Memecoins and Herd behavior: Investment Prospects of Memeable Financial Assets

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Abstract

Due to the onset of the COVID-19 Pandemic and the subsequent government response, the economy behaved in peculiar ways. While the stock market and other asset classes fell due to the uncertainty of the market, most of them quickly bounced back, and many of them even made all time highs. One of the most worthy classes of assets were cryptocurrencies, including the ones market deemed to be "memecoins." Regarding the recent rise in prices of cryptocurrencies, research was conducted to determine whether these memecoins will be a good addition to a well-balanced portfolio using traditional financial metrics. Furthermore, it was determined whether any coordination efforts – especially through social media like twitter – did have an observable effect on the coordination of the prices.

The dataset used for the research was obtained via Twitter API and Coingecko, which was made available by the popular cryptocurrency app. The data offered sales information for meme coins and the . Through the research, I was able to find the effect of various characteristics – especially the herd behavior. – and their impact on the Sharpe ratios. Comparing the Sharpe ratios of the various cryptocurrencies, I was able to determine what kind of factors one must consider when determining the memecoins as an asset class. Finally, the sharpe ratios of the memecoins were compared with traditional assets like S&P 500. The findings of the study suggest that memecoins – at least in the case of those observed by the paper – allow a higher risk-adjusted expected return when added to a traditional portfolio that includes stocks.

Introduction

The recent COVID-19 pandemic and the subsequent monetary policies implemented by the government to curb the economic effects have incurred novel changes to the financial market. With the increased M2 supply and rise of social media, more people actively attempt to synchronize buying signals through both asynchronous and synchronous communication means online, attempting to “pump” or move the prices in their favor. Consequently, the financial market saw an increase in both volume and volatility of the prices.

In light of these recent events, there have been notable attempts to ascertain, to a precise degree, the efficacy of these coordinated attempts to “pump” the prices. One of the most noteworthy examples of the coordinate attempts has been the Gamestop short squeeze incident in the January of 2021. The users of the r/wallstreetbets subreddit on the popular online social platform Reddit has convinced a significant portion of its users to purchase the stocks en masse in an attempt to short squeeze the hedge fund firms that were placing bets against the stock going up. To be more specific, in an attempt to force hedge fund firms to buy back stocks to cover the losses, the redditors successfully were able to move the price of the stock 140% in a single market day. Consequently, for a period of several days, some of the hedge funds who were pursuing the shorting strategy were put in financially dire situations, often having to borrow, overcollatorize, or close the firm entirely.

However, the social Platform Reddit has not been the only place where investors were coordinating their market activities for self-interest. For example, Twitter has become the dominant platform to signal market buys and sells. In the case of the Gamestop incident, there were synchronous attempt to coordinate the signals on Twitter; therefore, despite what the cursory overview of the phenomenon might suggest, the coordination is not a top-down, unitary, and segregated event but one that is highly bottom-up, spontaneous, and decentralized. Consequently, when studying these phenomena, they must be interpreted as a multiplatform effort, one where its effects far exceeds its immediate boundaries of a single website.

Some scholars have pointed out the post-hoc fallacy of calling a “meme stock.” For example, Michele Costola et. al has argued that it might not be not sound to assume that some assets or stocks are predefined to be a “meme stock” as it assumes “memeness” to be an intrinsic feature. However, the “memeness” of a stock is a function of social media activity and not based on the price action, “memability,” or the volatility of the stock, even though they can definitely have an effect.

Another asset class that exhibits even more “memeness” is cryptocurrencies. In order to measure the “memability” of a certain coin, traditional methods of analyzing “herd behavior” might be applicable. If one were to assume that “memability” is an expression of a “herd behavior,” one should expect the cryptocurrency coins to measure higher in degrees of “herd behavior.” The following paper will explore the validity of this assumption.

Methodologies

To gauge the coordination of the community to attempt to manipulate the stock market, I utilized the Twitter API as a barometer of users attempting to signal pumps and dumps. This was done so because of the easily accessible data and the fact that it is the *de facto* platform for the community to coordinate market movement for both cryptocurrency and stocks.

In order to retrieve cryptocurrency data, I utilized the Coingecko API, which provides one of the most reliable and extensive datasets of cryptocurrencies. The Coingecko API allows for 50 requests per minute; accordingly, I created a simple Python retrieval script that implemented a time lag to gather market historical data for all the coins in my list for 6 months from January 1st to June 30th of 2021.

For sentiment analysis, I utilized the Twitter API. To put it succinctly, I gathered a list of popular "memecoins" and pulled data for each of them from January 1st to June 30th. This memecoin list was calibrated according to the Coingecko website: the ones that were tagged with the "memecoin" keyword. Subsequently, I attempted to draw sentimental data from Twitter using each of these coins as a keyword for these days. In order to do so, I applied for a Twitter developer account and created a "full archive search" environment. For the control data, I gathered complementary cryptocurrencies with less volatility – and by extension less susceptible to "pumps" – and also performed similar sentiment analysis. The exhaustive list of cryptocurrencies is shown in Fig. 1 and Fig. 2.

After the data has been gathered, cross sectional absolute standard deviation has been measured to determine the measure of return dispersion. It follows the following formula:

$$csad\,(a,\,b) \;=\; \sum_{i=1}^{N} |r(i) \;-\; r(m,\,t)|$$

After the return dispersion has been calculated, the aggregate collection of cryptocurrencies has been recalibrated as to correct the weight.

$$c \;= \frac{1}{N} \sum_{i=1}^{N} |r(i) \;-\; r(m,\,t)|$$

Furthermore, to test for herd behavior, the following equation proposed by Chang et. al measure has been used:

$$measure\ of\ herd\ behavior \;=\; x_1 r(m,t) \;+\; x_2|r(m,\,t)| \;+\; x_3 r^2(m,t)$$

Results:

All the value for the coins failed to yield a negative number, suggesting that herd behavior could not be measured.

The results of the price movements are reported below:

Date	Bitcoin Price	Ethereum Price	Binancecoin Price	Cardano Price
20210101	29022.4	738.617	37.3946	0.182071
20210108	39547.1	-1	43.3995	0.300543
20210115	39232.7	-1	41.7611	-1
20210122	30913.7	-1	-1	-1
20210129	33128.3	-1	-1	-1
20210205	36816.5	-1	-1	-1
20210212	47816	-1	-1	-1
20210219	51733.1	-1	-1	-1
20210226	46992.7	1468.86	235.368	1.07691
20210302	49787.3	1570.4	256.183	1.30285
20210309	52328.5	1837.53	240.616	1.12333
20210316	55805.3	1791.05	253.499	1.03136
20210323	54370.1	1686.89	256.949	1.10688
20210330	57634.9	1817.63	274.957	1.20096
20210406	58706.8	2097.8	367.458	1.21382
20210413	59911	2142.48	598.553	1.31979
20210420	55721.2	2168.03	503.648	1.19486
20210427	53978.8	2532.39	533.584	1.23465
20210503	56600.7	2953.3	622.588	1.32809
20210510	58213.9	3932.75	661.892	1.77403
20210517	46585.1	3602	563.879	2.28621
20210524	34977.5	2120.04	261.262	1.32882
20210531	35714.8	2395.85	325.574	1.57685
20210607	35834.5	2711.55	392.027	1.68063
20210614	39147.7	2517.77	365.248	1.56682
20210621	35787.1	2251.56	340.228	1.43467
20210628	34607.3	1973.93	289.225	1.34252

Fig. 3 The Price of Coins over 6 months Control

Date	Akita Inu	Dogecoin	Pepemon Pepeballs	Poocoin	Shiba Inu	Smooth Love Potion
20210101	-1	0.0047066	43.2954	-1	7.72951e-11	0.0189556
20210108	-1	0.00977633	42.2814	-1	-1	0.0165893
20210115	-1	0.00946723	33.0554	-1	1.27291e-10	0.0130166
20210122	-1	0.00816032	-1	-1	1.26589e-10	0.0162087
20210129	-1	0.0326426	-1	-1	1.37546e-10	-1
20210205	-1	0.054285	-1	-1	1.07928e-08	-1
20210212	-1	0.0697547	-1	-1	-1	-1
20210219	-1	0.0601862	-1	-1	-1	-1
20210226	-1	0.0502168	155.426	-1	5.88782e-09	0.0425075
20210302	2.07116e-08	0.0510206	133.693	-1	1.39378e-08	0.036778
20210309	2.05061e-08	0.0616843	216.101	-1	2.16292e-08	0.068719
20210316	4.42649e-08	0.056882	411.724	-1	8.74394e-08	0.0907246
20210323	1.68929e-08	0.0555863	327.503	-1	4.87377e-08	0.0656672
20210330	1.95518e-08	0.0548976	291.41	-1	6.50827e-08	0.0583705
20210406	1.89194e-08	0.0598154	222.58	-1	-1	0.0642551
20210413	3.52594e-08	0.0710244	193.717	-1	1.79763e-07	0.0479717
20210420	3.77899e-06	0.40941	146.425	2.97754	3.61931e-06	0.0399828
20210427	1.2191e-06	0.271832	141.133	3.926	1.18236e-06	0.0403329
20210503	1.19261e-06	0.378688	142.079	4.34656	1.66217e-06	0.332249
20210510	7.67104e-06	0.573136	190.17	5.45351	1.56906e-05	0.23108
20210517	7.11743e-06	0.515315	110.299	10.0198	1.79267e-05	0.212812
20210524	2.27209e-06	0.309233	59.0785	3.67566	8.19513e-06	0.0820124
20210531	2.03577e-06	0.301429	73.27	4.31959	7.85726e-06	0.137515
20210607	1.77164e-06	0.372499	76.8121	4.53937	8.53603e-06	0.131763
20210614	1.4485e-06	0.32504	56.447	4.18194	6.85178e-06	0.13946
20210621	1.26992e-06	0.282547	47.1013	3.26474	7.82966e-06	0.133259
20210628	9.24211e-07	0.261878	53.9025	2.93004	7.79398e-06	0.135016

Fig. 4. The Price of Coins over 6 months Meme

Discussion:

Strictly analyzing the measure of herd behavior, coupled with the cross sectional absolute standard deviation, it seems that cryptocurrencies that are perceived to be “memecoins” – following the assumption that herd behavior equals memeability – do not qualitatively behave differently than the regular cryptocurrency coins. Thus, according to this research, the data reports evidence that obfuscates the hypothesis.

While it is true that the methodology failed to detect the presence of herd behavior in cryptocurrency markets, this might be due to shortcomings of either the logic or the limitations of the research. First, herd behavior might not match one-to-one with memeability; in order to ascertain the memeability of the coins, an alternate metric specific to cryptocurrency might need to be devised. Second, the duration of the study at interest might have also contributed to the results. That is, even though the study measured the herd behavior over a course of 6 months, the memeabilty might make sense only within shorter timeframes.

This study design was largely a byproduct of the Twitter api. Unfortunately, Twitter has a 50 request limit per environment. Needing data for the entire 6 months, this was the only environment that was an option for me. One request equates to a call that gives me data for one coin’s sentimental data for one day. I needed sentimental data for about 50 coins (including both “memecoins” and the top 20 cryptocoins) for every day of those 6 months. This would come to around 9000 requests needed. Twitter’s API subscription plan for the “full archive search” environment would cost about $100 per 100 requests, with their most expensive plan costing $1899 for 2,500 requests per month. It would cost an unreasonable amount of money and time to gather data that requires 9000 requests. To shorten the amount of calls I need, I optimized my strategy for collecting data and decided to gather data for each coin on a weekly basis and shortened my list of “memecoins” and cryptocoins. Now, I only need 500 requests to gather all my data for all my coins for those six weeks without losing much utilizable data.

Unfortunately due to financial constraints, a more fine tuned study could not be conducted. This was especially problematic for sentiment analysis as the study failed to establish the connection between the coordinated tweets and price volatility.

Conclusion

The study suggests that memeability, as defined as a herd behavior, might not be detectable in a longer time frame. Future studies should be conducted in finer time scales to determine whether herd behavior can be detected in coordinated cryptocurrency pumps and dumps. Coupled with this fine tuning to the study, a time series of sentiment analysis can be used to determine if any correlation can be established between coordinated pumps and herd behavior.

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