Is your digital neighbor a reliable investment advisor?

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ABSTRACT

The web and social media platforms have drastically changed how investors produce and consume financial advice. Historically, individual investors were often relying on newsletters and related prospectus backed by the reputation and track record of their issuers. Nowadays, financial advice is frequently offered online, by anonymous or pseudonymous parties with little at stake. As such, a natural question is to investigate whether these modern financial "influencers" operate in good faith, or whether they might be misleading their followers intentionally. To start answering this question, we obtained data from a very large cryptocurrency derivatives exchange, from which we derived individual trading positions. Some of the investors on that platform elect to link to their Twitter profiles. We were thus able to compare the positions publicly espoused on Twitter with those actually taken in the market. We discovered that 1) staunchly "bullish" investors on Twitter often took much more moderate, if not outright opposite, positions in their own trades when the market was down, 2) their followers tended to align their positions with bullish Twitter outlooks, and 3) moderate voices on Twitter (and their own followers) were on the other hand far more consistent with their actual investment strategies. In other words, while social media advice may attempt to foster a sense of camaraderie among people of like-minded beliefs, the reality is that this is merely an illusion, which may result in financial losses for people blindly following advice.

CCS CONCEPTS

• **General and reference** → **Measurement**; • **Applied computing** → **Digital cash**; • **Information systems** → **Social networks**.

KEYWORDS

Social Media, Cryptocurrency, Twitter, Bitcoin, Online Markets, Trading, Derivatives

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1 INTRODUCTION

The Web has ushered in a profound transformation in how financial assets are traded. Investors, who once had to ask brokers to execute their orders, and paid high commissions in the process, can now directly invest in financial assets at any time with lower fees, thanks to online platforms. Consequently, individual investors' influence on financial markets has increased. For instance, investors using Robinhood, an online platform for commission-free investment in stocks, ETFs, and cryptocurrencies, have shown to significantly impact trading volume and stock prices [7].

Multiple pieces of literature point out the importance of social media communication on individual investor strategy. A famous example is the "echo chamber" effect. Tang et al. [26] and Cookson et al. [13] show individual investors selectively acquire information via online sources to confirm their *a priori* beliefs. In turn, this biased information limits investor understanding of the market outlook, and results in below-market average performance. For instance, an investor who believes that the price of a stock will rise is inclined to gather positive outlooks on the stock and fail to correct their belief even when other sources recommend against buying or holding the stock.

An important corollary question is whether the people who produce this social media information truly believe in the outlook they publicly advocate. While we would expect them to, some of these advocates may be chasing other pursuits: acquiring more notoriety by espousing controversial positions, or, more perversely, trying to manipulate the market by tricking their followers to adopt a position they expect to be losing [23, 27].

The latter is plausible given that many social media accounts are anonymous, and do not have to take any responsibility for the outcome of their publicly stated positions. This is in contrast to more conventional channels, such as financial newsletters, which often include the name and company of their authors, who stake their reputation on the correctness of their predictions.

Unfortunately, with social media, even comments made casually or in jest can have an outsized influence on the market if they "go viral" [4, 17]. In short, we generally need to better understand the true impact of online influencers on market outcomes. We contribute to this goal by analyzing whether social media actors post outlooks about cryptocurrency prices consistent with their own positions in a cryptocurrency derivatives market.

To do so, we obtained hourly investment performance data for five million investors registered by April 2021 in one of the largest cryptocurrency derivatives market in the world. We use this data to infer the direction of their position on the market (long, short etc.). This market lets investors link to their Twitter accounts. By April 2021, 75,771 of their users had done so, and we collected the profiles and the tweets of these investors. From this combined dataset, we can measure the level of consistency between the market positions of these investors, and their statements on Twitter.

Our analysis shows that many of the Twitter users active on this derivatives market, who tout bullish outlooks in difficult times (e.g., the cryptocurrency market troughs of 2021), actually adjust their investments to bet *against* cryptocurrencies, while their followers tend to align their positions to the bullish outlooks trumpeted on Twitter. In other words, we find evidence of strong inconsistencies between publicly stated and actual positions of these investors.

On the other hand, investors that are encouraging caution on Twitter adopt market positions compatible with their public stance—they retreat to safer positions as major cryptocurrency prices start to drop, and keep holding cautious positions even when the prices rise again. Different from those who follow bullish accounts, followers of these moderate accounts adopt more careful positions.

Our study thus provides a strong word of caution to individual investors. Social media positions may suggest a certain sense of camaraderie among enthusiastic supporters in tough times, but actual investments provide ample evidence this is merely an illusion, and blindly following such advice is unlikely to be a good idea.

2 RELATED WORK AND BACKGROUND

Research has long shown the influence of social communication on potential investors. Hong et al. [19] found that the closeness of an individual to their neighbors was positively correlated with an individual's participation in stock markets, controlling for wealth, education, and race. Brown et al. [12] suggested a causal relationship between an individual decision to participate in stock markets and the average participation rate of the community the individual belongs to. In short, a person is more likely to invest if their neighbors invest. Word-of-mouth – even in casual conversation – appears to be a particularly important information propagation vector [5, 9, 11, 14, 15]. These results generalize beyond the U.S.[16].

With the emergence of the Internet in general, and of social media in particular, such individual advice is now easier to give and to receive than ever before: no need to run into a neighbor on the street to receive financial advice, when so many online acquaintances provide free advice on their social media feeds. Unfortunately, individual investors are inclined to exclusively gather the information consistent with their *a priori* beliefs, and as a result, underperform the market [13, 26]. Stated differently, "echo chamber" effects prevent investors from correcting their investment strategies and adjust their positions when needed.

Furthermore, many novel financial instruments, such as cryptocurrencies and modern trading platforms, are completely digital, which in turn leads people to spend even more time investing online. Understanding the behavior of these online investors is important, as they are increasingly influential: Barber et al. [7] show that individual investors on Robinhood, an online commission-free trading platform for stocks and cryptocurrencies, significantly affect the trading volume and price of stocks. This influence is stronger for attention-grabbing stocks, e.g., those explicitly marked as showing the largest price movements on the platform.

Along the same lines, cryptocurrencies such as Bitcoin, originally touted as novel digital payment systems [22], are nowadays primarily used as an investment instrument [8]. Soska et al. show evidence that individual cryptocurrency derivative traders trade 24/7 in an ecosystem that never shuts down, contrary to more traditional markets [25]. Those derivative markets consist of hundreds of platforms and account for 50–100 billion USD traded daily.[1] This number far exceeds that of cryptocurrency spot markets, and can be compared to the roughly 200 billion USD traded on the NASDAQ on a given day at the time of writing.[2]

Relying on the data-rich cryptocurrency derivative market environment, we further illuminate our understanding of individual online investor behavior. In particular, we complement existing literature by investigating potential inconsistencies between stated and actual preferences, as well as investor responses to online advice and influence.

3 DATASET

We employ two datasets to investigate investors' behavior. First, we collect, over a period of 2 years, investment returns data from a very large cryptocurrency derivatives exchange, by relying on their public API. Second, we collect Twitter data for those investors who advertise a Twitter handle on the exchange, as well as their followers, using the Twitter API.

3.1 Cryptocurrency derivatives exchange data

Cryptocurrency derivatives were originally pioneered by the BitMEX exchange in November 2014 [2, 3, 25]. A notable feature of these exchanges is the availability of *perpetual futures* contracts, extensively described in related work [25, Section 2.3].

Perpetual futures. To summarize, future contracts are a bet on the future value of an asset, e.g., the value of bitcoin (BTC) against the US dollar (USD). If BTC appreciates against the USD, an investor going long, i.e., betting on the appreciation of bitcoin, will see the value of their contract(s) appreciate. In addition, these contracts allow for leverage – a multiplicative factor on the bet placed. For instance, assume that somebody, convinced that BTC is going to rise against the USD, uses 100x leverage. If that investor wants to bid (roughly) 1 BTC worth of USD, they only need to invest 0.01 BTC (the "margin size"). If BTC does appreciate, their gains are multiplied by 100. On the other hand, as soon as BTC depreciates by 1% compared to its value in USD at contract acquisition time, the investor loses all of their money held in the margin account, a phenomenon known as "liquidation."[3] The platform we study

[1] https://coinmarketcap.com/derivatives/
[2] https://www.nasdaqtrader.com/Trader.aspx?id=DailyMarketSummary
[3] For simplicity's sake, this discussion assumes away transaction fees, and early liquidations.

allows (at the time the measurements we use in this study were taken) a 125x maximum leverage for perpetual futures. Importantly, perpetual futures common in cryptocurrency markets do not have an expiry date. That is, investors can hold the position as long as they can sustain their margin size at a necessary level to avoid liquidation. Finally, each contract has two sides (short and long). For instance, a long position worth USD 100 must be offset by (a) short position(s) worth USD 100.

Performance indices. Two major indices track investor performance: Profit and Loss (PnL) and Return on Investment (RoI). PnL, denominated in USD or BTC depending on products, represents the (absolute) amount of money made or lost over a given unit of time. An absolute number, PnL is dependent on the initial investment and leverage, and thus potentially favors investors with considerable initial endowment. To address this issue, the RoI shows performance for a unit of the fund considered, by dividing the PnL by the margin size. Given their PnL and their RoI, we can thus infer the margin size of a given investor.

Data collected. The exchange we study launched a leaderboard for its futures derivative platform in mid-2020. That leaderboard displays the top investors ranked by RoI and PnL, and is periodically updated. Specifically, until May 9, 2021, PnL, RoI, and corresponding ranking information were updated every hour for every investor. Thereafter, these indices were updated on a daily basis. In this paper, we will primarily focus on April 2021, therefore benefiting from the finer update resolution. In addition, each user may optionally link their account to a Twitter handle. We also collect that information.

Importantly, while the exchange's web front-end only displays the top investors, we can obtain information about all users from the exchange public API. We verify the exhaustiveness of our coverage as follows: if our coverage is appropriate, the lowest investor rank in our dataset should be equal (or very close) to the number of investors whose information we collected. A limitation of this technique is that two different investors with the same PnL are tied at the same rank. However, because of the volatile nature of cryptocurrency prices, the PnL of the maximum (i.e., lowest) ranked investor is a large *negative* value, in the order of tens or even hundreds of thousands of dollars, and it is thus unlikely that a large number of investors display exactly the same performance.

Figure 1 shows the number of investors, the lowest rank among them, and the ratio of these two numbers (i.e. coverage of our dataset). The ratio is larger than 0.9 throughout April 2021 and shows our dataset marks a good coverage of investors.

Bitcoin prices. The API also provides real-time major cryptocurrency prices in the market. We collected BTC price denominated in Tether (USDT), a stablecoin pegged to the USD, every minute in April 2021. Figure 2 shows the BTC price in the month on a daily basis. For context, the price rose from roughly 30,000 USDT to roughly 60,000 USDT from January 2021 through March 2021 and reached the highest price ever seen, approximately 65,000 USDT on April 14, 2021. However, the price dropped after the peak and hit a bottom of roughly 47,000 USDT on April 25—a loss of 28% in less than two weeks—before rising again. In short, that month was volatile, shifting back and forth between bullish and bearish trends.

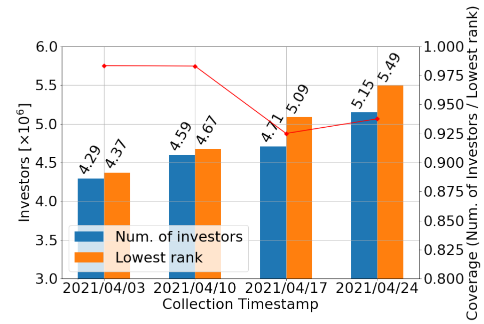

Figure 1: The number of investors and the lowest rank in our dataset in April 2021.

Figure 2: Daily BTC price in USDT (≈ USD) in April 2021.

3.2 Twitter users dataset

In our dataset, 75,771 investors (1.47% of all users) linked their Twitter handles to their market profiles by April 2021. We collected their tweets from Twitter's streaming API and back-filled any missing data, dating back to April 1, 2021, by querying Twitter's full archive. (The reason for using the streaming service is to capture tweets that could be subsequently deleted, and thus missing in the full archive search.) We collected both their followers and accounts they follow ("followees") across two intervals: April 9, 2021 to May 16, 2021 and September 16, 2021 to October 25, 2021. We conducted the second collection to ensure that we did not miss anything significant in the first collection, which took place at the time of the measurements we analyze. We confirmed that only using the first collection interval does not statistically change our results.

Table 1 summarizes our Twitter users dataset statistics. (See Appendix A for unlisted language-use distribution analysis.) The first and second rows show the number of tweets posted by investors in the market, separating out accounts which tweeted at least once in April 2021. More than half of investors are dormant, but a small fraction of them post more than 10,000 tweets in that month. Similarly, follower and followee counts present skewed distributions. The distribution of follower investors (fifth row) is particularly skewed: only 10% of investors have at least one other investor (defined, again, as somebody active on the derivative platform we are measuring) following them. Only a handful of "strong influencers" have more than 1,000 investor followers.

Table 1: Statistics for investors with Twitter accounts.

	Percentile						
	Min.	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	Max.
Tweets per acct.	0	0	0	0	5	40	13.0×10^3
- *excl.* dormant accts.	1	1	3	11	43	137	13.0×10^3
Followees							
- *excl.* non-investors	0	0	0	0	1	4	254
- *incl.* non-investors	1	27	84	266	741	1,987	406×10^3
Followers							
- *excl.* non-investors	0	0	0	0	0	1	5,111
- *incl.* non-investors	1	4	15	70	291	1,038	14.0×10^6

Figure 3 further emphasizes this, by showing the complementary cumulative distribution function (cCDF) for the per-investor number of followees and followers that have market accounts (third and fifth row in Table 1) and reveals that only 1.0% of investors have more than 20 followers that also participate in the derivative market. Follower counts appear to follow a power-law distribution

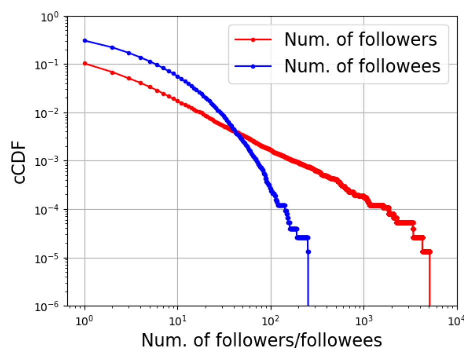

Figure 3: The complementary cumulative density function (cCDF) for the per-investor number of follower-investors and followee-investors.

$n(d) = C \times d^{-\gamma}$ where d is the per-investor number of followers, and $\gamma = 1.27$ (from an ordinary least square estimation), similar to other scale-free networks like the web [1]. In short, "the rich get richer:" an investor with many followers is likely to acquire additional followers at a faster rate than other investors [6], which in turn means that the most successful folks might have outsized influence on the rest of the community.

4 METHODS

4.1 Investor grouping

We compile three categories of advocate groups by looking at investors' tweets: bullish, neutral, and cautious. To create groups, we first search for common keywords tweeted by investors. We discard generic or project-specific keywords (e.g., #bitcoin, #ethereum), and then choose keywords based on the prevalence in investors' posts and their clarity of outlook. We put together investors who tweeted the keyword in April 2021 in a group and compile corresponding groups of followers from each advocate's followers. Table 2 summarizes our resulting groups. Advocates and followers are denominated A and F, respectively; numbers 1–5 specify the keyword used to form the group. For instance, groups A1, A2, and A3, all represent bullish advocates.

Bullish. For this category, after manually examining a number of tweets, we picked three keywords. First, *#HODL*, a deliberate misspelling of "hold," recommends going long despite downturns in the cryptocurrency investment community and is thus "bullish."[4] Second, *dip* conveys the idea that a "drop in price" is a good chance for short-term capital gain, and is also bullish.[5] Last, *moon* expresses a strong belief that the mentioned cryptocurrency will rise in price abruptly (i.e., "to the moon").[6] Contrary to the first two keywords, *moon*'s usage is not limited to downturns.

However, negatives (e.g., "don't #HODL") would completely change the meaning of a tweet. As a sanity check, we search for tweets containing both *#HODL* and a negation; there were 49 such tweets out of 919 (5.3%) in April 2021. We manually examined the 49 tweets and found only one tweet recommended holding stablecoins instead of unbacked cryptocurrencies. This shows that *#HODL* is predominantly used to encourage going long. A similar sanity check for *dip* and *moon* confirmed that they are also predominantly used to advocate for long positions.

Neutral. For this category, we choose the keyword *#blockchain*. This hashtag is frequently used in bot-like messages. In fact, *#blockchain* ranks 18th among the most-tweeted hashtags in investors' tweets in our dataset; four frequently tweeted messages irrelevant to major cryptocurrencies accounted for 1,324 out of 3,100 tweets (42.7%) in April 2021. The remaining tweets do not mention any major cryptocurrencies either, so this keyword does not convey any specific recommendation to buy or sell.

Cautious. Finally, the keyword *storm* is frequently used in the meaning of "perfect storm" in financial conversations, denoting an improbable combination of factors leading to a bad outcome.[7] We manually subsampled tweets with this keyword and confirmed that they were used to raise concerns about cryptocurrency prices in April 2021.

Table 2: Number of investors in each group. A/F and 1–5 will refer to each group (e.g., A3) in the text.

	Bullish			Neutral	Cautious
Groups	(1) #HODL	(2) dip	(3) moon	(4) #blockchain	(5) storm
(A) Advocates	387	1,283	2,741	1,375	595
(F) Followers	3,990	19,309	15,604	5,557	3,586

4.2 Inferring investor positions

To determine whether the investors belonging to each group are in a "long" position (i.e., betting that the price will go up) or a "short" position (i.e., betting that the price will go down) we check whether their returns correlate with the changes in the Bitcoin exchange rate. For instance, if from $t_n \rightarrow t_{n+1}$ Bitcoin went up in price, the returns of "long" investors will be positive and the

[4] https://www.investopedia.com/terms/h/hodl.asp
[5] https://www.investopedia.com/terms/b/buy-the-dips.asp
[6] https://www.investopedia.com/meme-stock-5206762
[7] https://www.collinsdictionary.com/dictionary/english/perfect-storm

returns of "short" investors will be negative. If Bitcoin went down in price, the opposite would hold. To measure the correlation, we use Spearman's rank correlation, which unlike Pearson's correlation, can accommodate high volatility and large returns.

For each week W in our measurement interval, and for each investor i, we compute this correlation as follows:

$$\text{Corr}_{i,W} = \text{Spearman}\left(\left\{\text{PnL}_{i,t}\right._{t\in d, d\in W}, \left\{\Delta P_t^{\text{BTC}}\right\}_{t\in d, d\in W}\right).$$

$\text{PnL}_{i,t}$ and ΔP_t^{BTC} denote the return of investor i and Bitcoin price return from the beginning of each day d at time t, respectively. This correlation measures the extent to which a given investor's most profitable days are highly (positively nor negatively) correlated with days where the bitcoin price appreciated the most.

For this analysis, we disregard all times t with 0 PnL, as the investor was not active during that time. This excludes delta-hedged positions involving various perpetual futures, but we believe these strategies to be rare across our sample. While users may trade perpetual futures of various coins, we only look at the change in Bitcoin price: Hu et al. [20] reports that price returns of cryptocurrencies positively correlate with Bitcoin's returns, which we confirmed for the top 10 cryptocurrencies (by open interest) for the exchange we study. The full analysis can be found in Appendix B.

We then proceed to compare the distributions of investment positions for each group with that for all active investors in the market using the two-sided Kolmogorov–Smirnov (KS) test [18]; KS is a non-parametric test with limited assumptions on the underlying distributions. In the null hypothesis, the two sample distributions compared are generated from the same underlying distribution. Hence, if the null hypothesis is rejected at a significant level, the positions of the two groups are different. However, because KS does not discriminate between the deviation to the long and short position sides, we also visually investigate how the advocates and followers deviate from the distribution of all active investors, using their distributions' cumulative distribution function (CDF).

5 RESULTS

In this section, we first explore the relationship between the tweets from advocates (A) and the Bitcoin market price. Then, we compare the portfolio positions of our investor groups (Groups A1–A5 for advocates across keywords, and Groups F1–F5 for followers across keywords) using the KS test. Finally, we visually investigate how their positions differ from all active investors.

5.1 Temporal distribution of tweets and KS statistics

5.1.1 Bullish advocates and their followers (groups A1-3 and F1-3).

#HODL. We first consider the groups A1 and F1 (*#HODL*). Figure 4 shows the number of daily tweets featuring the *#HODL* hashtag as well as the Bitcoin price from April 1 to May 31, 2021. These tweets appear more frequently during BTC price drops: *#HODL* is used to advocate going long during downturns as we expected.

Table 3 shows the number of active advocates and active followers and their KS statistics. Only 10% of *#HODL* advocates held positions in the market. In other words, 90% of advocates did not take risks via the derivatives market although they advised their

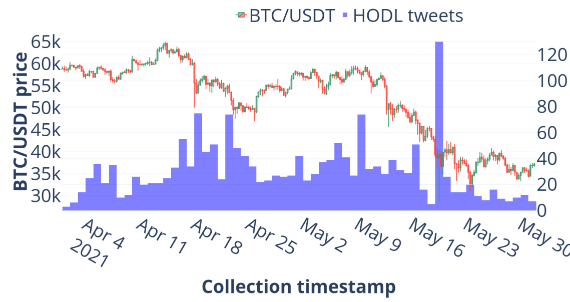

Figure 4: Number of *#HODL* tweets in April and May.

Table 3: Active *#HODL* advocates (A1) and followers (F1) and their KS statistics.

Period	Active advocates: Num. (% of all)	Active advocates: Stat. (p-val.)	Active followers: Num. (% of all)	Active followers: Stat. (p-val.)
4/3 – 4/9	41 (10.6%)	0.163 (0.201)	307 (7.7%)	0.076 (0.057)
4/10 – 4/16	37 (9.6%)	0.170 (0.211)	345 (8.6%)	0.082 (0.011)
4/17 – 4/23	41 (10.6%)	0.163 (0.200)	356 (8.9%)	0.080 (0.019)
4/24 – 4/30	36 (9.3%)	0.231 (0.035)	309 (7.7%)	0.102 ($<$ 0.01)

followers to go long. For advocates with a market position, the situation is even more remarkable. The KS test indicates these bullish advocates did not take positions significantly different from that of other investors ($p > 0.2$, null hypothesis holds) during the downturns (4/10–4/16, and 4/17–4/23), *even though these advocates used the #HODL hashtag the most in those weeks.* That is, advocates heavily advised their followers to enter long positions, while they themselves did not take risks by going long. Only in the week of 4/24-4/30 did advocates' position deviates from the baseline, a point at which the BTC price regained an upward trend.

A potential confounding factor, however, is that we only measure investor activity on a given derivative platform—albeit a large one. Perhaps, some of these investors do hold considerable amounts of currency, e.g., in spot markets, and are using the derivative platform as a hedge. Even if that were the case, this would still evidence a strong disconnect between the long strategy aggressively professed on social media and a far more cautious hedging position.

The situation is different for their followers: most of them appear to have had held positions *different* from the average user. The null hypothesis is indeed rejected at the 2% level (p-values in the order of 0.011 and 0.019). The CDF presented in Appendix C shows these followers went short in 4/10–4/17 compared to the average user, but they swung back to long 4/17-4/23. Their allocation of investment positions to the bullish side at the time their followees virulently touted bullish outlooks is compatible with the hypothesis they heed advice they receive on Twitter.

Dip. Figure 5 shows the number of tweets corresponding to the usage of the keyword "dip" compared to the BTC price. Similar to *#HODL*, the peaks in usage also coincide with the decline in Bitcoin price, so group A2 was, like A1, advocating for long positions. We observe the same patterns with groups A2 and F2 (*dip*), as summarized in Table 4. Less than 20% of advocates are active during

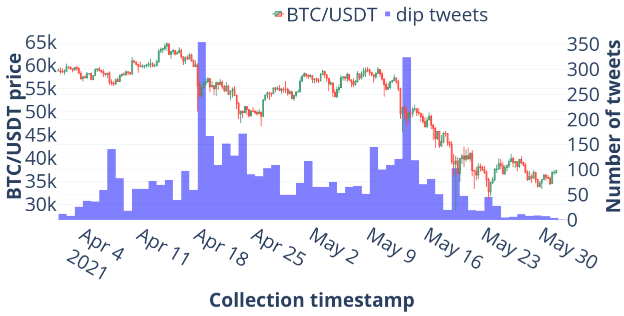

Figure 5: Number of tweets with *dip* in April and May.

Table 4: Active *dip* advocates (A2) and followers (F2) and their KS statistics.

Period	Active advocates		Active followers	
	Num. (% of all)	KS-stat. (p-val.)	Num. (% of all)	KS-stat. (p-val.)
4/3-4/9	202 (15.7%)	0.129 (< 0.01)	1,444 (7.5%)	0.079 (< 0.01)
4/10-4/16	214 (16.7%)	0.075 (0.167)	1,656 (8.6%)	0.046 (< 0.01)
4/17-4/23	210 (16.4%)	0.082 (0.109)	1,725 (8.9%)	0.052 (< 0.01)
4/24-4/30	186 (14.5%)	0.128 (< 0.01)	1,469 (7.6%)	0.059 (< 0.01)

the downturn, and those who are investing similarly to the average investor during a downturn (null hypothesis holds with $p > 0.1$ in the two weeks of interest). The smaller number of advocates samples cannot explain the insignificant KS-statistics (see Appendix D). On the other hand, their followers consistently invest differently from the average investor ($p < 0.01$). Examining the follower's CDF (Appendix C) shows that these followers disproportionately go long. In short, here too, we observe a disconnect between stated and deployed strategies from the advocates; meanwhile their followers aligned their positions to the bullish outlooks espoused on Twitter.

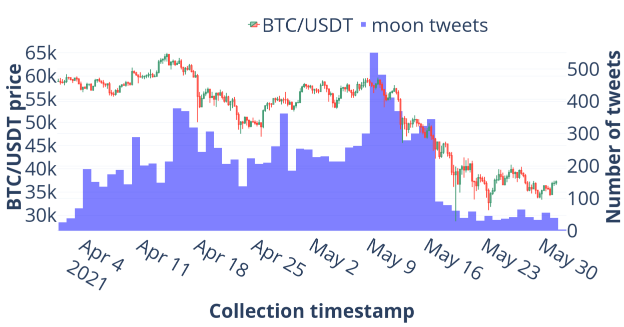

Figure 6: Number of tweets with *moon* in April and May.

Moon. Figure 6 shows the number of tweets with the keyword *moon* in April and May 2021. This demonstrates that this keyword is also mildly correlated with Bitcoin price. The exceptional peak around May 9 comes from Elon Musk's tweet referring to Dogecoin[8] and a flood of retweets.

[8]https://twitter.com/elonmusk/status/1391523807148527620

Table 5: Active *moon* advocates (A3) and followers (F3) and their KS statistics.

Period	Active advocates		Active followers	
	Num. (% of all)	KS-stat. (p-val.)	Num. (% of all)	KS-stat. (p-val.)
4/3-4/9	286 (10.5%)	0.113 (< 0.01)	1,247 (8.0%)	0.083 (< 0.01)
4/10-4/16	294 (10.7%)	0.059 (0.247)	1,426 (9.1%)	0.063 (< 0.01)
4/17-4/23	296 (10.8%)	0.074 (0.077)	1,484 (9.5%)	0.056 (< 0.01)
4/24-4/30	246 (9.0%)	0.123 (< 0.01)	1,261 (8.1%)	0.075 (< 0.01)

Table 5 summarizes KS statistics for the advocates and their followers (A3 and F3). The result for advocates gathered with the *moon* keyword (A3) also shows the same tendency as *dip* and *#HODL* advocates (A1 and A2). Namely, their participation is low and the distribution deviates from other investors' distribution before and after the downturn, but the KS statistics do not reject the null hypothesis during the downturn. Importantly, the smaller number of advocates samples cannot fully explain the insignificant KS-statistics in this case either (Appendix D). On the other hand, their followers (F3) significantly deviate from other investors, and were predominantly in long positions as seen in their CDFs (see Appendix C).

5.1.2 Neutral or cautious message advocates and their followers.

#blockchain (group A4 and F4). Figure 7 shows the number of tweets corresponding to the *#blockchain* keyword between April and May 2021 and the Bitcoin price. Tweets were rarely correlated

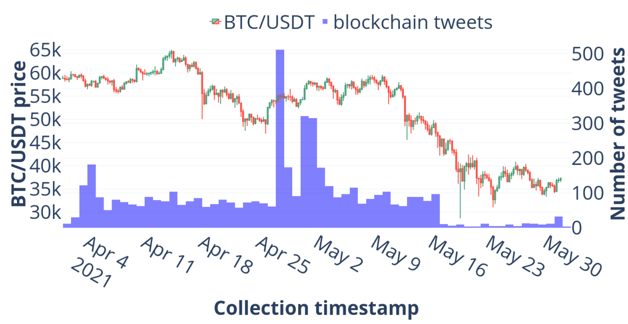

Figure 7: Number of *#blockchain* tweets in April and May.

with the Bitcoin price and peaked twice: on 4/27 and 4/30–5/1. Manual analysis indicated that several accounts posted the same spam-like messages irrelevant to investment strategies. Thus, *#blockchain* advocates (A4) do not advertise long/short positions to their followers (F4), and as such can be used as a baseline for comparison.

Table 6 summarizes the KS-test results for the #blockchain keyword. Reflecting the bot-like nature of advocates, the number of followers per advocate is the least among all keywords we consider in this study. Table 6 also shows that the ratio of active advocates and followers is lower than bullish advocates (A1–3). Moreover, the distributions for advocates (A4) and their followers (F4) do not deviate from other investors, even at the 10% significance level, during the 4/10-4/16 and 4/17-4/23 downturns.

Storm (group A5 and F5). Figure 8 shows the daily number of tweets with the *storm* keyword (indicating caution) are correlated

Table 6: The number of active *#blockchain* advocates (A4) and followers (F4) and their KS statistics.

Period	Active advocates		Active followers	
	Num. (% of all)	KS-stat. (p-val.)	Num. (% of all)	KS-stat. (p-val.)
4/3-4/9	100 (7.3%)	0.085 (0.445)	366 (6.6%)	0.075 (0.030)
4/10-4/16	118 (8.6%)	0.091 (0.267)	390 (7.0%)	0.051 (0.248)
4/17-4/23	136 (9.9%)	0.082 (0.309)	389 (7.0%)	0.038 (0.622)
4/24-4/30	104 (7.6%)	0.143 (0.026)	337 (6.1%)	0.080 (0.026)

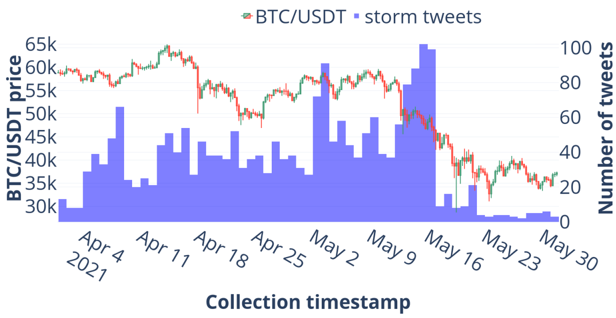

Figure 8: Number of tweets with *storm* in April and May.

with Bitcoin price drops. Table 7 summarizes KS-test results for the advocates and their followers. Investors advocating caution do not

Table 7: Active *storm* advocates (A5) and followers (F5) and their KS statistics.

Period	Active advocates		Active followers	
	Num. (% of all)	KS-stat. (p-val.)	Num. (% of all)	KS-stat. (p-val.)
4/3-4/9	47 (7.9%)	0.122 (0.455)	355 (9.9%)	0.090 (< 0.01)
4/10-4/16	45 (7.6%)	0.136 (0.342)	381 (10.6%)	0.067 (0.065)
4/17-4/23	51 (8.6%)	0.110 (0.532)	414 (11.5%)	0.043 (0.409)
4/24-4/30	42 (7.1%)	0.112 (0.622)	358 (10.0%)	0.071 (0.052)

participate much in the market (less than 9% participation), their positions are not significantly different from that of the average investor, and their followers present the same characteristics.

5.2 CDF analysis for advocates

This section discusses how advocates' investment positions deviate from the baseline. Figure 9 shows the cumulative distribution function (CDF) for Spearman's rank correlation coefficients for advocates and all active investors in April 2021.

All advocates bet more on long positions than other investors in 4/3-4/10. However, their distribution swung to short positions the next week, when Bitcoin price peaked and started to drop, as other investors did. That contradicts bullish advocates' stance on Twitter (*#HODL* (A1), *dip* (A2), *moon* (A3)). Namely, they should be on the right-hand side of the baseline distribution if they really believed in bullish outlooks on the market, but, in reality, they adjusted their position to the opposite side. In the following week, market participants generally regained bullish outlooks a bit, but the bullish advocates' distributions did not deviate so as to mark a significant aversion from the baseline. Again, this is the time they posted bullish outlooks on Twitter the most. Only in final week of April, their distributions significantly deviated from baseline to long positions; but this is also when Bitcoin rose in value.

These temporal transitions in bullish advocates' distributions indicate that they were closely watching the market and adjusting their positions not to be hit by the downturn, despite their professed bullish outlooks on Twitter. On the other hand, the cautious message advocates' positions were consistent with their public stance. That is, their CDF is close to the baseline throughout April 2021, as expected given the KS statistics. A smaller fraction of them took bullish positions when Bitcoin went up between 4/24–4/30.

As discussed above, our measurements are limited to that specific derivative platform, and we do not have access to the complete investor portfolio. However, as noted earlier, the mere fact that bullish advocates are at the very least using derivatives as a hedge (if not as their core position) makes their loud public pronouncements rather suspect. Likewise, as noted earlier, for followers, all the deviations from baseline except for *#HODL* followers (F1) in 4/10-4/16 are toward long positions. (See plots in Appendix C.)

5.3 Margin size

We next consider whether investors' margin size affects their role on Twitter. Table 8 summarizes investors' average and median weekly margin size.

Here, we first infer an investor's margin size for each time-slice from their PnL and RoI and calculate their median margin size in a week. Then, we calculate weekly mean and median margin size for groups from group members' weekly medians. The average margin size is orders of magnitude larger than the median size for all groups, meaning that some investors hold unusually large amounts of funds in the market. Median values also show an interesting feature. Although the average size of those who have Twitter handles is almost the same as active investors, the median size is about half of active investors' margin size. These results indicate that the typical investor with Twitter accounts are smaller individual investors.

Looking at each keyword group in detail, we find a different margin size distributions. The median value of *#HODL* (A1), *moon* (A3), and *storm* advocates' (A5) margin size is smaller than their followers (F1, F3, F5). Compared to conventional finance advisory channels, it is a surprising margin size reversal. Namely, on traditional channels for financial advice, experienced advisors distribute their outlooks, and relatively small investors receive them. That is, the margin size of advice distributors is much larger than receivers. This is not necessarily the case in this market. These results indicate that investors with smaller margin sizes may be providing advice to accounts with larger margin sizes.

6 CONCLUSION

We collected and matched investors' performance on a large cryptocurrency exchange to their Twitter accounts. We then identified 5 keywords associated with investment advice biases, and used these keywords to segment traders across three categories: bullish, cautious, and neutral, differentiating between accounts which advocate for positions (advocates) and accounts which follow these advocates (followers).

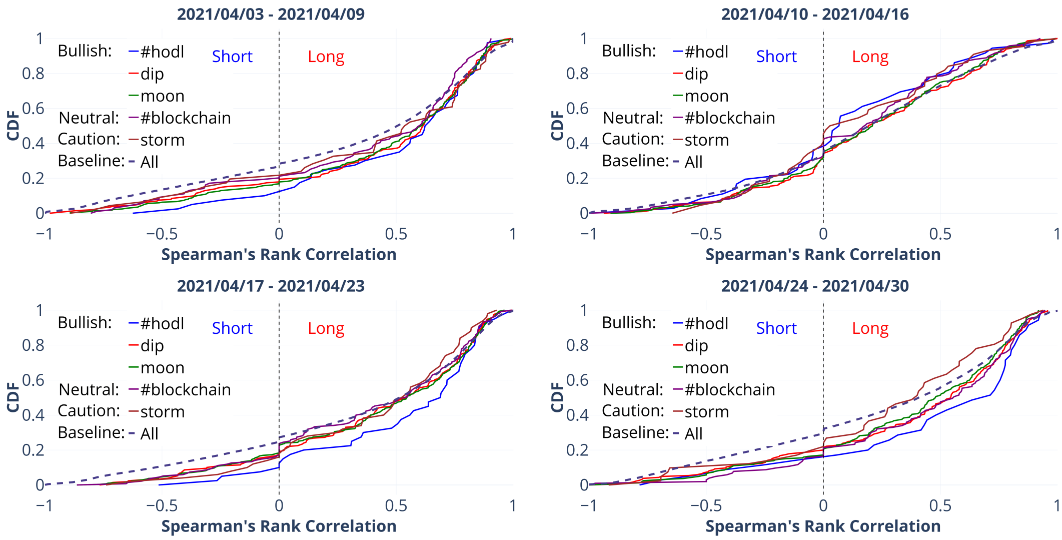

Figure 9: CDF plot of advocates' Spearman's rank correlation coefficient in 4/3-4/9 (top-left), 4/10-4/16 (top-right), 4/17-4/23 (bottom-left), and 4/24-4/30 (bottom-right).

Table 8: The mean and median value of the weekly margin size for advocates and followers in each group.

	4/3 - 4/9		4/10 - 4/16		4/17 - 4/23		4/24 - 4/30	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Active investors [USDT]	12,830	302	13,290	314	13,088	276	12,298	225
Investor w/ Twitter accts. [USDT]	10,543	167	13,902	176	12,787	148	10,769	135
Advocates [USDT]								
#HODL	4,008	134	2,671	108	2,433	66	2,782	82
dip	77,446	317	83,177	283	85,587	214	74,911	277
moon	34,351	139	30,874	125	37,996	103	21,263	93
#blockchain	1,057	51	1,161	46	1,497	47	1,329	38
storm	1,042	99	1,536	167	2,015	130	895	130
Followers [USDT]								
#HODL	13,186	145	12,953	170	14,034	144	11,025	103
dip	19,964	214	26,713	228	21,936	204	21,486	155
moon	23,253	224	31,035	250	24,524	206	25,437	157
#blockchain	4,108	134	3,801	174	3,370	172	2,667	133
storm	27,192	205	30,272	294	29,848	213	22,373	169

Through a novel use of Spearman's rank correlation, we identified whether investors are in long or short positions. We then used the two-sided Kolmogorov-Smirnov test to compare the positions of advocates and followers across the aforementioned three categories. We consistently found that while bullish advocates carefully manage their positions through market upturns and downturns, they publicly call for their users to enter or remain in long positions. Their followers, on the other hand, tend to align their positions to the bullish outlooks they see on Twitter. On the other hand, followers of neutral/cautious advocates do not seem to follow this pattern. Lastly, we also find that, across three groups, advocates seemed to have smaller margin sizes than their followers.

Our study is the first to provide evidence on the financial harm that may be caused by financial influencers on social media. Our results not only indicate that some influencers may be providing bogus advice, but that they may also be aware of this, given that their trades seem to deviate from their advice. Given the number of followers that these influencers garner and the fact that their followers may command even larger portfolios, our results may support the need for stricter scrutiny to the unofficial financial advice that is being offered through social media.

ACKNOWLEDGMENTS

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A LANGUAGE DISTRIBUTION OF TWITTER USERS

This section considers the language distribution of investors who linked their Twitter handle by April 2021. Figure 10 shows the top 10 languages used by investors in the market, where we estimate their languages using a language classifier [21] for all tweets of each investor we collected beyond April 2021. It shows that about 60% of investors with Twitter accounts are English speakers. Interestingly, Turkish comprises about 15% and ranks as the second largest language group in our dataset. It may reflect the high inflation in Turkey and the consequent accumulated interest in cryptocurrency investment in the country [24].

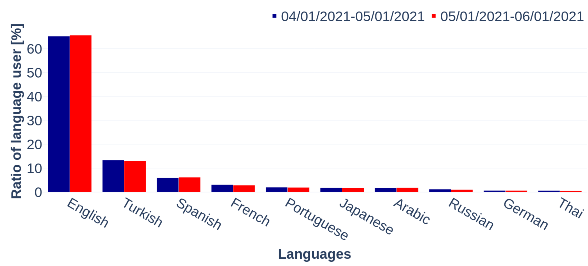

Figure 10: The language distribution of investors with Twitter accounts.

We manually confirmed the investors using languages other than English also post tweets with five keywords we consider in this study. This is a reasonable result since these keywords are popular in the global cryptocurrency investment community. Thus, although the keywords we consider in this study are of English origin, contributions from other language users are also well represented.

B CORRELATION BETWEEN THE RETURN OF MAJOR CRYPTOCURRENCIES

A possible concern for our approach to estimate investors' positions is that Bitcoin price does not work well as a proxy of other major cryptocurrency prices. For this point, Hu et al. (2019) show that the price returns of cryptocurrencies are positively correlated with Bitcoin's return [20]. However, to make sure it is the case for the market we study in April 2021, we independently check the BTC price's correlation with other cryptocurrency prices.

We select the top 10 cryptocurrencies by their open interests in the market (i.e., the amount of futures contracts held by market participants denominated in USDT) in April 2021: Bitcoin (BTC), Ether (ETH), Binance Coin (BNB), Ripple (XRP), Cardano (ADA), Polkadot (DOT), Litecoin (LTC), Filecoin (FIL), Chainlink (LINK), and TRON (TRX) in descending order from the top to the last. Figure 11 shows the open interest ratio in April 2021, where each point in the figure represents the average open interest over the five consecutive days from the labeled date. It shows that Bitcoin alone accounts for 30% of the open interest in the market, but the top 10 cryptocurrencies cover about 70% of it. Hence, the correlation between Bitcoin and these cryptocurrencies is a good indicator of whether Bitcoin represent the market trend well

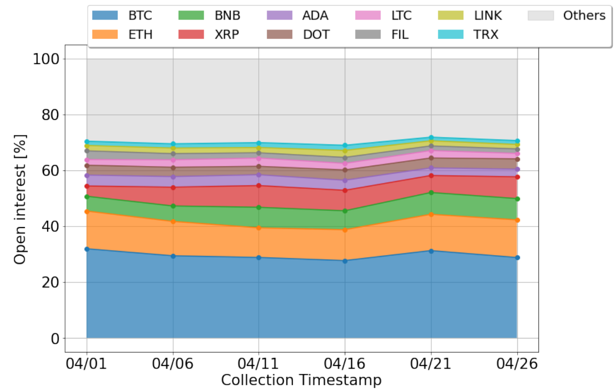

Figure 11: The ratio of open interest held by top 10 cryptocurrencies in April 2021.

We consider the correlation between the return of the 10 cryptocurrencies' daily average price in April 2021, where we calculate the daily average price of each cryptocurrency in a way robust to short-lived volatile price changes, following the prescription in Biais et al. (2022) [10], by calculating the average of median values over short time intervals (5 minutes). Table 9 summarizes the Pearson correlation coefficients.

Table 9: The Pearson correlation coefficients for the top 10 cryptocurrencies in open interest.

	BTC	ETH	BNB	XRP	ADA	DOT	LTC	FIL	LINK	TRX
BTC	1.00	0.78	0.63	0.74	0.86	0.74	0.74	0.60	0.75	0.58
ETH		1.00	0.47	0.53	0.79	0.75	0.71	0.48	0.79	0.45
BNB			1.00	0.49	0.64	0.41	0.43	0.33	0.43	0.38
XRP				1.00	0.68	0.54	0.75	0.28	0.62	0.45
ADA					1.00	0.71	0.72	0.44	0.80	0.57
DOT						1.00	0.71	0.48	0.73	0.67
LTC							1.00	0.45	0.79	0.48
FIL								1.00	0.43	0.49
LINK									1.00	0.49
TRX										1.00

It shows that Bitcoin is strongly correlated with other cryptocurrencies in April 2021. This result demonstrates that Bitcoin's price is a good proxy for the overall trend of cryptocurrency prices in the market.

C CDF ANALYSIS FOR FOLLOWERS

Figure 12 shows the cumulative distribution functions (CDF) of followers' Spearman's rank correlation coefficients in April 2021. The CDF plot for 4/3-4/10 clearly shows that all follower groups went long compared to average investors. As a result, the KS statistics other than *#HODL* followers (F1) exhibit the deviation from baseline distribution significant at the 5% level. This result indicates the bullish mind of followers at that time.

The distributions in 4/10-4/16 show followers' divergent reactions to the change in Bitcoin price trend. That is, whereas the followers of *#HODL* advocates (F1) went short, the follower of *dip*

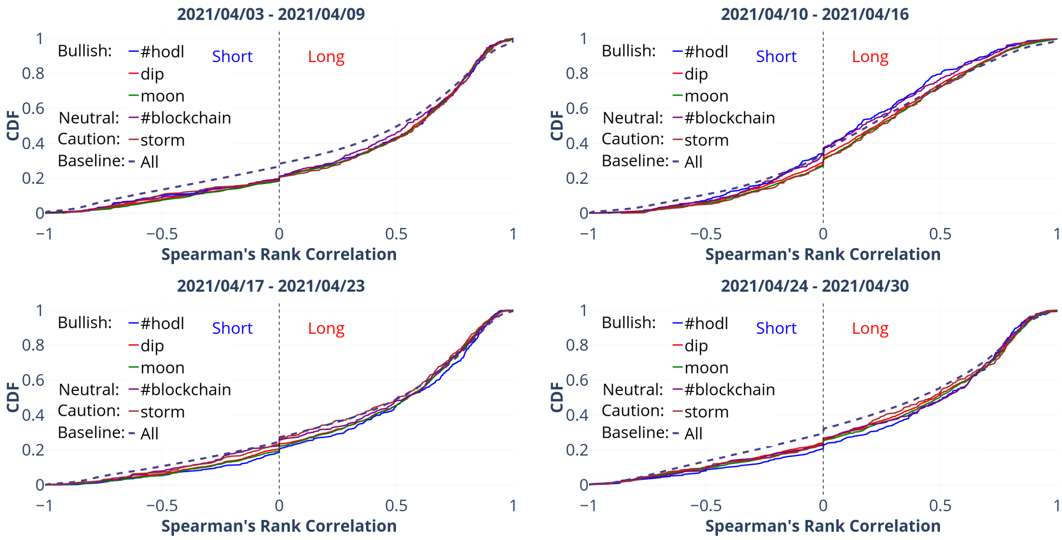

Figure 12: CDF plot of followers' Spearman's rank correlation coefficient in 4/3-4/9 (top-left), 4/10-4/16 (top-right), 4/17-4/23 (bottom-left), and 4/24-4/30 (bottom-right).

(F2) and *moon* (F3) continued to take long positions so that the deviation from the baseline is significant at the 1% level. The significance of the deviation of the followers of *#blockchain* (F4) and *storm* (F5) disappeared in the week. The deviation of *#HODL* followers (F1) from the recommended bullish positions on Twitter may be linked to the relatively smaller number of tweets with the hashtag than *dip* and *moon*.

In 4/17-4/23, *#HODL* followers (F1) re-entered long positions to the extent that their deviation from the baseline is significant at the 5% level as the followers of *dip* (F2) and *moon* (F3) advocates did. On the other hand, the followers of *#blockchain* (F4) and *storm* (F5) remained in positions whose deviation from the baseline is insignificant even at the 10% level.

In the final week of April 2021, 4/23-4/30, all follower groups went long compared to average investors. This implies the high sensitivity of the followers to the upward trends in Bitcoin price. However, the degree of sensitivity differs among the follower groups. Namely, the followers of bullish outlooks (F1-3) went long to the extent that the deviation from the baseline is significant at the 1% level. On the other hand, the deviations of *#blockchain* and *storm* followers (F4–5) remained the positions whose deviation are less significant (significant at 5% and 10% level, respectively) .

These results indicate followers' tendency to take positions consistent with the outlooks they see on Twitter.

D KOLMOGOROV-SMIRNOV TEST FOR ADVOCATES GROUPS

The critical value of the two-sided Kolmogorov-Smirnov (KS) test for two sample distributions $D(\alpha)$ is given by

$$D(\alpha) = C(\alpha)\sqrt{\frac{N_1 + N_2}{N_1 N_2}} \ ,$$

where $C(\alpha)$ is the coefficient for a significance level α, and N_1 and N_2 are sample sizes of tested distributions [18].

It shows that $D(\alpha) = C(\alpha)/\sqrt{N_2}$ is a good approximation when $N_1 \gg N_2$; the critical value $D(\alpha)$ is inversely proportional to the square root of N_2. Since the number of active investors is larger than the number of investors in our selected groups (A1-5 and F1-5), this approximation stands for our case, suggesting that the number of investors in each group determines the critical value $D(\alpha)$ for a significance level α.

This means that $D(\alpha)$ for each advocate group (A1-5) is almost the same throughout April 2021 because the number of investors in each advocates group is stable in the month. Therefore, the smaller number of investors in *dip* and *moon* advocates (A2 and A3) compared with corresponding follower groups (F2 and F3) cannot fully explain their insignificant KS-statistics in 4/10-4/16 and 4/17-4/23, given their KS-statistics in 4/3-9 and 4/24-4/30 that are significant at the 1% level. This indicates that the advocates adjusted their positions to the short side, although they touted bullish outlooks on Twitter at the same time (Figure 5 and 6).

Moreover, the KS-test for *moon* advocates in 4/10-4/16 will not reject the null hypothesis even if the number of investors is equal to #HODL followers (F1), where the number of investors is roughly 350 and corresponding $D(0.05) \simeq 0.073$, while fixing the KS-statistic (0.059). Also, given the general KS-statistic tendency to decrease as the number of samples increases, KS-test is unlikely to reject the null hypothesis for *dip* advocates in 4/10-4/16 and *moon* advocates in 4/17-4/23 even if their sample size is roughly the same as *#HODL* followers (F1). These results hint at the behavioral difference between advocate groups and their follower groups.