Exploring User Perceptions of Crypto Signals: An Empirical Study from Social Media Posts

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Abstract

Social media platforms have become pivotal in shaping user behavior and influencing market values within the cryptocurrency industry. However, assessing the impact of social media on cryptocurrency users is challenging given the market's volatility and evolving mechanisms. To that end, this paper investigates user perceptions of *crypto signals* on X (formerly Twitter). We introduce a novel dataset, *CryptoSignalMonitor*, and conduct a preliminary analysis to investigate the impact of X crypto signals on the behavior of users based on user engagement and investment decisions. Overall, our findings demonstrate that users frequently engage with crypto signals on social media, which correlate with a significant increase in the value of cryptocurrencies. We provide our dataset and data collection scripts [1] as a resource for future researchers to investigate the effects of crypto signals on X, and aim to motivate future work generating datasets to understand the impact of social media on the behavior of users.

Introduction

The cryptocurrency industry has evolved at high speed in recent years. Cryptocurrencies are an encrypted, digital, and decentralized form of money that utilize blockchain technology. As the system is decentralized, individual units of currency are managed by *crypto users*, or individuals who own the currency to buy or sell. Cryptocurrency assets are speculative because of their continuous uncertainty, which has generated a growing community and emerging subculture with an online community consisting of cryptocurrency investors, developers, influencers, businesses, news organizations, and more [7].

Crypto users frequently use online tools, such as CoinMarketCap,[2] to inform cryptocurrency investment decisions. Further, crypto enthusiasts often seek help from other sources, such as social media, to gain information about market trends. For example, X is one of the most prominent resources for individuals to obtain the most recent information on cryptocurrency markets, initiatives, and other updates [28]. X, formerly known as Twitter,[3] is a popular social media platform for users to communicate content within a 240 character limit to an audience online. The website has over 400 million active users worldwide and approximately 206 million daily active users [14]. X has become the primary platform for cryptocurrency speculation. Further, crypto influencers, users with high impact based on followers, also play a major role in determining followers' cryptocurrency activity [3].

Many studies have explored the relationship between social media and cryptocurrencies [26], concluding that social media posts impact the cryptocurrency market. Our study seeks to build on this work by examining user perceptions of *crypto signals*, or popular messages conveying information about cryptocurrencies. To examine how crypto users engage with popular crypto-related posts and understand their effects on cryptocurrency market dynamics, we take into consideration the theoretical framework of *signaling theory* [23], which posits that individuals engage in certain behaviors to signal specific characteristics or intentions to others [11]. By applying signaling theory to the context of cryptocurrency and social media, we seek to understand how users engage with crypto signals on X and the effects of these signals on the cryptocurrency market.

To delve into the engagement and behaviors of crypto users as they interact with and interpret signals, we introduce a novel dataset, *CryptoSignalMonitor*. *CryptoSignalMonitor* encompasses crypto signals shared on X, and was curated to facilitate research efforts focused on analyzing the impact of X posts on the cryptocurrency market. Through a preliminary evaluation, we use *CryptoSignalMonitor* to explore the following research questions (RQs):

RQ1 How do users engage with crypto signals on X?

RQ2 How do specific crypto signals influence user investment decisions?

RQ3 How do general crypto signals influence user investment decisions?

To answer these questions, we created a dataset of popular crypto tweets to analyze how users engage with crypto signals on X and how these posts impact user investment decisions. To measure investment decisions, we analyze the value of cryptocurrencies using relevant metrics adopted by

[1]https://anonymous.4open.science/r/IEEE_Blockchain-24_DataReplicationPackage-5458/README.md

[2]https://coinmarketcap.com/, a price tracking website for crypto assets

[3]https://twitter.com

the crypto community. We also aim to discover if different types of signals influence market behavior by analyzing *specific* and *general* crypto signals. Specific crypto signals refer to posts that explicitly mention a particular cryptocurrency, i.e., Bitcoin, while general crypto signals encompass broader indicators or trends in the cryptocurrency market without mentioning a particular cryptocurrency. To the best of our knowledge, no previous studies have analyzed the effects of specific and general crypto signals separately in the cryptocurrency market.

Our findings show crypto signals receive considerable attention and positive interactions on X, and that such posts impact crypto investment decisions. The contributions of our work are summarized as follows: 1) We introduce a dataset named *CryptoSignalMonitor*, consisting of multiple types of X crypto signals to understand their impact on user behavior; and 2) A preliminary evaluation using our dataset to investigate how users interact with crypto signals and how these posts impact the cryptocurrency market. Based on our analysis, we demonstrate the need for further datasets to investigate the impact of social media on user behavior.

Background

Cryptocurrency

Cryptocurrency is a medium of exchange, created and stored electronically using cryptographic techniques to protect data from outside observers and ensure its secrecy on blockchain [14]. Bitcoin,[4] the first cryptocurrency created as a decentralized digital money in 2008, introduced the notion of secure blockchain and a supply set by digitally "mining" new currencies [22, 29]. Blockchain is a decentralized, peer-to-peer, and immutable form of data storage–where users can validate transactions without the requirement of a centralized organization. In general, cryptocurrency refers to any digital or virtual currency on the blockchain, including altcoins, or any cryptocurrency other than Bitcoin (i.e. Ethereum[5]), and crypto tokens. As of March 2024, there are 13,217 cryptocurrencies in existence with a total market cap of $1.32 trillion, used by over 420 million people and 18,000 companies worldwide [16]. Cryptocurrency has undergone significant growth in a comparatively short period of time, leading to a "crypto gold rush" as users and industries seek to adopt and invest in cryptocurrency-related technologies.[6]

Cryptocurrency Signals

In economics, *signaling theory* aims to support transactions by considering the senders and receivers of relevant information [6]. Senders choose how to communicate a message, while the receiver must choose how to interpret the signal. Crypto signals are alerts sent out by users with cryptocurrency information, such as advice on which coin to purchase or sell at what timeframe [12, 2]. These trading signals for cryptocurrencies are based on technical analysis carried out by skilled and experienced traders. Although the cryptocurrency market is dynamic, the signals are often generated with great accuracy [27].

Cryptocurrency signals are able to predict trends and influence the investment decisions of thousands of people who are interested in the market [25]. On X, a user with a large number of followers can be considered an *influencer*. Prior work shows influencers have the ability to impact the behavior of their audiences based on their popularity [4, 18]. Crypto influencers, such as Elon Musk,[7] have the ability to generate signals that impact the cryptocurrency market. For example, Elon Musk raised the price of Dogecoin (DOGE), a popular memecoin,[8] by 50 percent just by a single post [5]. Influencers on X have the ability to impact the crypto market with their signaling post s [3], impacting the investment and trading decisions for crypto users. In this work, we aim to investigate the impact of crypto signals on message receivers, or X users viewing posts, using a dataset of crypto signals to analyze their impact on user behaviors.

Data Collection

Dataset Construction We constructed the *CryptoSignalMonitor* dataset using the X advanced search tool bar that allows you to search with specific keywords, date range, specific account, engagement activity, number of likes, and number of comments or reposts. We used the features of X search toolbar to search for the posts containing relevant words in any position (i.e. "crypto" or "dogecoin") and written in English. For our preliminary evaluation, we specified popular posts by selecting posts with at least 30,000 likes, or upvotes by other users on X. Additionally, we limited our data collection to a time frame of two years and nine months, from January 2020 to October 2023. We use this timeframe due to its pivotal role in shaping the crypto market—witnessing a surge in crypto adoption fueled by COVID-19, as evidenced by Bitcoin's $69,000 all-time high pricing[9] and "six times more tweets about crypto than ever before" between 2020-2021 on X [24]. Future iterations of this dataset can expand on these values to adjust the number of posts in the dataset for further analysis.

CryptoSignalMonitor We collected a total of 100 posts that met our criteria for a crypto signal from 63 different influencers on X. 54 crypto signals within our dataset refer to a specific cryptocurrency. The represented cryptocurrencies include Bitcoin, Dogecoin (DOGE), Ethereum (ETH), Binance (BNB), and Shiba Inu (SHIB). 46 posts in our dataset pertained general to "cryptocurrency" without mentioning a specific digital coin in their text. Further details on the specific coins derived for our dataset are available in Table 1. We observed crypto signals from a diverse group of influencers such as cryptocurrency experts, crypto trading resources, actors and actresses, professional athletes, popular musicians, meme accounts, and regular X users. Table 2

[4] https://bitcoin.org/

[5] https://ethereum.org/

[6] https://medium.com/coinmonks/best-crypto-apis-for-developers-5efe3a597a9f

[7] We began this research before Elon Musk's acquisition of X in October 2022

[8] A type of cryptocurrency that derives its value and popularity from internet memes and viral content.

[9] https://coinmarketcap.com/currencies/bitcoin/historical-data/

Table 1: Number of Signals and Influencers for *CryptoSignalMonitor* Cryptocurrencies

Coin	*Signals*	*Influencers*
Dogecoin	25	4
Bitcoin	23	16
Ethereum	3	3
Shiba Inu	2	1
Binance	1	1
General	46	42

Table 2: *CryptoSignalMonitor* Influencers with Multiple Crypto Signals

Influencer	*Signals*	*Followers*
Elon Musk (@elonmusk)	30	127.7M
Changpeng (CZ) Zhao (@cz_binance)	3	8.1M
Jack Dorsey (@jack)	2	6.5M
Marques Brownlee (@MKBHD)	2	6M
Michael Saylor (@saylor)	2	2.9M
Dogecoin Rise (@DogecoinRise)	2	465K
first-mate prance (@bocxtop)	2	286K

M indicates in millions (10^6), **K** indicates in thousands (10^3)

provides details on the influencers who had more than one crypto signal included in our dataset.

Preliminary Evaluation

To evaluate *CryptoSignalMonitor*, we devised a preliminary evaluation to understand user engagement with crypto signals and their impact on investment decisions.

Research Questions

Our initial investigation aims to answer the following research questions:

RQ1: How do users engage with crypto signals on X?

To measure how users engage with crypto signals, we first calculate metrics to describe the popularity of posts using different X features. Then, we conduct sentiment analysis on responses to the signaling posts in our dataset. We speculate that crypto signals are popular and bring about mostly positive sentiments and perceptions for users.

RQ2: How do specific crypto signals influence user investment decisions?

We also aim to investigate the impact of specific crypto signals that directly mention a particular cryptocurrency by name (i.e. Bitcoin), X handle (i.e. `@Bitcoin`), hashtag (i.e. `#bitcoin`), or cashtag (i.e. `$bitcoin`) on cryptocurrency investment decisions. For instance, Figure 1a depicts an example of a specific crypto signal mentioning Dogecoin.[10] To assess the impact of specific crypto signals on user investment decisions, we analyzed price market value and trading volume of cryptocurrencies before and after X posts.

[10]https://dogecoin.com/

RQ3: How do general crypto signals influence user investment decisions?

We also aim to investigate the influence of general crypto signals that broadly refer to cryptocurrency in correspondences without mentioning a specific coin. Figure 1b provides an example of a general crypto signal. We aim to investigate the impact of these messages on cryptocurrency trends by analyzing market value and trading activity before and after posts.

Measuring User Engagement

To answer our first research question, we gathered X metrics and comments with the Tweepy API[11] to observe the popularity of X crypto signals and analyze the replies from users on information from the targeted posts in order to assess the user engagement from crypto signals.

X Metrics To explore how users engage with crypto signals on X, we investigated metrics to describe the popularity of X posts. These metrics, provided by the X user interface, include the number of likes, reposts, and comments for crypto signals in our dataset. Likes refer to the number of upvotes of posts from other users, reposts indicate posts shared by other users to extend the range of posts on their own profile–with or without an additional message, and comments are replies from other users to the author of a post. The metrics were collected using the Tweepy API. We average these metrics across the selected posts in our dataset to measure the popularity of crypto signals on X.

Sentiment Analysis Sentiment analysis is a natural language processing (NLP) technique that automatically identifies the emotional tone conveyed in textual data. To perform sentiment analysis, we used the TextBlob[12], a Python library developed on top of NLTK (Natural Language Toolkit) that provides API for common NLP tasks. Various X studies show TextBlob is useful for predicting sentiment polarity score [8, 1]. To pre-process the data, we applied the following: all mention tags(@), hashtags(#), new line(\n), reposts(RT), emoticons, punctuation, and hyperlinks were removed from collected posts—as these special characters do not contribute to sentiment.

Collecting Replies We collected post replies with the Academic Research level access for Tweepy API v2. The Academic Research access of the Twitter Developer portal allows 10M posts retrieving per month usage, and dating back to the data in 2006. We firstly retrieved a list of all replies unique IDs from specific thread posts.[13] We then used the *get_tweet_status* get tweet status which it is a

[11]https://docs.tweepy.org/en/stable/

[12]https://textblob.readthedocs.io/en/dev/

[13]https://developer.twitter.com/en/docs/tutorials/retrieve-user-mentions-from-thread

(a) Specific Crypto Signal example

(b) General Crypto Signal example

Figure 1: Crypto Signal Examples from our Dataset

method from the API standard v1.1.[14] The *get_tweet_status* provides attributes including the language, number of likes, and number of reposts. We selected posts with at least 30K likes and in English.

Analyzing Replies We analyzed a total of 555,629 replies across 94 crypto signals on X from our dataset. In some cases, we were unable to retrieve the replies for crypto signals in our dataset. For example, posts that were posted but had since been deleted by the author ($n = 1$). Additionally, the Tweepy API does not have the ability to collect replies to popular posts that are reposts of existing posts. There were also several instances ($n = 4$) of crypto-related posts with a lot of likes and reposts, but little to no replies based on the profile settings of the author. Finally, for one post in our dataset we experienced issues with the link to the post.

Sentiment scoring (as positive, neutral, or negative) was performed with the use of TextBlob sentiment analyzer for a number of posts fetched within a concrete time period. The Tweepy API was used for collecting replies against a selected post by simply identifying the post ID. We collected the post replies, and then cleaned and analyzed the post comments. The sentiment analysis categorized comments as negative, positive, and neutral. However, we exclude all neutral replies for the sentiment analysis of how social media impacts the investment of cryptocurrencies.

Measuring Investment Decisions

To answer our second and third research question, exploring the impacts of crypto signals on user investment decisions, we analyzed to what extent influencers X activity affects cryptocurrency price, investments and trading volume. We collected the entire price history of crypto coins through CoinMarketCap. We used this platform to analyze the *market value* of coins. The market value of a cryptocurrency refers to the change in percentage price. If the value is 0 percent, it would imply that there is no change, no increase or decrease in the price of crypto. We calculated this metric 24 hours before the post and 48 hours (Day 01, Day 02) after the post to determine the impact of crypto signals by analyzing the change in value.

We also measured *trading volume* for each coin 24 hours before the posts and 24-48 hours after the post. Trading volume refers to how much a given cryptocurrency has traded in financial terms over a particular time period. A higher volume of cryptocurrency traded results in more equitable cryptocurrency prices and much less price distortion. A low trading volume may indicate a lack of market interest. The total volume traded for a given cryptocurrency is directly proportional to its volatility. Prior work suggests posts from a 24-hour period can guide day trading stock market behavior [21]. Although we detected changes within 24 hours of posts, we extended the time frame to 48 hours to ensure the robustness of our results and mitigate any potential noise or short-term fluctuations in the data. We identified the changes by calculating an increase or decrease in the trading volume before and after the post.

Specific Crypto Signals To understand the impact of specific crypto signals from influencers on the investment decisions of users, we measured the percentage change in market value for cryptocurrencies 24 hours before and 48 hours after posts for the 54 specific cryptocurrency signals. The value was collected through CoinMarketCap from the defined list of coins in our dataset. To calculate this, we utilized the Coinlib[15] tool to gather the percentage change values for cryptocurrencies. We started collecting data for 24 hours initially and by observing significant changes we moved to 48 hours window. Based on the changes in value we observed, we realized to collect values for trading volume of the coin to better notice the changes. We used Coinlib for collecting trading volume of the coins 24 hours before and 48 hours after the post. All the trading volume data for cryptocurrencies is collected in US dollar amount. This allowed us to understand better the changes in results as we could notice difference for both metrics concurrently.

General Crypto Signals To evaluate the user behavior based on general post signals from our dataset, we used CoinMarketCap and Coinlib concurrently. The Coinlib tool has a compare chart functionality, from which we could select up to 8 cryptocurrencies of choice for comparison. As the general crypto posts do not target a specific currency, our approach for the data collection of these posts is based on the top five cryptocurrencies at the time of this writing: Bitcoin, Ethereum, Binance coin, Dogecoin, and Cardano. For general posts, we looked up the price market value and trading volume for five different currencies at the same time and observed changes for all of them. The changes were not really visible in the first 24 hours, so we kept the 48 hour timescale for both the specific and general posts to keep the results

[14]https://developer.twitter.com/en/docs/twitter-api/v1/tweets/post-and-engage/api-reference/get-statuses-show-id

[15]Coinlib is an online tool for crypto traders that provides detailed price and market information, https://coinlib.io/

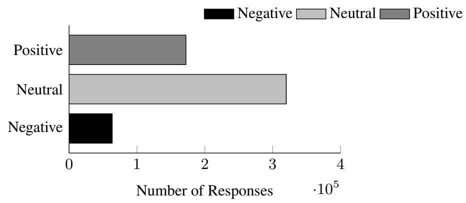

Figure 2: Sentiment Analysis Responses

fair. We used the date range metrics and specified the date on which the signal was posted in the tool. We examined the prices of coins with this tool and explored a series of details and graphs to see how their price, volume, and market value have changed over time. We could compare coins with specially filtered groups of coins using the comparison tool and collect the percentage change in values for the group of cryptocurrencies. Based on this tool, we were able to collect enough information to analyze the general posts and observe its consequences on user behavior.

Preliminary Results

RQ1: User Engagement

To analyze how crypto users perceive signals on X, we examined engagement with posts and conducted sentiment analysis on replies to popular crypto posts. In line with signaling theory, our aim is to understand how users interpret and respond to these signals, providing insight into their behavior and sentiment towards the signals.

X Engagement In order to better understand how users engage with crypto signals, we collected crypto signals with a minimum of 30K likes. The signals in our dataset averaged approximately 181,000 likes, 555,629 reposts, and 5,501 replies for each post. This indicates increased popularity and a high volume of user engagement and interactions with these signals on X. The crypto signal with the highest engagement in our dataset was a post noting "*You can now buy a Tesla with bitcoin*"[16] from Elon Musk, garnering approximately 834,500 likes and 103,300 reposts from users on X. The post with the most replies ($n = 82,738$) was posted by Michael Saylor, an entrepreneur, founder of MicroStrategy,[17] and crypto advocate, stating that "*In my next job, I intend to focus more on #Bitcoin*".[18]

Sentiment Analysis In addition to measuring engagement, we also aim to determine how users on X perceive signals from influencers. Based on the post's comments and replies, we were able to categorize the outcomes as positive, negative, and neutral. We collected 555,629 responses to all of the posts in our dataset, demonstrating a widespread user interest in crypto signals. We gathered 235,673 responses from the post signals. Of these, 172,270 were positive, 319,956 were neutral, and 63,403 were negative. Figure 2 presents these outcomes. These findings align with signaling theory, as the high engagement and positive responses imply that users generally have positive reactions and interpretations of crypto-based signals on X. Building upon these insights, our subsequent research questions aim to explore the influence of X crypto signals on user investment decisions, further examining the impact of signaling in the cryptocurrency market.

RQ2: Specific Crypto Signals Influence

We collected the percentage change in cryptocurrency prices before and after crypto signals along with the trading volume to analyze the impact of influencers on user behavior.

We assessed the impact of specific crypto signals on users by collecting the percentage change in cryptocurrency price for the selected posts. We compared the percentage changes in the cryptocurrency value 24 hours before and after the post. We also tracked changes in percentage prices 48 hours after the posts to see if the results were noteworthy. We analyzed the results by using a t-test to compare the percent changes in value 24 hours before and 48 hours after the post. For all of the 54 specific crypto signals, we saw a statistically significant change in the value of cryptocurrencies ($t = 3.39516, p = .000547$). Likewise, we noticed an average increase in the value (-0.7097 to 8.2571). This indicates an increase in user demand and cryptocurrency prices occurred after crypto signals were posted by influencers on X.

Furthermore, we collected the trading volume amount 24 hours before the post and 24 hours after the post, following 48 hours trading volume. We used a t-test to compare the average of values for the trading volume prices before and after crypto signal posts. For the overall results of 54 signals, we saw an average increase based on the trading volume (108.7077 to 140.9495) which is collected in billions. This indicates an increase in user demand after crypto signals were posted by influencers, however the results were not significant ($t = 0.22356, p = 0.411957$). The difference in trading volume is represented for the top five posts in Table 3.

RQ3: General Crypto Signals Influence

We also evaluated the effect of general crypto signals on users by collecting the percentage changes of the top five cryptocurrency prices (Bitcoin, Ethereum, Binance coin, Dogecoin, and Cardano) for signals post 24 hours before and 48 hours after the post. We collected data for a total of 46 general posts, for all of them we were able to see an increase or decrease in the percentage change value before and after the post. The results were significant for majority of the posts. Among the 46 general posts, 19 decreased in value based on the signal and 27 of them increased in value.

We observed an increase in average value of general signals (-0.6 to 7.058823529). This difference in the value of cryptocurrencies is statistically significant ($t = 3.21162, p = .000702$)—demonstrating the effect of crypto signals on user investment decisions.

Moreover, we collected the trading volume amount in dollars the same way, 24 hours before the post and 48 hours after the post using the same set of cryptocurrencies. All of the data for the trading volume of the coins was collected using

[16]https://twitter.com/elonmusk/status/1374617643446063105
[17]https://www.microstrategy.com/
[18]https://twitter.com/saylor/status/1554799841150214150

Table 3: Five Specific Crypto Signals Influencing User Behavior

Post	Influencer	Crypto	Value (% Difference)	Δ Trading Volume
Doge Barking at the Moon	@elonmusk	Dogecoin	78%	14.5B
Step 1: Resist the urge to buy Bitcoin at $32K	@MKBHD	Bitcoin	3%	2.29B
Bitcoin is a Declaration of Independence.	@saylor	Bitcoin	3%	$1.3B
I will keep supporting Dogecoin	@elonmusk	Dogecoin	18%	$417.77M
Crypto is the only money I still have, and today I can say without exaggeration that $BTC, $ETH, and #NFT are oing to save my life while I can't come back home.	@usleepwalker	Bitcoin	7%	-$1.6B

Δ denotes the difference between the before and after values, **B** indicates in billions (10^9), **M** indicates in millions (10^6)

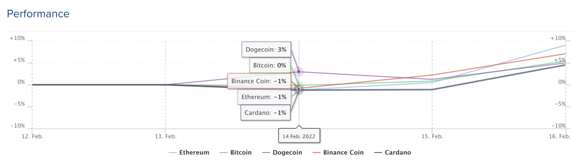

Figure 3: Example of General Crypto Value

Coinlib and we were able to notice an adequate change in the results. Figure 4 illustrates an overview of trading volume for all general crypto posts during this time period. Among the 46 general posts, 21 have a decrease in trading volume, similar to decrease in value and 25 of them has significant increase in trading volume similar to increase in value. We saw an overall increase in average trading volume (1,120.2333 to 1,234.65) which demonstrates active user involvement after crypto signals, however the results were not significant ($t = -0.16971, p = 0.4332$).

Discussion

We present a dataset named *CryptoSignalMonitor*, encompassing a diverse array of X crypto signals. This dataset incorporates various types of crypto-related posts from users, providing a comprehensive understanding of their impact on user behavior. The results of our preliminary analysis for *CryptoSignalMonitor* suggest crypto signals from X influencers impact users. We found that crypto consumers frequently engage with popular posts concerning cryptocurrencies. Additionally, we found that crypto signals affect the behavior of users' investment decisions, corresponding with significant increases in market value. By examining the impact of crypto signals on market behavior, we can shed light on the role of influencers in shaping investor perceptions and decisions. The results of this investigation have broader implications for crypto signals datasets on market participants, policymakers, and researchers.

Crypto Influencers and Users

Our preliminary analysis suggests a notable impact of signals from X influencers, fostering positive user engagement. As the prices and trends on the cryptocurrency market are significantly influenced by crypto influencers [3]. We found influencers have an impact on consumer behavior by compiling and analyzing a list of crypto signals from influencers on X. We identified significant positive abnormal returns in cryptocurrency values following crypto signals from popular X profiles (see Table 3). For example, Elon Musk posted a Dogecoin signal, "*No highs, no lows, only Doge*" and within 24 hours we observed a 39 percent increase in the coin's value. Thus, our results should caution influencers to monitor and supervise their posts, as signals from their accounts can impact cryptocurrency values and the decisions of users.

Policy Makers

CryptoSignalMonitor emerges as a resource to offer insights and motivate regulatory guidelines in the cryptocurrency domain. Our dataset can enrich policymakers' understanding of how social media signals influence cryptocurrency markets. Understanding the impact of social media signals and influencers' posts on cryptocurrency markets can assist policymakers in developing appropriate regulatory frameworks and establish guidelines to address potential risks and vulnerabilities associated with social media-driven market dynamics. For example, prior work suggests policymakers can utilize the predictive nature of social media to minimize the financial instability of Bitcoin [20]. In addition, understanding the impact of social media on cryptocurrency markets can enhance policymakers' market surveillance and monitoring capabilities to develop risk management strategies and frameworks to effectively mitigate potential threats. This proactive approach can help protect investors and promote market integrity by implementing policies to safeguard investors and ensure fair market practices–creating a level playing field and maintaining market stability, ultimately fostering investor confidence and participation.

Researchers

CryptoSignalMonitor serves as a starting point for future research to analyze the impact of crypto signals and motivates the value of available datasets. Researchers can utilize *CryptoSignalMonitor* to analyze different time periods, specific cryptocurrencies, or specific X users to gain further insights into the dynamics of social media signals on cryptocurrency markets. By leveraging this dataset, researchers can explore various research questions and hypotheses related to social media's impact on cryptocurrency market values, trading volume, and investor behavior. The availability of datasets promotes reproducibility and enables researchers to compare and validate their findings against the results pre-

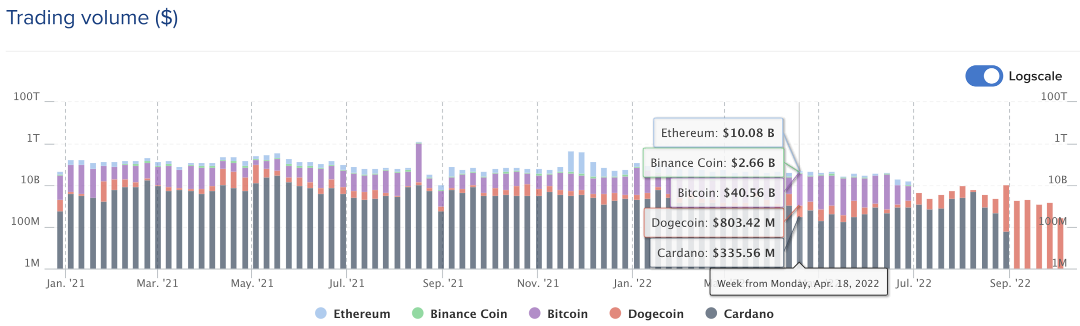

Figure 4: General Crypto Trading Volume

sented in this research. Furthermore, this research opens up avenues for future benchmarks in the domain of cryptocurrency and social media contexts to explore post content, the credibility of signals, and the impact of social media signals on investor decision-making processes. By delving deeper into these areas, researchers can provide valuable insights into the effectiveness of signals and the role of influencers in shaping market sentiment and investment behavior.

Limitations and Future Work

We acknowledge the small size of our dataset. However, we developed criteria to collect the most popular X posts to investigate their effects on user behavior–and only 100 posts met this criteria. Future work can extend our dataset by modifying the parameters from our initial construction. Our results may not generalize to posts on other social media platforms, such as Reddit.[19] Future work can apply our methodology to other social media platforms used in the crypto community. Additionally, future crypto signal benchmarks can explore other popular coins, altcoins (i.e. Litecoin[20]), and other blockchain-based technologies.

There are limitations to using X posts for our dataset. Posts from influencers appear to impact the crypto market–but it is not possible to detect if individual investments are motivated by specific posts. All posts and replies collected were in English, which limits our results as crypto signals are spread internationally on social media and attract investors around the world. Finally, limiting sentiments to positive, neutral, or negative may not accurately reflect the attitude of commenters in replies to crypto signals.

Lastly, further research is needed to analyze the impact of crypto signals on cryptocurrency markets through the lens of signaling theory. For example, using advanced AI techniques to detect and minimize information gaps and misinformation between senders and receivers. Our dataset provides motivation to investigate how messages are conveyed by senders, and future work can further inspect posts to analyze their content and how users perceive crypto signals.

[19]https://reddit

[20]https://litecoin.org/

Related Work

Prior work contributes to our understanding of the effects of social media on cryptocurrency markets. Hutto et al. [17] examine variables related to message content, social behavior, and network structure to understand the factors influencing follower count and growth on X–providing practical and theoretical implications for the design and development of social media technologies. Moreover, Garcia et al. [13] investigated the role of social media activity and algorithmic trading in the Bitcoin market to show social media posts lead to increased trading volume and price volatility in the cryptocurrency market.

Maule and colleagues [21] demonstrate the value of modeling microblog discourse for predicting stock trading and price fluctuations prior to and during the COVID-19 pandemic. Researchers have also revealed that trading volume plays a role in determining market behavior, with higher trading volumes leading to increased efficiency [19, 10]. This implies that social media can influence trading activity and impact market efficiency in the cryptocurrency space. Market efficiency, in this context, refers to how promptly and accurately cryptocurrency prices adjust to all available information.

There is limited work exploring signaling theory in the context of cryptocurrencies and social media. Dutta et al. [9] explored the signaling role of cryptocurrencies in predicting stock market risk, indicating cryptocurrency price movements can serve as signals for stock market risk. Signaling theory research also shows social media signals dictate message receiver behaviors, such as donating to non-profit organizations [15]. Building upon this work, our study contributes a dataset for understanding the relationship between social media signals, crypto users and influencers, and cryptocurrency market dynamics.

Conclusion

Crypto investment decisions are often affected by signals on social media, in particular from influencers with a large audience. In this work, we present a novel dataset, *CryptoSignalMonitor*, consisting of 100 popular crypto-related posts on X. We conducted a preliminary investigation with our dataset to explore user engagement and behavior, and found X crypto signals receive mostly positive interactions and impact crypto investment activities according to market metrics. Our results provide insight for how relevant datasets can benefit cryptocurrency influencers, users, policymakers, and researchers to further analyze the impact of social media on cryptocurrency-related technologies.

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