NCRI
NETWORK CONTAGION RESEARCH INSTITUTE

bright data

GOVERNOR'S STEM SCHOLARS

BOT DRIVEN GOLD RUSH

UNMASKING THE ROLE OF INAUTHENTIC SOCIAL MEDIA ACTIVITY ON THE CRYPTO MARKET AND BEYOND

Anthony Boyle
Analyst, Social Cyber Forensics Lab

Nima Fallah
Analyst, Social Cyber Forensics Lab

Joel Finklestein, Ph.D.
Chief Science Officer and Director Network Contagion Research Institute; Senior Research Fellow, Miller Center for Community Protection and Resilience, Rutgers University

Alex Goldenberg
Lead Intelligence Analyst, Network Contagion Research Institute; Research Fellow, Miller Center for Community Protection and Resilience, Rutgers University

Prasiddha Sudhakar
Analyst, NCRI

Alexander Reid Ross, Ph.D.
Senior Data Analyst, Network Contagion Reserch Institute; Senior Instructor, Portland State University; Senior Fellow at the Centre for Analysis of the Radical Right

Ankita Jagdeep
Analyst, NCRI

Anisha Jagdeep
Analyst, NCRI

Sagar Patel
Analyst, NCRI

Tayler Glover
Analyst, NCRI

EXECUTIVE SUMMARY

- Twitter activity played a crucial role in amplifying the value of FTX listed cryptocurrencies: FTX listings were immediately followed by surges sustained by Twitter activity.

- NCRI analysis shows that bot-like accounts comprised a substantial proportion (about 20%) of online chatter mentioning FTX listed coins.

- This bot-like activity forecasted the price of many FTX coins analyzed in the data sample.

- After promotion by FTX, activity for the coins grew increasingly inauthentic over time: The proportion of inauthentic, bot-like comments steadily grew to approximately 50% of the total chatter.

- This kind of inauthentic amplification of cryptocurrency is currently ongoing: PEPE and PSYOP cryptocurrencies, more recent coins launched with market caps greater than 1 *billion* dollars. Both were found to possess similar dynamics to FTX listed coins and for PEPE, bot activity, but not authentic activity forecasted changes in price.

- As cryptocurrency grows increasingly mainstream, the potential for market manipulation through social media and inauthentic activity presents considerable risks to investors and the stability of financial markets.

INTRODUCTION: INSIDER TRADING AND THE INFLUENCE OF INAUTHENTIC ACTIVITY

The FTX scandal comprises the single largest cryptocurrency scandal since the inception of digital currencies. Valued at 32 billion dollars, cryptocurrency giant FTX collapsed completely, primarily as a result of a liquidity crisis in November of 2022[1], and when the company's operations came under scrutiny, federal investigators pressed charges for market manipulation and the mismanagement of funds. In spite of its technological allure, in many regards, the FTX episode emerged as a highly traditional financial scandal - insider trading by Alameda Research[2], sister company of FTX, permitted the organization to create a shell game to hide underlying assets, even as FTX hired professional athletes, purchased stadiums, and partnered with celebrities and major influencers to broker public trust and enthusiasm. The zeal of major investors created sustained investment, but with no underlying value, FTX collapsed rapidly once federal scrutiny came.

One aspect of the FTX scandal that has not been closely examined is the role that inauthentic social media might have played in elevating the value of FTX, its currencies, and key activities. Though the notion that social media played an outsized role in the scandal is commonly trumpeted in popular media[3], quantitative examination of this subject is lacking. Similarly unresolved is the specific role that bot-like accounts, or accounts engaged in inauthentic coordinated activity on social media platforms may have played in amplifying engagement around FTX listed cryptocurrencies. Could such accounts actually drive changes in the price of the FTX assets themselves?

Cryptocurrency and stock conversations are replete on platforms such as Reddit, and especially Twitter, and findings relevant to the FTX scandal may have broader ramifications - they may implicate underlying and widespread mechanisms for market manipulation in the cryptocurrency sphere fundamentally. Even as federal regulators slowly re-examine policy regimes, large, mainstream risk management and investment firms now begin experimenting with exchange traded funds (ETFs). A landscape of complex instruments evolving with little transparency, regulation and potential vulnerability is rapidly coming into focus.

It is thus essential to reexamine new components of the FTX scandal in an expanded and data-driven lens because the manipulation mechanisms hypothesized in this research may expand far beyond crypto space, to stocks and other securities. For example, previous research identified bot-driven coordinated inauthentic activity on social media intended to artificially inflate the price of Gamestop[4]. Left unchecked, these mechanisms may undermine consumer trust, accelerate widespread criminality or even catalyze a crisis of confidence in the free market.

1 https://www.investopedia.com/what-went-wrong-with-ftx-6828447
2 https://www.sec.gov/news/press-release/2022-219
3 https://fortune.com/2022/11/12/sbf-vs-cz-ftx-binance-crypto-billionaires-social-media-bloodsport-32-billion-blowup/
4 https://www.reuters.com/article/us-retail-trading-gamestop-robots-idUSKBN2AQ2BH

SCALED DATA COLLECTION ON FTX PROMOTED CRYPTOCURRENCY – AN OUTSIZED ROLE FOR INAUTHENTIC ACTIVITY

NCRI began to investigate the role of social media in the FTX scandal by performing a scaled analysis on Twitter and examining over 3,000,000 tweets from January 1, 2019 to January 27, 2023. NCRI specifically collected mentions of 18 coins that had both been publicly listed on FTX exchange while also being directly promoted in the form of an advertisement tweet by FTX's Twitter handle (@FTX_Official).

NCRI obtained price data on these from the Polygon API as well as trading volume and number of transactions in daily intervals. NCRI also found and obtained all data available on the API for this subset, a total of 6 FTX listed and promoted coins[5], and collected tweets for all coins on Twitter based both on the mention of the coin name as well as mention of its ticker symbol (e.g. $BOBA). The number of tweets in this subset (mentioning any of these 6 coins in particular) is 970560.

Given how inauthentic accounts create notorious challenges for Twitter on a number of security domains[6], NCRI investigated the potential prevalence of such inauthentic accounts in shaping market sentiment and trends. To achieve this, inauthenticity or "bot" scores for each Twitter handle in the datasets of coin tweets were obtained through Botometer API[7].

From this data, NCRI conducted analyses to discover the magnitude of authentic and inauthentic social media activity for these cryptocurrencies. Out of a total of 182,105 unique accounts that tweeted about the coins, 172,451 accounts were given "bot" scores; the accounts that were not given scores were likely accounts which had since been suspended by Twitter. 11,215 accounts were deemed to be inauthentic or bot-like (bot score >= 0.6). The bot-like accounts amount to around 6.5% of the total number of accounts investigated. In spite of their small proportion of accounts, these accounts contributed to about 20% of all tweets in the sample.

5 *Coins collected include $BOBA, $GALA, $IMX, $RNDR, $SAND, and $SPELL - these coins were publicly discussed as targets for insider trading by Alameda and trading data on the coins was accessible from Polygon.io.*

6 *https://www.barrons.com/articles/twitter-remove-spam-bots-93d36291*

7 *https://rapidapi.com/OSoMe/api/botometer-pro/details - Botometer collects a username and yields a 'bot score' after analyzing the Twitter user by examining various aspects of their account, including tweet content and patterns in account activity (and over 1000 features overall). NCRI used the Lite version of Botometer which gives a score from 0 to 1 (0 being not bot-like, 1 being highly bot-like).*

INAUTHENTIC CHATTER FORECASTS PRICE FOR HALF OF FTX LISTED CRYPTOCURRENCIES IN THE SAMPLE

While the previous analysis demonstrates a strong relationship between inauthentic tweets and FTX listed cryptocurrencies, it provides no insights into the direction of the relationship itself. Does online chatter respond to changes in coin price, or do coin prices respond to changes in online chatter? To better parse this question, NCRI applied Granger causality analysis[8], a test which statistically establishes relationship directionality, over all coins in the data sample[9]. NCRI tested directionality between these factors: Twitter chatter surrounding each of these coins, the coin price, the coin transaction volume, and the coin trading volume.

Because previous analysis suggested an outsized role for inauthentic chatter, NCRI segmented authentic tweets from inauthentic tweets so their relationship with price and trade volume could be analyzed separately.

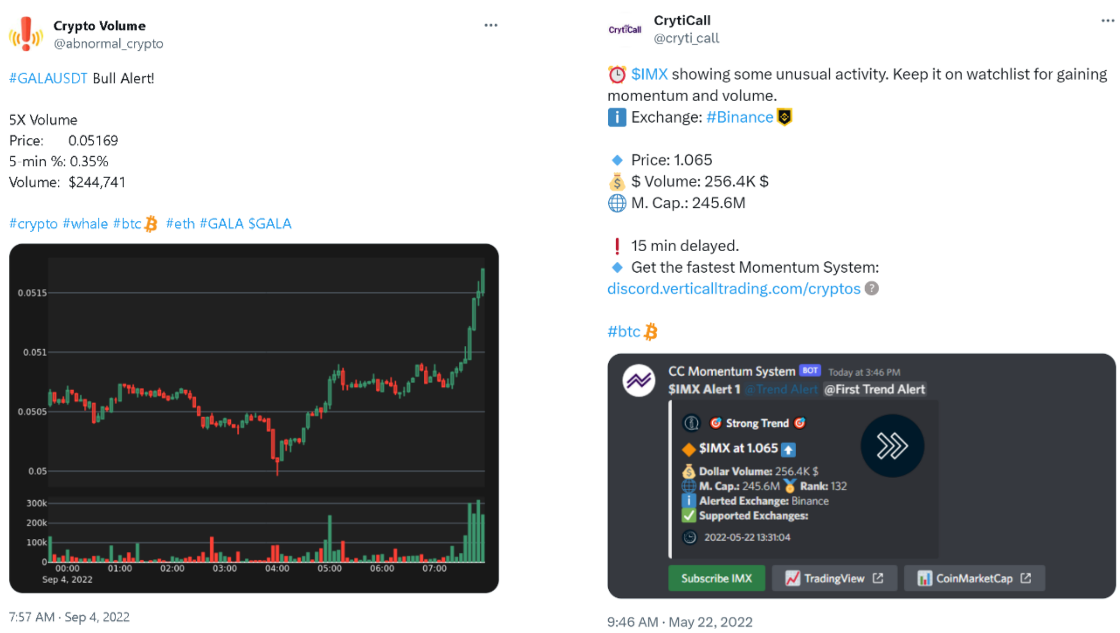


Figure 1: Inauthentic Tweets Promoting $GALA and $IMX

Granger causality testing revealed several distinct patterns in the data. Generally speaking, authentic chatter was more predictive of subsequent price changes than inauthentic chatter (Appendix A - Table 7). However, the apparent influence of inauthentic chatter was nevertheless substantial: Close inspection of a time-series analysis of inauthentic activity showed strong peak-to-peak similarity with significant price changes ($RNDR, for instance - Figure 2). In fact, for half of the FTX listed coins in the sample, inauthentic tweet volume showed signs of forecasting subsequent price (Table 1). This suggests that inauthentic networks successfully and deliberately deployed to influence changes in FTX coin prices. For other coins, $SAND and $BOBA, inauthentic activity followed changes in coin prices, suggesting that inauthentic networks were responding to price changes as well as instigating them.

8 https://www.aptech.com/blog/introduction-to-granger-causality/
9 See Appendix A for Granger causality results for max lag parameters and statistical thresholding.

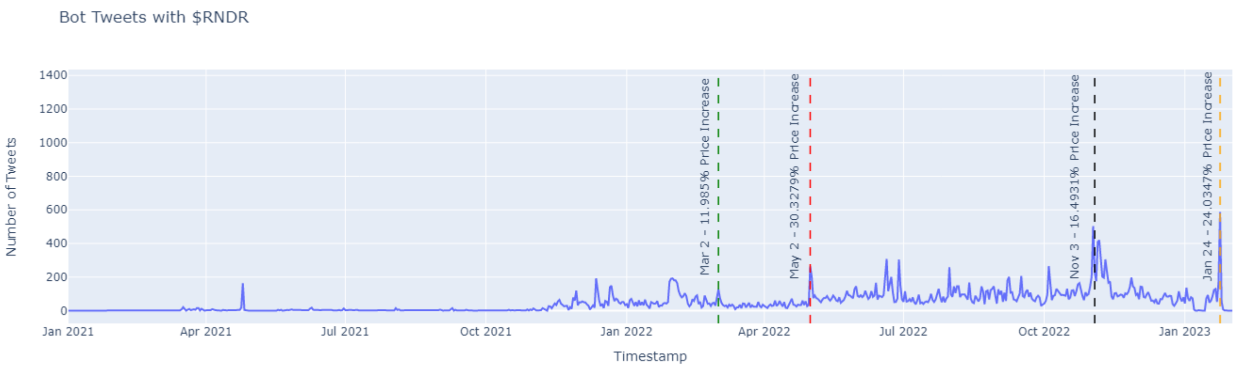


Figure 2: Time-series of Bot Tweets about $RNDR (Price increases are indicated at certain spikes.)

	Granger Causality Between Tweet Volume and Coin Price
	Inauthentic → Price
$BOBA	No Causality
$GALA	No Causality
$IMX	Causality
$RNDR	Causality
$SAND	No Causality
$SPELL	Causality

	Granger Causality Between Coin Price and Tweet Volume
	Price → Inauthentic
$BOBA	Causality
$GALA	No Causality
$IMX	No Causality
$RNDR	Causality
$SAND	Causality
$SPELL	No Causality

Causality	
No Causality	

Table 1: Granger Causality Tables for all 6 Coins

FTX PROMOTION ON TWITTER SIGNIFIED COIN CHATTER BECOMING MORE BOT-LIKE OVER TIME

That inauthentic activity forecasted price for FTX listed cryptocurrencies raises two important questions: Firstly, what role, if any, did FTX listing/advertising have in promoting inauthentic amplification? Secondly, how bot-like did this amplification become over time? To determine the relationship between FTX promotion and bot activity, NCRI began by examining the resulting changes in bot chatter after FTX's investment or advertisement of each coin. After using Botometer to calculate bot scores for each account that tweeted about each coin, NCRI interposed the average monthly scores in the graphs above. The vertical line shown in each graph represents the date when the coin was officially advertised by FTX on Twitter (see Appendix B). The average bot score was obtained by taking every tweet mentioning each coin, generating a list of all unique users for that timeframe, and, for each coin, taking the mean value of the collected users' bot scores. In general, the average monthly Botometer score for the tweets increased for each coin after the respective advertisements (Figure 3).

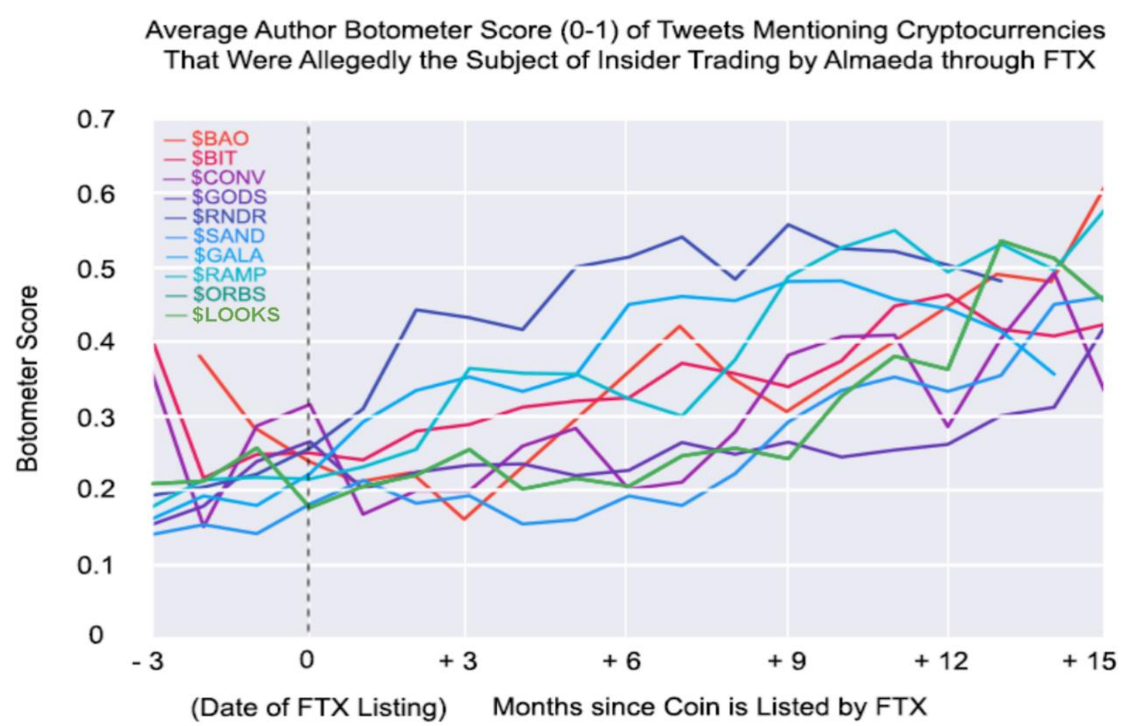


Figure 3: Graphs of Average Botometer Scores for all Coins

It is notable that bot activity appears to rise beginning with official promotion by FTX. This suggests that FTX promotion may have proven catalytic for attracting inauthentic amplification. While listing on FTX attracted substantial increases in overall chatter for each coin, it is notable that the proportion of inauthenticity in this chatter significantly increased over time.

The date when these coins were listed on the FTX exchange (when @FTX_Official put out their advertisement tweets for each coin) is marked with the vertical dashed line. After the promotion, the average bot scores of accounts who tweeted about those coins rose sharply, steadily increasing to comprise nearly 50% of all tweet volume after 15 months.

MEMES, MANIPULATION, AND MARKET MAYHEM

The data above suggests that the collapse of FTX was signified by inauthentic activity and this activity played a more important role than previously understood, but could the role of bot-like accounts and their impact in forecasting prices be occurring more generally? Might it still be happening today? To examine these questions, NCRI began investigating two coins at the vanguard of the most recent "memecoin" craze, $PEPE and $PSYOP, both of which at their peak reached a market cap surpassing $1 billion.

NCRI's research into $PEPE and $PSYOP tokens revealed notable trends, both in their rise to fame, high market caps ($PEPE reached $1.7 billion at its height[10]), and in their correlation with the activities of social media bots. PEPE is a cryptocurrency inspired by Pepe the Frog, a meme created by Matt Furie, often co-opted by the far-right despite its innocuous origin. The coin launched on April 17th, 2023, and reached a $1.7 billion dollar market cap in just a few weeks. Dogecoin, as a contrast, took nearly 4 years to reach a billion-dollar cap[11].

The rapid growth prompted a "memecoin" craze, leading to the emergence of derivatives and meme coins like BABYPEPE, WOJAK, PSYOP and others. As of July 17, 2023, $PSYOP has accrued a market capitalization of roughly $1 billion[12]. The coin took its name from a popular meme, often amplified on subcultural sites like 4chan that has seeped into mainstream discourse, that references US' history of psychological warfare. It was launched by crypto influencer ben.eth, just days after Twitter owner Elon Musk inferred a mass shooting at a Texas mall was "the weirdest story ever or a very bad psyop!"

The tokens capitalized on their meme value, further bolstered by tweets from influencers, including Elon Musk - as evidenced, for example, by Musk's retweet of a post featuring a kitten and the caption, "I wake up there is another PSYOP" on June 24, 2023. With regard to the PEPE token, Musk's tweet on May 13, 2023 which featured Pepe the Frog memes appeared to cause the price of $PEPE to increase by over 50% within 24 hours[13]. This activity was fueled by a combination of both authentic and inauthentic bot-driven activity.

10 https://www.barrons.com/articles/pepe-coin-crypto-price-explained-fe6cf942
11 https://www.coindesk.com/markets/2018/01/04/dogecoin-market-cap-hits-1-billion-to-its-creators-dismay/
12 https://coinmarketcap.com/currencies/psyop/
13 https://coinmarketcap.com/community/articles/645fbb2275b33b63e47bccad/

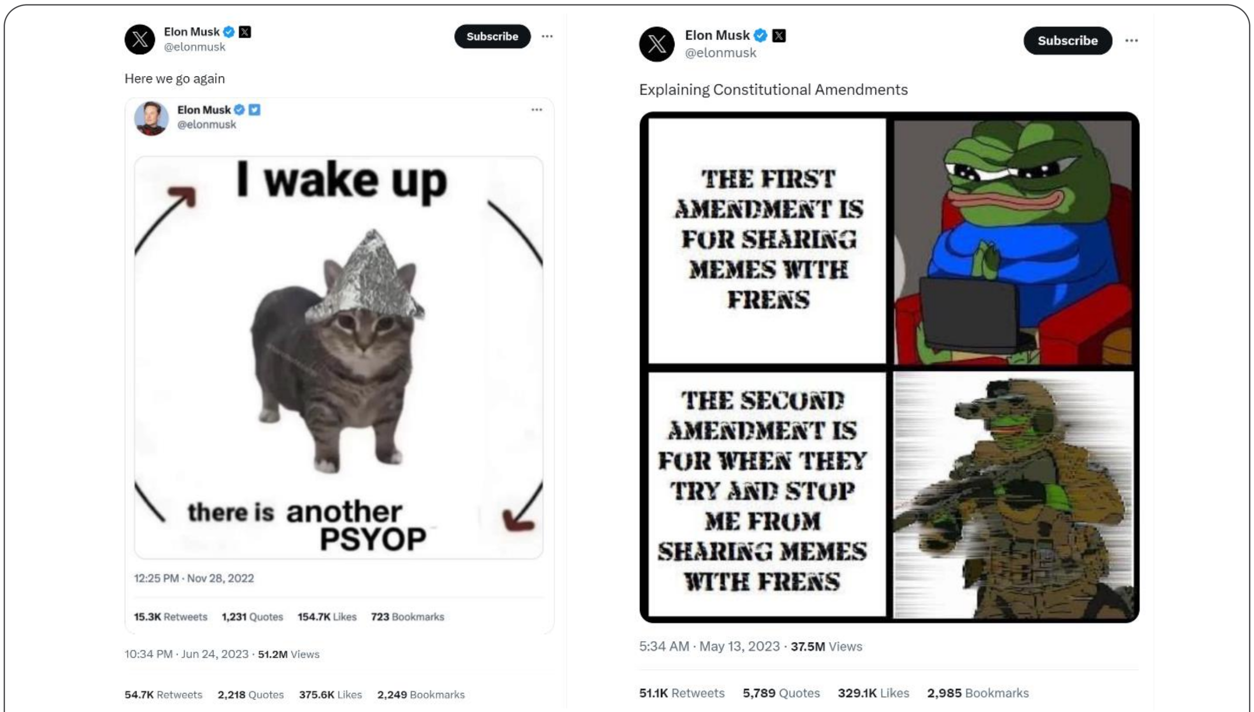


Figure 4: Musk's Tweets Regarding 'PSYOP' and Pepe the Frog

Contrary to assertions that bot activity on Twitter had diminished since his takeover, NCRI's analysis tells a different story. A considerable presence of bots[14] was observed in relation to tweets about $PEPE and $PSYOP. A Granger causality test suggested a predictive relationship between tweets from bot-like accounts and $PEPE price movements[15]. This implies that bot-like activity may not merely be a side effect but potentially a driver of $PEPE's price dynamic. While tracking the early rise of $PEPE in real-time, NCRI identified the most engaged tweets mentioning $PEPE which received thousands of retweets and likes just minutes after being posted. The tweets contained fraudulent links intended to infiltrate crypto wallets. Notably, the comments were disabled on many of the top tweets, likely to hide users from comments pointing out the fraudulent link. When comments were enabled, an overwhelming majority of the comments contained identical messages from different bot-like accounts.

14 In this case, the normal version of Botometer was used which gives an overall score from 0 to 5. A score greater than 3 was judged as implying bot-like behavior.

15 p<.05, F = 3.7070. See Appendix D.

Figure 5: Pepe Tweet with Identical Comments from Bots

NCRI also conducted a time-series analysis of account creations of accounts mentioning the tokens in Tweets. NCRI detected an abnormal surge in account creations on two separate occasions in 2023, shortly before the launch of the tokens; one in September 2022, and the largest on April 16th 2023, a day before the launch of $PEPE (Figure 6). This sudden influx of new accounts suggests manipulative tactics, potentially using bots to artificially amplify these tokens' apparent popularity.

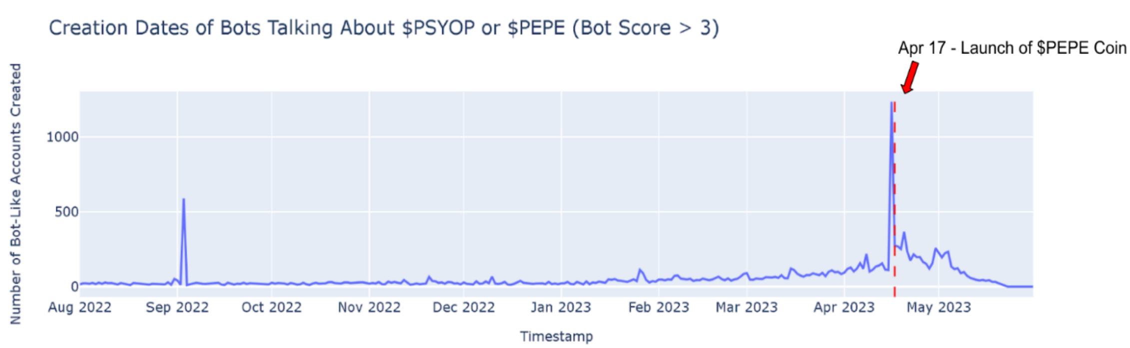


Figure 6: Time-series of Bot Creations to Promote $PSYOP or $PEPE

The pattern of account creations and bot-like activities paints a picture of an orchestrated effort, possibly aiming to artificially manipulate market sentiment and trading behavior around these tokens[16]. While further investigation is needed to fully understand the intricacies of this phenomenon, NCRI's current findings underscore the intersection of inauthentic social media activity and cryptocurrency market dynamics.

16 For trace activity for both $PSYOP and $PEPE bot tweets, see Appendix C.

CONCLUSION

The FTX scandal, analysis of FTX listed coins, alongside the analysis of $PEPE and $PSYOP provides significant insights into the complex dynamics of the cryptocurrency market, the crucial role of social media, and the impact of inauthentic social media activity and potential manipulation by bot-like accounts. NCRI's investigation revealed that Twitter activity, especially from bot-like accounts, effectively forecasted price changes in FTX's holdings, and the coins' exposure on Twitter increased in tandem with inauthentic bot-like activity over time.

The situation brings to mind the 'magic box' analogy propounded by FTX's former CEO, Sam Bankman-Fried, a figure now enmeshed in scandal and legal troubles. Bankman-Fried, at the height of FTX, once illuminated a disturbing trend within the crypto industry, where perceived value, often fueled by social media hype, would eclipse any intrinsic worth, leading to inflated market capitalizations. He stated, "In the world that we're in, if you do this, everyone's gonna be like, 'Ooh, a box token. Maybe it's cool. If you buy a box token,' you know, that's gonna appear on Twitter and it'll have a $20 million market cap."[17] Bankman-Fried's explicit mention of Twitter suggests an acute awareness of its influence on the cryptocurrency market. It begs the question, did FTX or Alameda engage in coordinated inauthentic activity on social media to artificially inflate market values?

NCRI's study suggests that the intensification of social media activity was not merely an organic outcome of the coins' popularity, but potentially a strategic ploy to influence market sentiment. Contrary to conventional wisdom, NCRI's findings show that it was not just price variations that significantly influenced tweet volumes, but that the reverse was true as well.

The implications of such manipulative mechanisms on the broader financial markets cannot be overstated, given the accelerated adoption of cryptocurrencies. The surge of bot-like activity around $PEPE and $PSYOP coins suggests that this phenomenon is ongoing and underscores the crossroads of inauthentic social media activity and cryptocurrency market dynamics.

In conclusion, it is evident that as cryptocurrency grows increasingly mainstream, the potential for market manipulation through social media and inauthentic activity presents considerable risks to investors and the stability of financial markets. Regulators, platforms, and the public must be aware of these tactics and develop methods to identify and counter such strategies.

It's also worth noting the alarming trend of social media companies, including Twitter and Meta, limiting data accessibility to researchers. This action may obstruct external observers from identifying fraudulent and consequential activities, creating a barrier for transparency in financial markets.

The findings of this study underscore the urgent need for transparency and regulated cryptocurrency markets. The dynamics described in this research were extremely pronounced and impacted losses of *billions* of dollars and seismic and ongoing scam activity. In spite of this magnitude, recent public press and media around these scams is markedly silent, with virtually no headlines in major media outlets about billion-dollar meme scams such as Pepe and Psyop. These findings also highlight the necessity for further research into the influence of social media on these and other financial markets. This situation should serve as a reminder of the intricate link between social media influence and financial market stability, especially in the rapidly evolving realm of cryptocurrency and the loss of transparency on social media.

17 https://www.ft.com/content/eac0e56c-f30b-4591-b603-f971e60dc58b

Appendix A: Granger Causality Tables for FTX Coins

Those results that indicate a highly predictive relationship are highlighted.

The lags for each combination were calculated using the Vector Autoregression Test (VAR).

Table 1:

$BOBA					
Bot Tweets			**Authentic Tweets**		
Tweets → Price	**Tweets → Trading Volume**	**Tweets → Transaction Volume**	**Tweets → Price**	**Tweets → Trading Volume**	**Tweets → Transaction Volume**
Lag = 2 p-value: 0.4219 F-value: 0.8655	**Lag = 1** p-value: 0.8989 F-value: 0.0162	**Lag = 2** p-value: 0.6323 F-value: 0.4591	**Lag = 2** p-value: 0.3427 F-value: 1.0747	**Lag = 1** p-value: 0.0905 F-value: 2.8828	**Lag = 1** p-value: 0.0352 F-value: 4.4753
Price → Tweets	**Trading Volume → Tweets**	**Transaction Volume→ Tweets**	**Price → Tweets**	**Trading Volume → Tweets**	**Transaction Volume→ Tweets**
Lag = 2 p-value: 0.0213 F-value: 3.8990	**Lag = 1** p-value: 0.2616 F-value: 1.2652	**Lag = 2** p-value: 0.1686 F-value: 1.7907	**Lag = 2** p-value: 0.8483 F-value: 0.1646	**Lag = 1** p-value: 0.0880 F-value: 2.9285	**Lag = 1** p-value: 0.0105 F-value: 6.6272

Table 2:

$GALA					
Bot Tweets			**Authentic Tweets**		
Tweets → Price	**Tweets → Trading Volume**	**Tweets → Transaction Volume**	**Tweets → Price**	**Tweets → Trading Volume**	**Tweets → Transaction Volume**
Lag = 8 p-value: 0.8837 F-value: 0.4603	**Lag = 11** p-value: 0.4032 F-value: 1.0479	**Lag = 1** p-value: 0.1104 F-value: 2.5602	**Lag = 7** p-value: 0.0001 F-value: 4.2808	**Lag = 6** p-value: 0.0018 F-value: 3.5765	**Lag = 6** p-value: 0.0244 F-value: 2.4524
Price → Tweets	**Trading Volume → Tweets**	**Transaction Volume→ Tweets**	**Price → Tweets**	**Trading Volume → Tweets**	**Transaction Volume→ Tweets**
Lag = 8 p-value: 0.0871 F-value: 1.7428	**Lag = 11** p-value: 0.0000 F-value: 5.2704	**Lag = 1** p-value: 0.9785 F-value: 0.0007	**Lag = 7** p-value: 0.0109 F-value: 2.6517	**Lag = 6** p-value: 0.1550 F-value: 1.5684	**Lag = 6** p-value: 0.0001 F-value: 4.7777

Table 3:

$IMX					
Bot Tweets			**Authentic Tweets**		
Tweets → Price	**Tweets → Trading Volume**	**Tweets → Transaction Volume**	**Tweets → Price**	**Tweets → Trading Volume**	**Tweets → Transaction Volume**
Lag = 11* p-value: 0.0568 F-value: 1.7849	**Lag = 1** p-value: 0.3344 F-value: 0.9351	**Lag = 1** p-value: 0.3992 F-value: 0.7130	**Lag = 11** p-value: 0.0000 F-value: 3.8521	**Lag = 1** p-value: 0.8069 F-value: 0.0598	**Lag = 1** p-value: 0.8587 F-value: 0.0318
Price → Tweets	**Trading Volume → Tweets**	**Transaction Volume→ Tweets**	**Price → Tweets**	**Trading Volume → Tweets**	**Transaction Volume→ Tweets**
Lag = 11 p-value: 0.9073 F-value: 0.4924	**Lag = 1** p-value: 0.0895 F-value: 2.9029	**Lag = 1** p-value: 0.0083 F-value: 7.0549	**Lag = 11** p-value: 0.7336 F-value: 0.7048	**Lag = 1** p-value: 0.5812 F-value: 0.3050	**Lag = 1** p-value: 0.2826 F-value: 1.1587

**Very close to 0.05 and shows Granger causality when lags are 2-10*

Table 4:

$RNDR					
Bot Tweets			**Authentic Tweets**		
Tweets → Price	**Tweets → Trading Volume**	**Tweets → Transaction Volume**	**Tweets → Price**	**Tweets → Trading Volume**	**Tweets → Transaction Volume**
Lag = 4 p-value: 0.0026 F-value: 4.1706	**Lag = 4** p-value: 0.0026 F-value: 4.1708	**Lag = 5** p-value: 0.0061 F-value: 3.3252	**Lag = 4** p-value: 0.0000 F-value: 6.7298	**Lag = 4** p-value: 0.2243 F-value: 1.4281	**Lag = 4** p-value: 0.0322 F-value: 2.6689
Price → Tweets	**Trading Volume → Tweets**	**Transaction Volume→ Tweets**	**Price → Tweets**	**Trading Volume → Tweets**	**Transaction Volume→ Tweets**
Lag = 4 p-value: 0.0497 F-value: 2.4023	**Lag = 4** p-value: 0.0048 F-value: 3.8160	**Lag = 5** p-value: 0.0113 F-value: 3.0100	**Lag = 4** p-value: 0.6930 F-value: 0.5584	**Lag = 4** p-value: 0.0038 F-value: 3.9419	**Lag = 4** p-value: 0.0496 F-value: 2.4030

Table 5:

$SAND					
Bot Tweets			**Authentic Tweets**		
Tweets → Price	**Tweets → Trading Volume**	**Tweets → Transaction Volume**	**Tweets → Price**	**Tweets → Trading Volume**	**Tweets → Transaction Volume**
Lag = 2 p-value: 0.0777 F-value: 2.5756	**Lag = 6** p-value: 0.6555 F-value: 0.6929	**Lag = 5** p-value: 0.5632 F-value: 0.7820	**Lag = 2** p-value: 0.0008 F-value: 7.3365	**Lag = 3** p-value: 0.5555 F-value: 0.6953	**Lag = 3** p-value: 0.8148 F-value: 0.3146
Price → Tweets	**Trading Volume → Tweets**	**Transaction Volume→ Tweets**	**Price → Tweets**	**Trading Volume → Tweets**	**Transaction Volume→ Tweets**
Lag = 2 p-value: 0.0008 F-value: 7.3380	**Lag = 6** p-value: 0.1421 F-value: 1.6161	**Lag = 5** p-value: 0.3958 F-value: 1.0370	**Lag = 2** p-value: 0.8139 F-value: 0.2060	**Lag = 3** p-value: 0.8234 F-value: 0.3028	**Lag = 3** p-value: 0.8856 F-value: 0.2156

Table 6:

$SPELL					
Bot Tweets			**Authentic Tweets**		
Tweets → Price	**Tweets → Trading Volume**	**Tweets → Transaction Volume**	**Tweets → Price**	**Tweets → Trading Volume**	**Tweets → Transaction Volume**
Lag = 10* p-value: 0.4277 F-value: 1.0176	**Lag = 3** p-value: 0.5015 F-value: 0.7874	**Lag = 5** p-value: 0.0003 F-value: 4.7842	**Lag = 12** p-value: 0.0000 F-value: 3.9754	**Lag = 11** p-value: 0.6374 F-value: 0.8027	**Lag = 12** p-value: 0.0148 F-value: 2.1258
Price → Tweets	**Trading Volume → Tweets**	**Transaction Volume→ Tweets**	**Price → Tweets**	**Trading Volume → Tweets**	**Transaction Volume→ Tweets**
Lag = 10 p-value: 0.5108 F-value: 0.9241	**Lag = 3** p-value: 0.9062 F-value: 0.1855	**Lag = 5** p-value: 0.3883 F-value: 1.0493	**Lag = 12** p-value: 0.0000 F-value: 5.3832	**Lag = 11** p-value: 0.0230 F-value: 2.0524	**Lag = 12** p-value: 0.0077 F-value: 2.3021

**Shows Granger causality when lags are 2-4 and 6-9*

Table 7:

	Granger Causality Between Tweet Volume and Coin Price	
	Inauthentic → Price	Authentic → Price
$BOBA	No Causality	No Causality
$GALA	No Causality	Causality
$IMX	Causality	Causality
$RNDR	Causality	Causality
$SAND	No Causality	Causality
$SPELL	Causality	Causality

	Granger Causality Between Coin Price and Tweet Volume	
	Price → Inauthentic	Price → Authentic
$BOBA	Causality	No Causality
$GALA	No Causality	Causality
$IMX	No Causality	No Causality
$RNDR	Causality	No Causality
$SAND	Causality	No Causality
$SPELL	No Causality	Causality

Causality	(green)
No Causality	(red)

Appendix B: Botometer Score Graphs

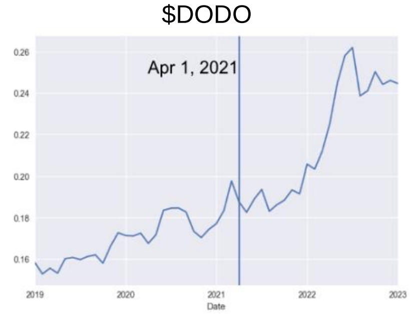
$BAO

$BIT

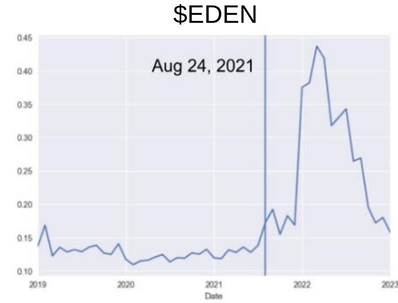
$BOBA

$CONV

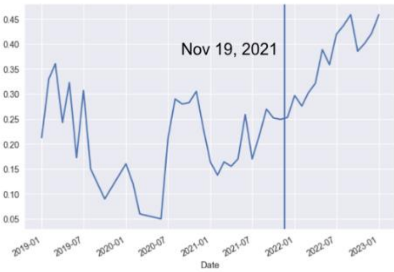
$DODO



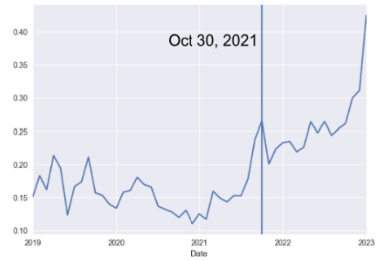
$EDEN



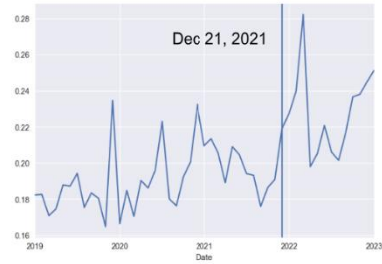
$GALA



$GODS



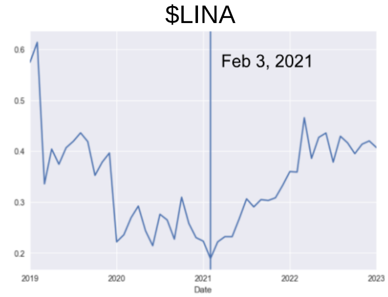
$GOG



$IMX

$INDI

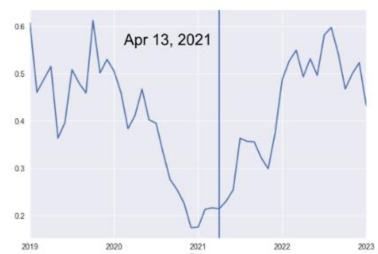
$LINA



$LOOKS

$ORBS

$RAMP

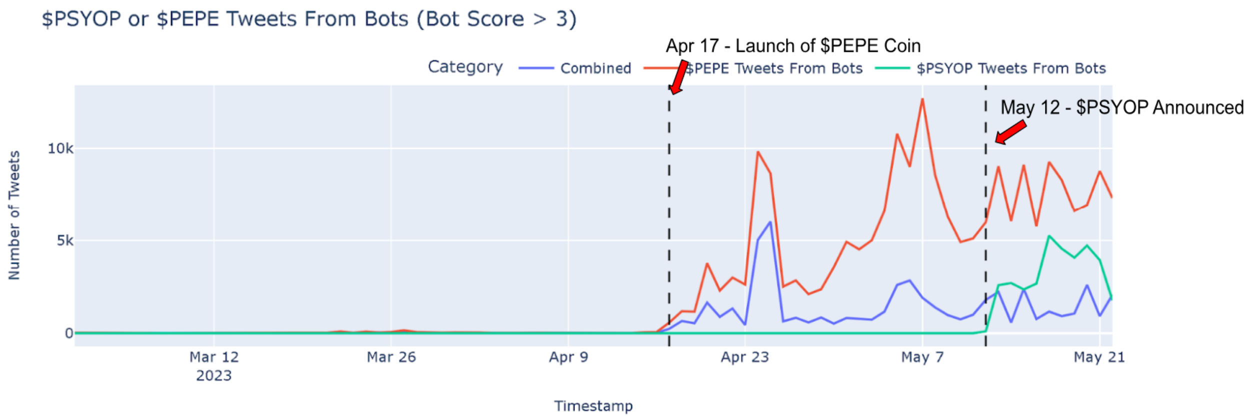


$SAND

$SPELL

$RNDR

Appendix C: PEPE and PSYOP Bot Tweets Graph



Appendix D: Granger Causality for $PEPE Bot Tweets

```
Granger Causality
number of lags (no zero) 4
ssr based F test:         F=3.7070  , p=0.0162  , df_denom=26, df_num=4
ssr based chi2 test:   chi2=19.9607 , p=0.0005  , df=4
likelihood ratio test: chi2=15.7944 , p=0.0033  , df=4
parameter F test:         F=3.7070  , p=0.0162  , df_denom=26, df_num=4
```

Appendix E: Past Studies

Past studies on the subject of market status fluctuations of cryptocurrency have mainly focused on the influence of legitimate social media engagement. Most of these studies use sentiment analysis for that purpose, whereby sentiment analysis involves investigation of the emotional tone and attitude of a particular message or post; the post is labeled either ‘positive’ or ‘negative’ following the analysis. For instance, there have been past explorations of whether positive Twitter chatter on Bitcoin and Ethereum is related to spikes in BIT and ETH prices, having preceded bumps in prices by a few days[18]. Past analyses have also introduced the significance of a celebrity’s - for instance, Elon Musk’s - promotion of a coin and its effects on the market[19]. On the contrary, what NCRI's report aims to do is to analyze the influence of inauthentic social media activity on prices and trading volumes of various cryptocurrencies.

18 Alipour, Peyman, and Sina E Charandabi. Analyzing the Interaction between Tweet Sentiments and Price Volatility of Cryptocurrencies. Vol. 8, no. 2, 2 Apr. 2023, pp. 211–215, https://doi.org/10.24018/ejbmr.2023.8.2.1865. Accessed 27 July 2023.

29 HAMURCU, Cagri. “Can Elon Mask’s Twitter Posts about Cryptocurrencies Influence Cryptocurrency Markets by Creating a Herding Behavior Bias?” Fiscaoeconomia, vol. 6, no. 1, 25 Jan. 2022, pp. 215–228, https://doi.org/10.25295/fsecon.1028730.