qualitative content that we can use our topic. As a result, we eliminated some channels with low number of subscribers and also channels posting only technical analysis information, and after all, we kept five channels that had more members, more posts, and were active (see Table 1).

Table 1. *List of Telegram channels used as data*

Channel name	Subscribers
Binance Royal Pump	15659
Cryptic Pumps	89136
Hotbit Crypto Pumps	430325
Hit pump angels	13507
Wall street Wsb	6138

Source: Compiled by the authors

In the following step to collect data, we choose Python as a tool and Telegram API[2]. With the help of API, we got access to our telegram account, and after that, we chose which channel data we wanted to download as we decided channels already, got text data from these channels. Telegram

[2]https://telethon.readthedocs.io/en/latest/

is a popular messaging platform. Telethon library makes the process easy to collect data from that social media platform. In the first step, you should have API ID and hash. It can be obtained from the Telegram account and used for the Telethon. After applying the API ID and the hash to the code, gets access to your account. In the following step, the library requires the channel link from which you want to collect data.

Table 2 show the descriptive statistics of collected data from telegram and combined with cryptocurrency prices data from Binance and Kucoin. There is 72 coins in total with 100 observation. The reason is that there is some coins have been pumped several times during mentioned period in the Telegram channels that we took the data. From the descriptive statistics (Table 2) of all

Table 2. *Descriptive Statistics (Telegram)*

Variables	Obs.	Mean	Std.Dev	Min	Max
Price difference (%)	100	73	214	0.03	1721
Views	100	1010	611	231	3584
Forwards	100	3	2.5	0	15
Rank by marketcap	100	501	267	75	1379
Year 2019	100	0.28	0.35	0	1
Year 2020	100	0.36	0.48	0	1
Year 2021	100	0.36	0.48	0	1

Source: Compiled by the authors

variables in the dataset, we see that the rank of coins is an average of 501, showing that social media influencers mostly choose coins with a lower rank.

Telegram channels mostly includes some messages that are not suitable for our research (see Figure 1). This kind of Telegram channels have own templates, usually they use same template for all pump actions. In our analysis we need to detect pump actions, we focused only messages directly related to pump action such as included the name of the coin, time when coin will be pumped etc.

The templates usually announce the pump approximately 1-3 days beforehand and then they post regularly until the pump date and time. With using Python we removed messages which include information about news in cryptocurrency world. Influencers keep posting news, to keep

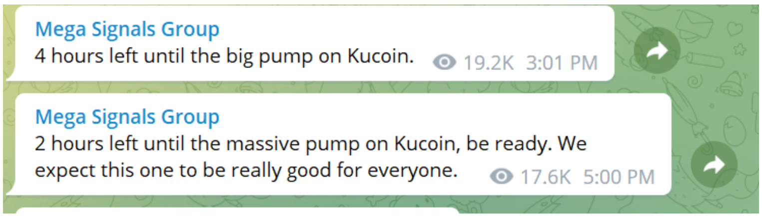

Figure 1. *Telegram message example that includes information*

Source: Telegram

channel active and increase the awareness.

After pump starts, in the following post, they give information about the result of pump. Since we are using 1 minute price data interval we can see easily changes even during 1 minute. For the better understanding of pumping process we kept the result information posts as well.

In the following step, we merged the data of messages with coin price data using date and time of Telegram data. Figure 2 shows an example of pump action according to our data from Telegram. After combining price data with pump message date, we see clear visual of pump and dump.

Figure 2. *Pump message example*

Source: Telegram

The Viberate coin and Bitcoin (VIB/BTC) pair is shown on the Figure 3, also we show number of volumes. The graph include 15 minutes interval data, it is seen that in the short period of time price and volume of data reach to the peak.

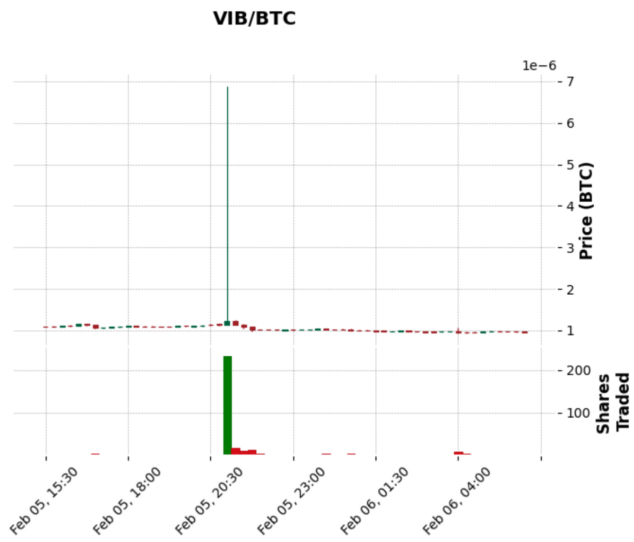

Figure 3. *Pump graph example*

Source: Compiled by the authors

3.2 Twitter data collection

Twitter is another social media that we consider in our research. It is a widely known and used platform and especially suitable for cryptocurrency users (Beck et al., 2019). It makes it comfortable for users to share their idea by tagging the cryptocurrency's name and promoting it. Users can easily follow the news, get up-to-date information about cryptocurrencies, and mainly focus on the projects behind each crypto. This allows the person to invest by relying on information caught on Twitter. Many users share information on Twitter that creates the huge interest around the coin. These can conduct false information but also lead to earning money as well. This thesis will mainly focus on the interest around the coin during the pump time and will observe the changes that can come as a result of the manipulative activity. We aimed to analyze if we can observe an increase in the number of coin-related posts during the week before announcement day and what trend it follows after one week period. Our aim is to see if there were any positive changes in the number of posts for specific coins during the announcement period. Suppose we observe significant changes during the pre-announcement week. In that case, the activity also involves Twitter, and the people behind the activity organize fake interest around the coin beforehand. Data mainly includes daily number of tweet counts for two-week period with specific keyword related to coin. To collect data, we used the official Twitter API[3]. Twitter provides free API for researchers; despite limitations, it is still helpful to collect data. Collection method includes using Jupyter notebook and provided access token got from Twitter. It allows for collecting detailed information such as the date of the post, number of likes, retweets, and other.

3.3 Cryptocurrency prices data collection

Currently, there are many different options to observe digital coin prices (Norman, 2017). These markets can vary according to their giving opportunities. In our research, we choose Binance[4], Kucoin[5], as data sources that are very popular worldwide. The main reason behind why we choose these cryptocurrency markets is that after checking Telegram pump and dump channels, and as a result we observed the main used digital coin markets are Binance and Kucoin. We collected totally 72 coins from Binance and Kucoin with the Python-Binance[6] and Python-Kucoin[7] packages.

Both the Python-Binance and Python-Kucoin are tools that allow connecting to Binance and Kucoin account servers via Python programming language. After connecting to the personal account, it is possible to make orders, trade, and get real-time data from the Binance and Kucoin cryptocurrency market. They also allow to get more extensive historical data from the market according to different pairs of crypto coins. The API key needs to be created from the account and used in python code later. The API creates a connection between python and the account. As a result, it is possible to get the desired data from the mentioned markets.

We stored all price data for the selected coins between 01.01.2019 and 01.01.2022 in the .csv file from both markets. Since we need to see the effect of posts on the prices of coins, we collected pricing data in 1 minutes frequency. The packages require an API key to proceed. We used account credentials to access prices data. In the following step, the code creates a client according to the API key of the market account. We choose the correct sets of coins, select Bitcoin pair coins for our analysis. It is essential to decide the starting date and interval for the Binance and Kucoin APIs; they select every coin pair in order and then collects historical data in a .csv file one by one.

[3] https://developer.twitter.com/en/docs/twitter-api
[4] https://www.binance.com/en
[5] https://www.kucoin.com
[6] https://python-binance.readthedocs.io/en/latest/
[7] https://python-kucoin.readthedocs.io/en/latest/

4 Methodology

This research provides data from Telegram channels and influencers' posts on Twitter that can impact cryptocurrency market prices. We collected data from mentioned social platforms with the help of Python's tools and packages. Since all messages on the Telegram channels we got and tweets are text data, we performed data cleaning to remove stop words and emojis. Then we filtered the data to choose only the coin-mentioned messages.

We apply the Logistic regression model (Logit model) to our data to analyze the influence of social media on cryptocurrency prices. The logistic regression model predicts binary variables using dependent values and models them. The modeled binary variable is often called the response or dependent variable. (Hilbe, 2016).

Regression is widely used in data analysis and research to describe the relationship between dependent and independent variables.The Logistic regression shows the success probability divided by the failure probability (Hilbe, 2016), and it is recognized as log-odds ratio with the following formulas:

$$f(\pi) = \frac{1}{1 + \mathrm{e}^{(-\pi)}}$$

$$logit(\pi) = ln(\frac{\pi}{1-\pi})$$

where

$$\ln(\frac{\pi}{1-\pi}) = \beta_0 + \beta_1 x_1 + ... + \beta_k K_k$$

In the context of logistic regression, the *logit(*π*)* serves as the response variable, with the independent variable *x* representing the predictor variables. In our case the binary dependent variable is the success rate of pump actions, the number of independent variables are 6 (denoted as sub-index k), and π is the probability of the success of pump actions.

In this model, the beta parameter, or coefficient, is frequently determined via maximum likelihood estimation (MLE). This method iteratively examines alternative beta values to find the best fit of log-odds ratio. All these rounds produce the log-likelihood function, and logistic regression aims to maximize this function to get the optimal parameter estimate. (Hosmer & Lemeshow, 2013).

Under the linear regression model, maximum likelihood is the general estimating strategy that leads to the least squares function (where the error terms are regularly distributed). This concept will be the foundation for our approach to estimating logistic regression models. In general, the maximum likelihood method generates unknown parameter values that maximize the probability of retrieving the observed data set. We must first develop the likelihood function before we can employ this method. This function expresses the likelihood of the experimental results as a function of the unknown factors. (Hosmer & Lemeshow, 2013).

The least squares method is used in multiple regression analysis to minimize the sum of squares of the difference between the actual and estimated values for the dependent variable. Because logistic regression is nonlinear and requires logistic transformation, it employs the maximum likelihood method. Logistic regression seeks to maximize rather than minimize the chance of an event occurring by squaring variances. (Çokluk, 2010).

We use the Logit model to predict whether social media influencers are successful in their manipulation techniques. We considered the price increase percentage as a variable for our model; based on that, we defined the number of successful signals over the years. To detect successful signals, we used a quartile metric on price increase percentage (Table 3). We created three parameter sets based on these values with different numbers of successful pump attempts. For example, in the first parameter set, we considered a price difference of more than 11.31% considered as successful pump activities and the same logic applied to other sets, then we consider the pump as successful and mark it as 1; otherwise, 0.

Table 3. *Quartile values on Price difference, %*

	Quartile 25	Quartile 50	Quartile 75
Price inc. %	11.31	23.10	50.12

Source: Compiled by the authors

To successfully apply the Logistic model, we need to define independent variables for our analysis. We choose independent variables according to pumped coins.

The independent variables we used in our study are listed below:

- Forwards: the number of forwards after the post date on Telegram. The number of forwards will show us how much reaction got to the message after posting.

- Views: Number of views for each pump message on Telegram.
- Rank by market cap: Rank of each pumped coin on the global cryptocurrency market during pump in ascending order.
- Dummy variables for pump years: We give dummy variables for pump years of coins.

The Views and Forwards as independent variables have 15 minutes time intervals after the post date and time. Since after the post, people immediately react to the message and Views and Forwards changes by that time, 15 minutes interval is quite enough to get data. We set the base year as 2019 and give dummy variables for the years (2019, 2020, 2021) of pump actions. For example, if the pump happened in 2019, we give 1 for the Year 2019 variable, 0 for the Year 2020, and Year 2021.

We observed the Twitter and chose our primary indicator as the daily total number of posts on the platform related to a specific coin during the two weeks. The time we chose is one week before and after the announcement day. Because based on our dataset taken from Telegram channels, on average, it takes seven days for the channel to post another pump-related activity with a specific coin name. Using Twitter API, we successfully get the daily number of posts on Twitter with the '$coin abbreviation' keyword. In currency-related posts and mainly in cryptocurrency, the '$' sign is much more popular and gives more insight into the post. Instead of using the coin name, we used the abbreviation of the coin, which is common in the posts, to keep it simple. The usage of '$' sign also helps us eliminate irrelevant posts and keep our focus on the currency.

After collection, we noted the announcement day as a base day (0) and took the number of posts on that day as 1. Then we compared each day's result with the base day number and found a relative count of tweets to the base day. We applied this method for each coin on our dataset. Then we find an average the relative count of tweets for all the coins for each day on the day interval, taking announcement day as 1. In the next section we discussed the results and trend based on this data.

5 Results

Based on descriptive statistics for each year, we can observe the increasing trend results on view for each year (Table 5). While the calculated average value for 2019 is 579 views, we can see that it nearly tripled after two years. In 2021, the value observed is 1633.39, which also reached the peak with 3584 views for one observation.

Table 4. *Descriptive statistics based on parameter set*

	First parameter set	Second parameter set	Third parameter set
Number of pumps	100	100	100
Number of successful	75	50	25
Percentage of successful	75	50	25
Average view	1059	1209	1315
Average forward	3.3	3.8	4.2
Average rank	516.7	527.9	497.2
Average price increase (%)	96.4	136.1	239.4

Notes: Table represents overall descriptive statistics based on 3 different parameter sets which conducted by authors. Data includes pump signals taken from 5 different Telegram channels and covers 3-year period of time starting from 2019.

Source: Compiled by the authors

This can be explained by the increase the interest among people in cryptocurrencies. In 2021, we had maximum numbers for each metric; in the same year, Bitcoin reached its all-time high value by passing over 69000 US dollars. It also had a market value of over a trillion US dollars for the first time. With this awareness of people, interest in pump and dump activities also increased; as a result, the year 2021 has a significant difference compared to previous years.

Based on the exploratory analysis, we can apply the same logic for the number of forwards per message, which also nearly doubled during the two years, having a peak number average of 4 forwards per signal. Rank by market capitalization also increased, but it can be explained differently. As previously mentioned in this paper, coins with low ranking based on the market cap have more liquidity on volume, making it easy to pump and mostly in favour of using in such activities. The other explanation can be based on the increase in coins over the years. Reportedly having around 2000 coins in 2019, this number increased to approximately 6000 in 2021[8]. It makes it easy for the activity trigger to choose from a wide selection of coins with a lower ranking. Based on our dataset, we can see the average rank by market capitalization per coin used to pump was 630 in 2021, while two years ago, it was 403. The primary variable we took here is the price difference in percentage, having the highest number with, on average 151% increase per signal in 2021. It also peaked in the same year with a 1721% increase. We can easily detect that the success numbers behind the pump activities are increasing each year if we accept base year as 2019.

We can observe the dependent variable: price difference during the specific period has different numbers per parameter set. Based on three different parameter sets, we generated statistics to identify a number of successful pumps and dump activities (Table 4). While setting third parameter set, we noted 25 of the activities as successful, which has, on average, 1315 views per signal and which is more than the medium and first parameter set. Compared to third, second, and first parameter sets noted, 50 and 75 successful pumps, respectively.

Model results of logistic regression are concluded in Table 6 for each parameter set. Here we can note that the independent variables we included in the model have a significant effect on the first parameter set where we have more successful pump observations compared to others sets, including less price difference. However, here we observed a negative estimated coefficient of view with a 95% significance level on the success of the pump attempt, which can be interpreted as having more people involved in the activity makes it hard to coordinate. On the other hand, we can not observe a significant estimated coefficient regarding the variable view.

The second variable, the number of forwards, has a positive estimated coefficient with 95% significance in the parameter set. The lower number of forwards also makes it easy for the model to detect the positive correlation between variables. The positive number of forwards helps the signal reach out to more people, which can be a factor in involving more people in the activity to increase the success rate. The numbers of the forward variable are positive in all sets but only significant in the first set with values of 0.505 and 0.21 standard error.

The model could not detect a significant correlation between the rate of success pump attempts and rank of the coin based on market value.

[8]https://currency.com

Table 5. *Descriptive statistics based on year*

Group		Price Difference (%)	Views	Forwards	Rank by marketcap
Year 2019					
	Obs.	28	28	28	28
	Avg.	11.78	579.25	2.21	403.10
	Std.Dev	13.38	299.76	1.49	208.22
	Min	2.51	231	0	75
	Max	72.21	1270	8	949
Year 2020					
	Obs.	36	36	36	36
	Avg.	43.86	721.11	2.25	447
	Std.Dev	70.49	353.17	2.53	236.14
	Min	5.14	291	0	102
	Max	442.70	1860	15	1313
Year 2021					
	Obs.	36	36	36	36
	Avg.	151.95	1633.39	4.44	630.58
	Std.Dev	333.92	464.70	2.55	283.60
	Min	2.59	920	1	170
	Max	1721.46	3584	12	1379

Notes: Table represents statistical information of all observations based on each year in the data taken from 5 different Telegram channels. Price difference based on the data taken from cryptocurrency exchanges Binance and Kucoin with 1 minute interval.

Source: Compiled by the authors

Table 6. *Effects of independent variables on the success of pump and dump*

Independent variables	First parameter set	Second parameter set	Third Parameter set
Views	-0.002**	-0.0006	-0.0007
	(0.0009)	(0.0007)	(0.0007)
Forwards	0.505**	0.214	0.169
	(0.2132)	(0.1451)	(0.1204)
Rank by marketcap	0.0002	-0.0008	-0.001
	(0.0013)	(0.0009)	(0.0011)
Year 2020	3.55***	3.12***	2.04*
	(0.857)	(0.836)	(1.117)
Year 2021	3.64***	4.07***	3.99***
	(1.111)	(1.095)	(1.355)

Notes: Standard error showed in parentheses

* Significant at the 90% level.

** Significant at the 95% level.

*** Significant at the 99% level.

Data covers 3 year period starting from 2019 and observations taken from Telegram channel. Parameter sets conducted by authors based on percentage of price difference during specific time interval.

Source: Compiled by the authors

We included three years to detect any increase or decrease in the success level of pump activity. We took 2019 as a base year and compared it to the other two years (2020, 2021). Comparisons show that over these two years, there is a positive estimated coefficient with 99% significance in the first and medium-level parameter set with values of 3.55 and 3.12 for the year 2020 and 3.64 and 4.07 for the year 2021, respectively. This yearly increase can be a reasonable indicator of the success rate while having a huge interest in cryptocurrencies among people.

The tables (7, 8, 9) show Pearson correlation coefficients between the variables for each parameter set. We have low correlation of View and Forward on price increase on first and second parameter sets. The highest value was observed on the parameter set 3, where the forward value positively correlated with a Price increase (0.46), showing a moderate degree correlation (Table 9).

Table 7. *Correlation between variables for Parameter set 1*

Variable	Price inc. %	View	Forward	Rank
Price inc. %	1			
View	0.2345	1		
Forward	0.2680	0.6440	1	
Rank	-0.0u025	0.2962	0.1201	1

Source: Compiled by the authors

Table 8. *Correlation between variables for Parameter set 2*

Variable	Price inc. %	View	Forward	Rank
Price inc. %	1			
View	0.1998	1		
Forward	0.2595	0.5758	1	
Rank	-0.0199	0.2201	0.0681	1

Source: Compiled by the authors

View value has a low positive correlation with the price difference for all set of parameters. However, it has a strong positive correlation with the forward variable, which makes it correct: a higher number of views can bring more forwarded signals which also helps to spread the signal to more audiences. The highest value between the View and forward variables observed in Table 8 with 0.66 which has moderate correlation. Additionally, rank did not show any strong correlation on any variable, but Table 7 shows a low positive correlation with the View variable (0.29).

Results from the Twitter data indicate that the number of published tweets mainly shows an increasing trend during the announcement day and the day after (Figure 4). It is evident that during the pump activity, people not aware of the scam also joined, which can be why it also increased the hype around coins on the day of the announcement and the day later. This hype can be observed in the number of messages posted on Twitter. We aimed to observe if there was any increase in the number of coin-related posts on Twitter during the week before the announcement. Based on the

Table 9. *Correlation between variables for Parameter set 3*

Variable	Price inc. %	View	Forward	Rank
Price inc. %	1			
View	0.2575	1		
Forward	0.4584	0.6624	1	
Rank	0.0326	0.1944	-0.0790	1

Source: Compiled by the authors

results, we can not claim that the same group of people who tries to manipulate the market involves twitter to the activity that they can create fake interest beforehand about the coin. One week after the pump announcement, we see a decreasing trend that returns to the initial point where we can see regular posts about the specific coin.

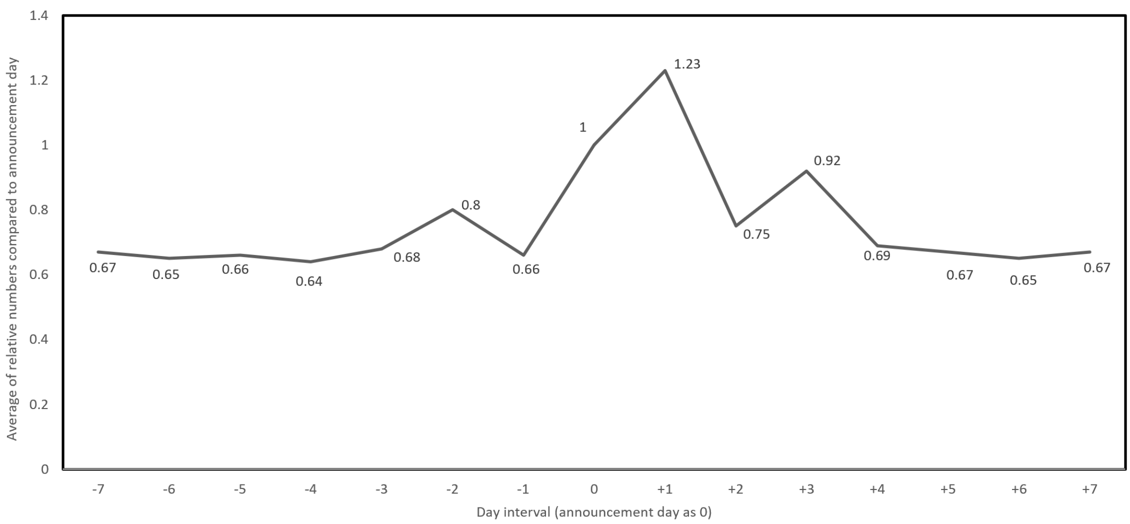

Figure 4. *Relative comparison about number of posts on Twitter*

Source: Compiled by the authors

6 Conclusion

The main focus of our study was to determine how successful social media is in cryptocurrency market manipulation by using logistic regression on Telegram pump dump channels and coin price data and find out how Twitter is affected by these price changes. The data we used has been taken from the most popular and active Telegram channels, which positively impact the cryptocurrency market. To find out their influence, we took an additional dataset that included the price of coins. In total, we observed 100 strong pumps from 5 Telegram channels which contain 72 unique coins from the current cryptocurrency market. We created a list of coins to observe coin-related tweets from Twitter and examine the changes before and after the pump action. As a result, we determined that Twitter is primarily not used by Telegram channel admins to create awareness about coins and pumps. But after the pump action, people observed the considerable price difference and started discussing it on social media platforms like Twitter. As variable groups, we chose forwards, views of each message posted on the pump and dump channels, and also we included dummy variables as years of pump action. Another variable is the rank of coins by market cap, which is essential to consider the success rate of social media market manipulation.

Considering our analysis results, social media influencers have a substantial impact on the cryptocurrency market. They can manipulate the market with a massive group of people using social media tools. As a result, we observed that the rank of coins could be an essential factor for market manipulation. Our research examined that Telegram channels usually choose low-ranked coins specifically. Because there was a lack of interest in low-ranked coins, nobody considers to trade them; it became an easy target to pump. Research shows that from 2019 to 2021 trend of interest in the cryptocurrency market is enormous; with the increase of awareness among people, social media influencers are more effective on the market. They can manipulate interested people and influence the market. From the Twitter point of view, our analysis shows that people usually share their thoughts and discussion about market changes after manipulations happen. Even though some people are not part of pump dump channels, they are manipulated by pump channels, and by sharing their thoughts, they prove how successful manipulation is. That's why after pump action, there are many activity cryptocurrency-related tweets. In summary, the paper shows the positive impact of Telegram channels on the cryptocurrency market.

There might be some limitations that affect the accuracy of model results. Since the topic is relatively new, more research must be done. Also, some APIs like Python-Kucoin for taking data have limitations, or it is not even possible to take data because it is private. Whether APIs are not free accessed, they allow taking around 1500 rows of data. Another area for improvement is that most effective Telegram channels have paid subscriptions. They are not open channels; getting data after even joining the channel is impossible. Also, there are several famous markets for trading cryptocurrency, and pump actions can include a couple of them. Still, there is no official APIs to get coin price data from some of them, and APIs have limitations that cause a lack of data. (Norman, 2017)

Because of some limitations, it needs future investigation to analyze more social media tools and influencers. There might be helpful additional research about the influence of individuals on the cryptocurrency market and the impact of NFTs or stock markets on the cryptocurrency market. Also, including more variables and time frames can increase the accuracy of results. To better understand the implications of these results, future studies could address several different trading markets.

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"Krüptovaluutade turuga manipuleerimine sotsiaalmeedia kaudu: mõjutajate roll"

Magistritöö eesmärk on välja selgitada sotsiaalmeedia mõjutajate rollid ja mõjud krüptovaluutade turgudele. Oma uuringus keskendume peamiselt Telegrami kanalitele kui turgu massiivselt mõjutavate pumpamis- ja tühjendus (pump and dump) aktsioonide (teatud turumanipulatsiooni tehnika) kasutamise põhjustele ning Twitterile, kuna nii Telegramis kui Twitteris on arutelukogukondi, kus inimesed jagavad oma mõtteid krüptovaluutade kohta.

Varasemad uuringud on seda teemat käsitlenud erinevate sotsiaalmeedia platvormide ja analüüsi meetoditega ning keskendunud peamiselt krüptoraha hindade tulevaste muutuste ennustamisele. Me valisime oma peamiseks andmeallikaks Telegrami ja analüüsisime seda tegemaks kindlaks, kas sotsiaalmeedia mõjutajad on turuga manipuleerimisel tõhusad. Varasematest uuringutest lähtudes suurendasime ka kuupäevavahemikku umbes kolmele aastale, valides võrdluseks eeldatavalt kõige enam turumanipulatsioonist mõjutatud krüptovaluutad.

Meie uuring keskendus kolme-aastasel (2019–2021) perioodil 72 unikaalsele mündile (krüptorahale) viielt erinevalt Telegram-i kanalilt. Varasemad uuringud on näidanud, et pumpamis- ja tühjendustegevuse analüüsil on potentsiaal müntide hindade prognoosimisel. Niisiis uurisime, kui edukad ja usaldusväärsed on sotsiaalmeedia mõjutajad turuhindade mõjutamisel, rakendades sellel eesmärgil logistilist regressiooni. Meie uurimus keskendus ka sellele, millised tegurid võivad mõjutada müntide valimist turumanipulatsiooniks.

Oma uuringus me analüüsisime muutusi Twitteri säutsudes üks nädal enne ja peale turumanipulatsiooni (pumpamist). Analüüsimaks, kas konkreetse mündi taga on organiseeritud võltsitud huvi, kasutatakse uuringus igapäevaste postituste arvu mündiga seotud konkreetsete märksõnadega.

Meie analüüsitulemuste põhjal on Telegrami kanalid turumanipulatsioonis edukad ning suudavad lühikese ajaintervalli jooksul saavutada väga suuri hinnavahesid. Twitteri andmete analüüsi tulemused näitavad, et mündiga seotud postituste arv on maksimaalne pumpamise väljakuulutamise päeval ja sellele vahetult järgneval päeval.

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