Elon Musk, Memes and Cryptocurrency: An Empirical Analysis

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Abstract

This paper conducts an event study on high frequency Dogecoin price and trading volume data in an effort to test the Efficient Market Hypothesis. The events concerned are a sample of Elon Musk's tweets, varying in their information content and format, which occur between April 2019 and January 2022. This study makes the first attempt to isolate the financial effects of tweets present and absent of memes within the cryptocurrency market, finding abnormal returns of -9.43% and 11.41%, respectively. Various insights are combined to explain these observations. These include ideas on influence, the composition of Dogecoin's value and the role of investor decision making.

1. Introduction

Since its inception in 2006, Twitter has grown from a unique and novel microblogging service into a huge online platform boasting over 396 million users (Dean, 2022). It functions as a "digital town square" (Musk, 2022) where individuals and institutions access and share a variety of news, entertainment and education in short messages called 'tweets'. Although it is better described as an information network rather than a social network (Williams, 2013), this paper accepts that the exchange of information is a social interaction (Hepler, Chapel, 2022) and therefore explores, empirically, how different types of tweets affect the interactions between economic agents.

Coined by Richard Dawkins in 1976, he described a 'meme' as "a unit of cultural transmission". Through the evolution of the internet, it has become known much more widely as a comedic apparatus (Young, 2014) and is a key part of Dogecoin's identity, with its logo derived from a meme that went viral in 2010.

The Efficient Market Hypothesis (EMH) states that all public and private, past and present information is incorporated into market prices. This hypothesis is tested by analysing the Twitter activity of Elon Musk, considered the wealthiest person on the planet, and how it affects Dogecoin (DOGE), a cryptocurrency. While Musk is among several influencers to tweet about cryptocurrency markets, he is arguably one of the most influential. For example, in Appendix 1, a succession of 4 of his tweets appear to drive a 50% increase in Dogecoin's price within a one-hour period.

On 25th April 2022, Elon Musk's hostile takeover of Twitter was accepted by the board of directors. Valued at $44B, it is the largest deal in two decades to take a company private (Isaac, Hirsch, 2022) and speculations are rife as to the ramifications of this event. Following the announcement, Musk posted two comedic tweets concerning the problems he could solve after acquiring Coca-Cola (KO) and McDonald's (MCD), figures 1 and 2, respectively. As non-informative tweets, the EMH suggests that they will have no impact on the price of these stocks as there is simply no information to incorporate. The EMH suggests the same concerning Musk's Dogecoin-related tweets, though we have seen on multiple occasions, that this does not seem to be the case.

Figure 1 McDonalds, non-informative tweet

Figure 2 Coca-Cola, non-informative tweet

This study is therefore centred around an analysis which aims to empirically understand how Elon Musk's tweets can affect the Dogecoin market. To build on the existing literature, it will scrutinise the separate effects of non-informative and informative tweets, as well as those containing and not containing memes.

Arguably unlike fiat currencies, the value of Bitcoin and other cryptocurrencies is derived purely from supply and demand forces; they have no intrinsic value. Dogecoin is an even more peculiar asset. While Bitcoin aims to solve some of the issues inherent in the trust-based model of fiat (Farell, 2015), it is widely debated whether Dogecoin has any utility whatsoever (Hunt, 2021). Despite this, it still qualifies as a means of exchange and a cryptoasset (Young, 2018). Studying the drivers of its demand is therefore still worthwhile, especially as it seems to deviate from traditional schools of economic thought. For example, during the minute that Twitter announced their acceptance of Musk's bid, Adeyemi (2022) found highly significant abnormal returns (ARs) of 1.23% and further cumulative abnormal returns (CARs) of up to 4.62% lasting till 55 minutes after the event. It is worth noting that between then and at least the 60^{th} minute, returns were still statistically significant at the 10% significance level.

imilarly, this study found significant abnormal trading volumes and prices for at least 60 minutes following a tweet. Informative tweets were found to be the main drivers in price movements (up to 35x greater than non-informative tweets) though once the non-informative tweets were categorised by the presence or absence of memes, this paper found positive and negative returns following no-meme and meme-tweets, respectively, hence why their overall effect was closer towards 0. Finally, albeit a small diversion from this study's main research objectives, at the end of the Literature Review (Section 3), and later in the Discussion (Section 7), is a brief exploration into the market effects of making retail investors feel like "genuine stakeholders".

2. Background

Developed independently by Samuelson (1965) and Fama (1963, 1965), the Efficient Market Hypothesis (EMH) states that the value of assets within efficient markets constantly reflect all publicly available information. There are three forms of the EMH (weak, semi-strong and strong) and these vary in how strictly they hold to the hypothesis. This paper seriously examines only the semi-strong form, which states that all information announced to the public is incorporated into market prices without bias or delay, thus removing the possibility of abnormal returns for investors. This concept is illustrated in Figure 3 below.

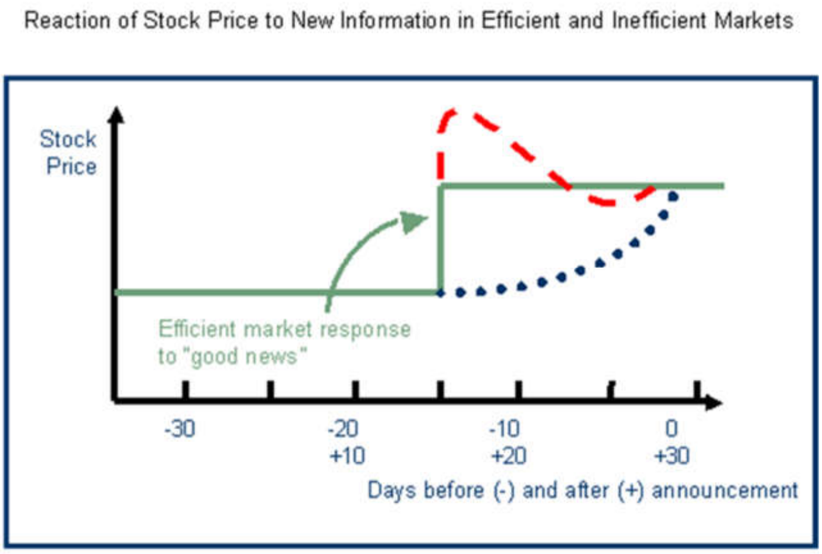

Figure 3 Different market responses to new information (graph sourced from: https://financeunleashed.blogspot.com/2007/12/market-efficiency-and-financial.html)

The straight, green line shows an efficient response to new information perceived as "good"; it occurs instantly and without bias. In contrast, the dotted, blue line shows a delayed response, and the dashed, red line shows an overreaction and consequent reversion, both of which allow enough time for investors to realise abnormal returns. The latter responses are regarded as inefficient, though interestingly, some argue that it is investors' efforts to exploit the market inefficiencies which make markets efficient. (Sezer, 2007) Perhaps this is why Shleifer (2000) considers the speed and correctness of market reactions, acknowledging that the quickness and precision with which investors take to the market is what constitutes its efficiency.

Following this idea, some researchers prefer to test the semi-strong form efficiency through an indirect approach. Instead of analysing market returns, they compare investors' gains against a broad-based market index in what are called performance evaluations studies. This paper opts for a direct approach. It uses event studies to show how Dogecoin's returns were affected by tweets (considered here as public announcements) at various points in time.

The recent literature concerning the relationship between Twitter and the cryptocurrency market suggests that the EMH does not hold. This could be due to the information overload faced by retail investors (Ante, 2022) who, as a consequence, find it difficult to meaningfully navigate it all. Compared to institutional investors, they have relatively high search costs and are less likely to consider all available information, instead focussing on information that draws their attention. (Barber and Odean, 2005) In the midst of this uncertainty, Barret and Maglio (1999) find that people lean towards human sources of information rather than non-human sources. Twitter facilitates this need by allowing users to subscribe to the online activity of others. In recent years, individuals with large followings have become known as 'influencers' for the effect they have on their followers. While Musk is far from the only person to tweet about cryptocurrencies, he is arguably, with over 90 million followers, one of the most influential ones. (Ante, 2022) Furthermore, although institutions are the largest investors in cryptocurrency industry (Phemex, 2022), Barber and Odean (2005) assert that they are less prone to attention-driven investing. This study does analyse Dogecoin trading volumes, although it cannot test this hypothesis without data on Google search activity or some other indicator of retail investor attention.

3. Literature Review

Since 1969, event studies have been used to test the Efficient Market Hypothesis (EMH). Initially, the research was focussed on how financial announcements, such as dividend reports and stock splits, can impact financial markets. However, with the rise of social media, economists have become increasingly concerned with the effect of non-financial announcements posted to online platforms. As an extension to the current literature, this paper explores the effect of Elon Musk's twitter activity on cryptocurrency markets, differentiating between different the types and formats of tweets. Therefore, this review will consider a variety of studies; some of which are directly relevant to the topic of interest, and others which are instead crucial towards a firm methodological understanding.

Fama, Fisher, Jensen and Roll (1969) pioneered the use of event studies to test the semi-strong form of the EMH. With the market model, they explored whether current prices adjusted rapidly to the announcement (or effection) of a stock split. They argued that, following a split, the real driving force behind any increased returns was not the split itself, but rather the information implicit in the split. Fama et al. reasoned the following: 1) stock splits are often accompanied or followed by dividend increases and 2) directors are reluctant to reduce their dividends (Lintner, 1956), thereby indicating their confidence in maintaining them and their higher earnings. Therefore, following the news of a split, investor uncertainty is reduced, and the company stock becomes more attractive, generating higher returns. Fama et al. concluded from their results that, once the effects of the dividend changes were controlled for, the effects of a stock split were no longer statistically significant. This suggests that the stock market does readily incorporate new information and that the EMH holds. Although my paper too uses an event study to test the EMH, there are some crucial differences. In place of the market model, I will be using the Mean Adjusted Returns (MAR) model. I will also use intraday price data on Dogecoin with respect to Tether4 (USDT) as I expect Elon Musk's Twitter activity to have more short-term effects. Also, while Fama et al. were investigating the persistence of abnormal returns following a stock split, this paper is instead concerned with whether a non-financial announcement on Twitter can result in any abnormal returns at all. Since the Fama et al. (1969) paper was released, it has been hugely influential within various disciplines, such as economics, finance and accounting (Binder, 1998), sparking a variety of research in these areas.

Binder (1998) researched the methodology surrounding event studies since 1969. He found that the market model (MM) is prone to statistical issues surrounding the variability and covariability of its estimators. Although researchers, over time, have provided solutions for these problems, implementing this model within the realm of cryptocurrencies remains difficult. The reason for this lies in that the MM requires a proxy for the market return. Within papers that consider the stock market, the S&P500 has been a popular choice. However, when considering cryptocurrency markets, it is less straightforward. There are no reliable proxies for the cryptocurrency markets (Hashemi Joo, Nishikawa, Dandapani, 2020) and while some indexes do exist, Ramos et al. (2021) found that the most popular ones applied a large weighting on Bitcoin. It follows that if these were to be used, the results of an event analysis on Bitcoin would be strongly correlated with the index, while analyses on smaller-cap[6] coins may falsely produce statistically insignificant results. Interestingly, Shanaev et al. (2019) decided to use the returns of Bitcoin itself as a proxy for market returns, acknowledging the methodological issues that may arise from this choice. I did consider constructing my own cryptocurrency market index but decided against it due to time constraints and limited data availability. As an alternative to the MM, Ramos et al. (2021) introduced the Constant Means Returns (CMR) model as it doesn't rely on a market index. Instead, it uses the average return of the cryptocurrency during an estimation window as a benchmark for its normal returns. While the CMR model is not as powerful as the MM, Brown and Warner (1985) did find that they yielded similar results.

With the rise of the internet, economists and researchers have been increasingly concerned with its influence on financial markets. One study by Tetlock (2007) explored the impact on stock markets of a popular Wall Street Journal column, an avenue through which industry professionals offer their views on stocks. After analysing the column's daily content and classifying it as either pessimistic, negative or weakly negative, he found that high levels of pessimism brought about downward pressure on market prices. He noted that this was only temporary, with negative returns following negative sentiment often reversing within the trading week. Ranco et al. (2015) instead explored the relationship between Twitter sentiment and abnormal returns in the stock market. They found a positive correlation between the polarity of Twitter sentiment and the following direction of cumulative average abnormal returns (CAAR). For example, during the U.S. earnings season, they found CAARs of 4.22% on the day of a positive tweet and -5.64% on the day of a negative tweet. Combined with the fact that these effects persisted in the market for up to 10 days, the results suggest inconsistency with the semi-strong form EMH. They found similar results during non-earning season periods. Although this dissertation explores how Elon Musk's Twitter activity affects cryptocurrency markets, the study performed by Ranco et al. (2015) inspired me to explore, as a secondary analysis, of the difference in impact within and without lockdowns. Unfortunately, I had to drop this idea, as only one of my events occurred before lockdowns were implemented; my results would have been heavily biased, and any inferences made would not be reliable.

Born, Myers and Clark (2017) tested whether the semi-strong form of the EMH holds when considering President-elect Trump's tweets and the stock market. Similar to Ranco et al. (2015), they found that a positive (negative) tweet from Trump induced positive (negative) abnormal returns on the day of the event. Assuming that institutional traders would use professional services, they used Google search activity and trading volume data to test the hypothesis that smaller, retail traders were the ones acting on Trump's tweets. They suggested that, because of this, the effects would only be temporary, which is supported by their findings that any observed CAARs were no longer statistically significant within 5 trading days.

Ante (2021) compiled six events whereby Elon Musk referred to either Bitcoin or Dogecoin on Twitter and assessed how they affected the cryptocurrencies' prices and trading volumes. To calculate abnormal returns, he used the CMR model due to uncertainty surrounding the applicability of a more complex model to cryptocurrency markets. Despite using a simpler model, Ante found that four of the six events resulted in statistically significant cumulative abnormal returns (CARs) while all events corresponded to abnormal levels of trading. Of these events, two particularly stood out. These were when Musk changed his Twitter bio to "#bitcoin," which resulted in a CAR of 18.99% within six hours, and when he tweeted "One word: doge", which resulted in a CAR of 17.31% within one hour. The author notes that the results collected for the other four events may have been affected more by other market events. In a revised version of the same study, Ante (2022) expands his sample to include 47 tweets relating to Bitcoin, Ethereum and Dogecoin, reporting that only Dogecoin-related tweets produced statistically significant returns. His assertion that these tweets at least partially represent Musk's personal sentiments is supported by an interview transcript where he claims his tweets on Dogecoin are "just meant to be jokes." (Zamesin, 2022) Exploring how mere "jokes" are able to so consistently and substantially move the Dogecoin market is a phenomenon worth studying in greater detail. Thus, to contribute to the existing literature, this paper groups tweets by their content or lack of information, and whether or not they contain memes. The hope is to understand precisely how mere "jokes" can drive abnormal returns within a market, a concept unfamiliar to the EMH and other traditional schools of thought.

Another major contribution from Ante (2022) is his description of the framework through which figures, such as Musk, can exert their influence on followers. Combining ideas and concepts from Scheer and Stern (1992), Gaski and Nevin (1985) and Dwyer at al. (1987), he explained that influencers use their resources of power, namely "their information, expertise, prestige, service and attractiveness", to appeal to their followers' satisfaction and trust. This insight inspired this paper's exploration, as a secondary analysis, of two specific events (Appendix 10). The first event is a poll, from Musk to his followers and the wider public, on whether Tesla (of which he is CEO) should accept Dogecoin as a method of payment. 3.9 million users responded to the poll, with 78.2% choosing 'Yes.' The second event, occurring eight months later, is an announcement that Tesla merchandise can now be bought with Dogecoin. Although it may not be obvious, these two events together could be very powerful. The importance of making investors feel involved as “genuine stakeholders” is widely documented. Some have argued that simply being given the opportunity to take part in a vote is just as important as the vote’s outcome. (BIS, 2016) It follows that many of the participants in Musk’s vote would have felt satisfied at the privilege and even more so at its outcome, allowing Musk to exert even more influence over them. This paper wishes to discover the extent to which this is true.

4. Data Collection

4.1. Tweet Collection

To compile this paper’s sample of Dogecoin-related tweets, a variety of methods were employed. After using the sample collected by Ante (2022) as a foundation, I used an algorithm developed by Twlets.com to download all of Musk’s tweets from his account @elonmusk (www.twitter.com/elonmusk). I then combed through these in Microsoft Excel to identify cryptocurrency-related tweets by searching for terms such as ‘doge’ and ‘crypto’. Knowing that Musk regularly posts memes, I then filtered for tweets which contained media and scanned them for cryptocurrency references. After this, I manually scrolled through his Twitter account to identify tweets that occurred after Ante’s study and weren’t picked up by Twlets.com. Finally, acknowledging these methods were susceptible to human error, a variety of reports and articles were consulted to confirm my sample’s completeness.

Tweets which were responses to other users’ tweets were then discounted. This ensured that Musk’s followers specifically were being addressed and that therefore only his influence on cryptocurrency markets would be observed. Furthermore, tweets posted within the same six-hour period were clustered under the first one to guard against overlaps in their estimation windows. Otherwise, an event included in another's estimation window would become a confounder and affect both the dependent and independent variables. This is a violation of the third assumption of event study methodology: "there are no confounding effects in the estimation window." (McWilliams and Siegel, 1997) Mc Williams and Siegel conclude that any following results would be biased and imprecise while inferences drawn from them would be problematic.

After this final selection, my sample was comprised of 40 events between April 2019 and January 2022, expanding on the existing literature and ready for statistical analysis.

4.2. *Tweet Classification*

Initially, to quantify the sentiment of Musk's tweets, the valence aware dictionary and sentiment reasoner (VADER), an open-source analysis tool "specifically attuned to sentiments expressed in social media" was used. (Singh, 2020) Using a regularly updated dictionary of social media terms, and more recently, emojis, it is commonly used to capture the polarity and intensity of emotions conveyed through text. Unfortunately, it was found to be ineffective within the context of this study for two reasons:

1) Elon Musk's tweets can be obscure in meaning and it is unable to ascertain implicit information, which according to Fama et al (1969), is the real driver of price movements following an event. For example, the tweet in Figure 4, below, received a total score of 0[1], indicating complete neutrality, whereas investors would be able to understand the implied, positive support.
2) Half of the tweets in the sample contain memes or a combination of memes and text, which again cannot be analysed accurately using VADER. Figure 5 shows another

tweet scored as perfectly neutral[2], despite the clear, positive support of DVADER results are available in Appendix 2.

Figure 4 Musk states his company's acceptance of Dogecoin as a method of payment

Figure 5 Musk tweets a meme where Dogecoin is depicted as taking over the global financial system

As an alternative, tweets could be classified qualitatively as either positive or negative. However, negative tweets constitute only 10% (4 tweets) of the sample. It follows that estimates generated from these would be less robust due to the bias involved. In the absence of a reliable, quantitative measure or a sufficiently large sample, this paper chooses not to separate events based on their sentiment.

Instead, the categories under which tweets are placed are: meme or no meme and informative or non-informative. These were also classified without the use of an analysis tool. The first two categories were simply identified by the presence or absence of a meme, respectively. The second two were slightly more complicated; this study defines an informative tweet as one which contains some constructive information towards the current and/or future value of Dogecoin. Although this may deviate from commonly accepted concepts of financial information, Dogecoin, too, is an asset which deviates from traditional schools of thought. For the sample of informative tweets and their justifications, see Appendix 4.

While the informative category is comprised of only 4 tweets (10%), this study persists in its consideration and accepts the potential bias of any results. The reason for this is that they are an extension to the current literature and will still allow for meaningful conclusions to be drawn. On the other hand, the differing effects of Elon Musk's negative and positive tweets have already been studied rigorously by Ante (2022).

Financial Data Collection

Financial data is obtained from FirstRate Data[1]. With data aggregated from 19 exchanges[2], they provide minute-by-minute closing prices and trading volumes for 180 minutes before each event until 60 minutes after. The reference asset used is Tether dollar (USDT), a blockchain-based cryptocurrency whose value is pegged to the US dollar. (Frankenfield, 2022)

The minutely Dogecoin returns, $R_{i,t}$, for each event *i* during a given period *t* are calculated by taking the first differences of logged closing prices:

$$R_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}) \qquad (1)$$

Where $P_{i,t}$ and $P_{i,t-1}$ denote the the closing price for event *i* at minute *t* and the closing price for event *i* during the previous minute, respectively. The events studied are those compiled using the methods outlined in the previous section.

Despite its lack of accessibility, minute-by-minute data is used in place of lower frequency data, such as daily, for two reasons. The first is to minimise the risk of confounding events interfering with the effects of each event (Marshall, Nguyen, Visaltanachoti, 2017); this paper can now analyse the separate effects of events occurring on the same day while avoiding spurious issues. (Kenton, 2021) Furthermore, due to the speed with which events can be incorporated into an asset's price, as documented by Wongswon (2005), these effects could remain unobserved when using lower frequency data. Finally, various studies, including Brown and Warner (1980) and Peterson (1989) stress the importance of obtaining the most precise times of events in order to maximise the power of any ensuing tests.

Trading volumes measured in USDT, also obtained from FirstRate Data, are transformed logarithmically in accordance with the existing literature (Ante, 2022):

$$\log(x_{i,t} + 1) \qquad (2)$$

Where *x* is the volume traded in event *i* at time *t*.

5. Methodology

5.1. Event Study Construction

The event windows for this paper's event studies are defined below in Figure 6; it shows the key points within the period over which the event occurs.

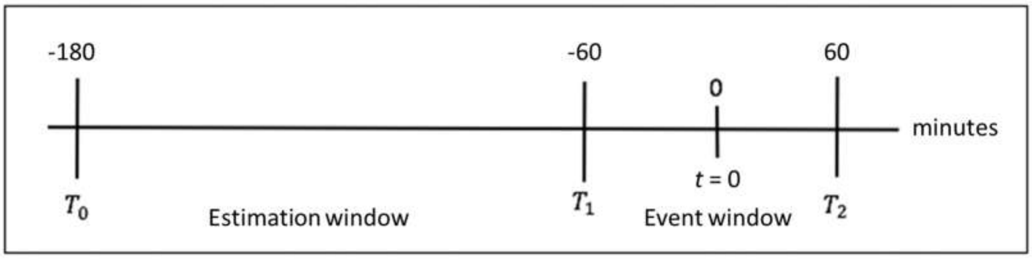

Figure 6 Event study timeline

t = 0 represents the minute in which the event occurs while T_1 and T_2 denote the first and last days of the event window, respectively. McWilliams and Siegel (1997) assert that the length of the event window and its justification are of critical importance to event studies. This paper opts for relatively short event windows spanning from 60 minutes before till 60 minutes after each event. The reason for this is that this paper's primary aim is to discover whether non-informative events can impact the price of Dogecoin at all. While Ryngaert & Netter (1990) demonstrated that an event's significant effects are likely to be captured within short windows, the speed with which these effects are incorporated is of secondary importance to this paper. Thus, long event windows are not necessary.

Similarly, at a length of 120 minutes, the estimation windows used in this study are also relatively short. Although longer estimation windows are perceived as more precise, windows which starter sooner before the event window are less prone to capture traits which are no longer characteristic of the asset. (Krivin et al., 2003) Moreover, McWilliams and Siegel (1997) acknowledge that increases in length present a greater difficulty when controlling for confounding events

5.2. <u>Sample Selection</u>

The steps outlined in the section, *Tweet Collection*, were followed to arrive at a sample of 40 Dogecoin-related tweets. The following table shows how these events were distributed through categories based on their information content.

Table 1 Table showing distribution of tweets through two categories based on their information content.

Content	Event Count
Informative	4
Non-informative	36

Tweets considered to be non-informative were further partitioned in Table 2 to analyse the separate effects of their format (whether they contain a meme or not) on the market. Informative tweets were excluded here because all tweets containing memes were found to be non-informative; this paper did not want to contaminate the effect of tweets containing no memes with the effect of informative tweets.

Table 2 Table showing non-informative tweets further categorised by their content or lack of a meme

Format	Event Count
Meme	20
No meme	16

The full sample of tweets, along with their respective categories and links can be found in Appendix 7.

5.3. Expected and Abnormal Return Calculations

Various models, including the market model (MM), market-adjusted model (MAM) and the mean-adjusted model (CPMAM), can be used to estimate an asset's abnormal returns. All three involve some calculation of the asset's expected return under normal conditions, which is then subtracted from returns at desired points during the event window.

According to the thinking outlined in the literature review, this paper uses the CPMAM. This model does not control for wider market returns and uses only the mean return during the estimation window to estimate expected returns. Although, computationally, it is the simplest model, Brown and Warner (1980) assert that, when there is no clustering, it can compare favourably to more complex models. Furthermore, Marshall, Nguyen and Visaltanachoti (2017) conclude from their research that it generates well-specified and robust results. Mean-adjusted expected returns are thus obtained via the following:

$$ER_{i,t} = \overline{R_{i,t}} + e_{i,t} \qquad (3)$$

where $ER_{i,t}$ is the expected return during event *i* at time *t*, $\overline{R_{i,t}}$ is the mean of absolute returns during the estimation window of the same event. $e_{i,t}$ denotes the error term. Abnormal returns are then obtained by subtracting the expected returns from returns at points of interest during the event window:

$$AR_{i,t} = R_{i,t} - ER_{i,t} \qquad (4)$$

where $AR_{i,t}$ and $R_{i,t}$ are the abnormal and observed returns, respectively, during event *i* at time *t*. The abnormal returns for the events in each group are aggregated together to produce average abnormal returns (AARs):

$$AAR_{i,t} = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \qquad (5)$$

where *N* denotes the number of events within the group.

Similarly, cumulative average abnormal returns (CAARs) can be constructed for various windows of interest via the following:

$$CAAR_{i,t} = \sum_{i=t_1}^{t_2} AAR_{i,t} \qquad (6)$$

where t_1 is the first minute of the chosen window and t_2 is the last.

5.4. *Significance tests – Crude Dependence Adjustment and Adjusted Boehmer, Musumeci and Poulson*

Pioneered by Brown and Warner (1980), the construction of the Crude Adjustment Test makes it very suited towards testing for the significance of AARs and CAARs. Its value lies in that it uses the variance of the *averages* of abnormal returns during the estimation window, thereby accounting for the unequal variances across observations and allowing its application to cross-sectional data. However, this test relies heavily on the assumption that returns follow a normal distribution. (Brown and Warner, 1985) The Jarque-Bera statistics in Appendix 3 show that this study's data frequently departs from normality. Although Amsden (2019) notes that this is not always cause for concern, there is still a risk that significance tests will become misspecified as a result. To avoid this, this paper makes use of Kolari and Pynnonen's (2010) Adjusted Boehmer, Musumeci, and Poulson (ADJ-BMP) test, which was developed to counter the some of the original BMP test's shortcomings. Still unperturbed by event-induced variance, the ADJ-BMP test now also retains its effectiveness when applied to cross-sectional data, matched in robustness and power only by the Corrado and Zivney (1992) nonparametric rank test. (Kolari and Pynnonen, 2010)

5.5. *Significance test for Average Abnormal Returns*

Following the methods outlined by Xu (2018) and Kolari and Pynnonen (2010), this paper begins its significance tests by standardising the abnormal returns in the event window by using their standard deviation in the estimation window:

$$SAR_{i,t} = \frac{AR_{i,t}}{\sigma_{AR_i}} \qquad (7)$$

and taking the averages of these for the events within each sample (category):

$$ASAR_t = \frac{1}{N}\sum_{i=1}^{N} SAR_{i,t} \qquad (8)$$

Before calculating the t-statistic, the average cross-correlation, $\bar{r}$, and standard deviation, S, of abnormal returns in the estimation window must be obtained. I used the Data Analysis tool in excel to compute $\bar{r}$, while S was derived as an average of standard deviations during the estimation windows of each event within a sample:

$$S = \sqrt{S^2} \qquad (9)$$

where:

$$S^2 = \frac{1}{N-1}\sum_{i=1}^{N}(SAR_{i,t} - AAR_t \qquad (10)$$

Finally, the t-statistic can be generated as:

$$t_{AAR} = \frac{ASAR_t\sqrt{N}}{S} * \sqrt{\frac{1+\bar{r}}{1+(N-1)\bar{r}}} \qquad (11)$$

5.6. *Significance test for Cumulative Average Abnormal Returns*

In accordance with Kolari and Pynnonen (2010), the average standardized abnormal return, $ASAR_t$, in equation (11) can be replaced with the average standardized cumulative abnormal returns $ASCAR_t$ to provide the t-statistic for cumulative average abnormal returns, t_{CAAR}.

First, the standardized cumulative abnormal returns are calculated:

$$SCAR_{i,t} = \sum_{i=t_1}^{t_2} SAR_{i,t} \qquad (12)$$

and then averaged:

$$ASCAR_t = \frac{1}{N}\sum_{i=1}^{N} SCAR_{i,t} \quad (13)$$

before substituted into equation (11) to generate:

$$t_{CAAR} = \frac{ASCAR_t\sqrt{N}}{S} * \sqrt{\frac{1+\bar{r}}{1+(N-1)\bar{r}}} \qquad (14)$$

These t-statistics, which are displayed in all results tables, were transformed into p-values using Excel formulae. Statistical significance at the 1%, 5% and 10% significance levels are denoted by *, ** and ***, respectively.

5.7. Expected and Abnormal Trading Volume Calculations

Abnormal trading volumes (AVs), average abnormal trading volumes (AAVs) and cumulative average abnormal trading volumes (CAAVs) are calculated in the same way as ARs, AARs and CAARs. The only difference lies is in the first step, the log transformation of the raw data. Instead of $\ln(x)$, logged trading volumes ae obtained using: $\ln(x + 1)$ to account for periods where the trading volume is 0. This is consistent with previous studies that deal with abnormal trading volumes in cryptocurrency and other financial markets (Ante, 2022; Cready and Ramanan, 1991).

To avoid needless repetition, the full calculations for AVs, AAVs, and CAAVs can be found in Appendix 5.

5.8. Significance Tests for AAVs and CAAVs

Following Cheung and Roca (2013), the significance of AAVs and CAAVs are also tested for using the ADJ-BMP test statistic outlined in the previous sections. Again, for conciseness, the full calculations can be found in Appendix 5.

5.9. Hypotheses Tests

To discover whether the semi-strong (and weak) form(s) of the EMH is (are) relevant within cryptocurrency markets, this paper uses the following null (H_0) and alternative (H_1) hypotheses:

$$H_0: AAR = 0$$

$$H_1: AAR \neq 0$$

If the null hypothesis is rejected, the presence of statistically significant AARs is confirmed and it can be argued that Elon Musk is able to use Twitter to affect Dogecoin's price.

CAARs are then tested to confirm the amount of time for which these effects persist in the market.

$$H_0: CAAR = 0$$

$$H_1: CAAR \neq 0$$

Had this study been able to access sufficiently high frequency data on Google search activity, Barber and Odean's (2005) attention-based hypothesis could have been tested, assuming that retail investors use Google for market research whereas institutional investors use services such as Bloomberg Terminals. Instead, and similar to above, Dogecoin's AAVs and CAAVs will be tested to explore whether, and for how long, Musk's tweets influence abnormal trading in the market.

$$H_0: AAV = 0$$

$$H_1: AAV \neq 0$$

$$H_0: CAAV = 0$$

$$H_1: CAAV \neq 0$$

5.10. Additional Research Questions

This study also aims to explore the following questions:

1) *How does the (information) content of a tweet affect its effect on the market?*
2) *How does the format of tweet (whether or not it contains a meme) affect its effect on the market?*

Dogecoin was created to make fun of other modern forms of money and, consequently, is expected by this paper to behave most illogically and contrary to current theory. Thus, this paper expects non-informative tweets and those containing memes to affect the market to a greater extent than informative tweets and those absent of memes, respectively.

For clarification, tweets containing memes are hereafter referred to as 'meme-tweets', while tweets which don't contain memes are referred to as 'no-meme-tweets'.

6. Results

6.1. AAR - Informative and Non-informative Tweets

Table 3 Average Abnormal Returns for Dogecoin tweets based on their content (informative or non-informative)

AAR: Content of tweet	Informative (n=4)		Non-informative (n=36)	
	(1)		(2)	
Time (t)	AAR	t-stat	AAR	t-stat
15	23.64%	-0.94	3.13%	-8.2*
14	-24.17%	-2.14**	-0.88%	-9.85*
13	23.93%	1	-0.43%	-0.68
12	-0.44%	-1.88***	-1.99%	11.72*
11	0.15%	0.84	2.22%	-5.32*
10	-23.13%	2.36**	-2.68%	-0.7
9	23.56%	-0.82	0.21%	11.17*
8	-0.60%	-2.49**	6.27%	-0.63
7	-23.40%	1.17	-8.77%	6.85*
6	-0.76%	-2.88*	4.86%	-0.43
5	22.41%	-5.72*	4.20%	0.35
4	-23.39%	-0.15	-3.29%	-13.22*
3	-0.20%	-1.68***	1.44%	2.95*
2	24.06%	-4.38*	-4.88%	6.27*
1	-0.87%	2**	4.00%	2.32**
0	24.29%	1.82***	-0.17%	5.58*
-1	-45.90%	18.87*	-0.46%	59.61*
-2	0.25%	1.59	-5.11%	-7.34*
-3	-0.12%	0.19	7.53%	5.07*
-4	23.56%	1.8***	0.20%	-1.09
-5	-23.73%	-3.03*	-2.73%	-1

, ** and * denote significance at the 10%, 5% and 1% significance levels, respectively*

Table 3 displays the Average Abnormal Returns (AARs) for those of Elon Musk's tweets which are informative in Column (1) and those which are not in Column (2). The sample is split highly unequally between the two categories, with 4 tweets (*10%*) in the first and 36 (*90%*) in the second. The left-hand-side column shows a portion of each event's timeline (from 5 minutes before until 15 minutes after the event, with the event occurring at $t = 0$). For the informative tweets in this sample, there is an abnormal return of *24.29%* within the minute of the event, while non-informative tweets produce an abnormal return of *-0.17%* on average. It is worth noting that these two values are not meaningful to this study by themselves. This is because the result for non-informative tweets, though significant at the 1% significance level, is very small in magnitude, while the result for informative tweets, though very large in magnitude, is only significant at the 10% significance level. These must therefore be analysed alongside more data to make any reliable inferences.

Looking at the rest of the table, a greater-than-half proportion (*55%)* of the AARs are statistically significant at the 1% and 5% significance levels. This constitutes strong evidence to reject the null hypothesis that Elon Musk's tweets do not generate abnormal returns. Interestingly, the returns here for non-informative tweets are much smaller in magnitude than those for informative tweets. This conforms, to some extent, to traditional forms of economic thought; investors heed more closely communications they perceive as informative than those which they don't. Because the statistically significant AARs for this sample are distributed throughout this table, it is not immediately clear for how long they persist in the market. This can be explored by considering the CAARs in Table 4.

6.2. CAAR - Informative and Non-informative Tweets

Table 4: Cumulative Average Abnormal Returns for Dogecoin tweets based on their content (informative or non-informative)

CAAR: Content of tweet	Informative (n=4)		Non-informative (n=36)	
	(1)		(2)	
Event Window	CAAR	t-stat	CAAR	t-stat
(60, 0)	43.19%	-6.86*	1.15%	11.21*
(45, 0)	20.13%	-12.47*	1.30%	-7.92*
(30, 0)	21.66%	-12.54*	-1.25%	-7.47*
(15, 0)	45.09%	-13.89*	3.24%	8.18*
(10, 0)	21.98%	-10.77*	1.19%	20.51*
(9, 0)	45.10%	-13.13*	3.86%	21.21*
(8, 0)	21.54%	-12.31*	3.65%	10.04*
(7, 0)	22.14%	-9.82*	-2.62%	10.67*
(6, 0)	45.54%	-10.99*	6.16%	3.82*
(5, 0)	46.30%	-8.11*	1.30%	4.25*
(4, 0)	23.89%	-2.4**	-2.91%	3.89*
(3, 0)	47.28%	-2.25**	0.38%	17.12*
(2, 0)	47.48%	-0.56	-1.05%	14.17*
(1, 0)	23.42%	3.82*	3.83%	7.9*
(0, 0)	24.29%	1.82***	-0.17%	5.58*
(-1, -15)	-22.57%	17.14*	-3.51%	46.96*

, ** and * denote significance at the 1%, 5% and 10% significance levels, respectively*

Firstly, we see that in the 15 minutes before the event, there are highly significant cumulative returns for both informative and non-informative tweets. This suggests that the ensuing results were contaminated by preceding events and could therefore be a sign of insider trading, perhaps with the knowledge of an impending tweet being the information traded on. Alternatively, it could be a sign that Musk's tweets were, on average, were a reaction to abnormal returns in the market rather than a catalyst of abnormal returns.

Looking beyond the minute of the event, we find CAARs of *46.3%* within 5 minutes for informative tweets. Contrasted to *1.3%* for non-informative tweets, this reinforces the idea that Dogecoin investors are much more moved by what they perceive as valuable information that what they don't. The highest cumulative return for non-informative tweets of *6.16%* is found at the interval (6, 0) in Column 2 though the market gradually adjusts and by the end of the hour, (60, 0), the remaining CAAR is only *1.15%*. Despite this, nearly all (*94%*) of the returns in Table 2 are statistically significant, up until at least the 60^{th} minute following the event. A possible reason for this is that Musk's tweets are almost constantly reaching new people due to the millions of likes, retweets and comments they receive (all three of these interactions relay his tweets to other users at an exponential rate). However, this idea is countered by the fact that Musk's informative tweets are not his most widely shared. Rather, his more comical, non-informative tweets, especially those containing memes, garner the most attention. This group of tweets are explored under greater scrutiny below. In general, the findings in Table 3 and 4 are not supported by the semi-strong form of the EMH; they show Musk's tweets are able to consistently generate statistically significant abnormal returns within the market for at least one hour.

6.3. *AAV - Informative and Non-informative Tweets*

Table 5: Average Abnormal Trading Volumes for Dogecoin tweets based on their information content (informative or non-informative)

AAV: Content of tweet	Informative (n=4)		Non-informative (n=36)	
	(1)		(2)	
TIME (t)	AAV	t-stat	AAV	t-stat
15	-19.85%	-0.81	26.35%	0.66
14	106.34%	2.23**	-19.82%	-0.76
13	0.30%	-0.27	5.10%	0.04
12	16.89%	0.19	5.93%	0.23
11	-58.74%	-1.43	-6.01%	-0.20
10	-44.85%	-0.38	3.50%	0.05
9	126.14%	2.10**	-30.94%	-0.54
8	-65.03%	-1.2	5.37%	0.10
7	-38.95%	-0.58	-9.19%	-0.23
6	17.41%	-0.35	15.07%	0.11
5	157.62%	2.86*	-25.42%	-0.34
4	-85.54%	-0.82	10.57%	0.63
3	-32.67%	-1.04	52.00%	0.72
2	-56.94%	-0.91	-14.18%	-0.34
1	37.33%	0.19	-53.36%	-1.28
0	-0.36%	0.01	39.47%	1.02
-1	71.65%	2.81*	28.53%	1.13
-2	-55.07%	-1.37	0.53%	0.03
-3	37.64%	0.99	36.97%	0.68
-4	53.01%	0.84	-36.25%	-0.85
-5	-69.84%	-1.19	47.77%	1.23

, ** and * denote significance at the 1%, 5% and 10% significance levels, respectively*

In Table 5 above, Columns (1) and (2) show the average abnormal trading volumes (AAVs) for informative and non-informative tweets, respectively. We can see that during the minute of an informative tweet, there is no statistically significant abnormal trading activity despite the abnormal returns of 24.29% witnessed in Table 3. Interestingly, and by contrast, even though the abnormal returns during the minute of a non-informative tweet are near zero, trading volume still increases abnormally by 39.47%. This value is statistically insignificant and is therefore not a reaction to the event. Despite this, it could indicate some confusion felt by investors, with many buying and selling at the same time, resulting in an average return of only *-0.17*. At the 5th minute, trading volume following informative tweets surges by 157.62%, indicating the presence of many more traders in the market. Although this lagged reaction may be due to the lesser attention Musk's informative tweets receive, this paper cannot consider this theory empirically without data on retail investor attention.

CAAV - Informative and Non-informative Tweets

Table 6: Average Abnormal Trading Volumes for Dogecoin tweets based on their information content (informative or non-informative)

CAAV: Content of tweet	Informative (n=4)		Non-informative (n=36)	
	(1)		(2)	
Event Window	**CAAV**	**t-stat**	**CAAV**	**t-stat**
(60, 0)	**-190.97%**	-4.27*	**-96.19%**	-2.41**
(55, 0)	**-60.78%**	-2.27**	**-125.72%**	-3.14*
(50, 0)	**-121.73%**	-3.49*	**-87.47%**	-2.4**
(35, 0)	**-21.26%**	-1.55	**-62.12%**	-1.88***
(30, 0)	**-112.27%**	-3.51*	**-76.28%**	-1.65
(15, 0)	**59.12%**	-0.20	**4.44%**	-0.13
(10, 0)	**14.17%**	-0.11	**-7.11%**	-0.10
(9, 0)	**59.02%**	0.27	**-10.60%**	-0.15
(8, 0)	**-67.12%**	-1.83***	**20.33%**	0.40
(7, 0)	**-2.09%**	-0.63	**14.97%**	0.30
(6, 0)	**36.86%**	-0.05	**24.16%**	0.53
(5, 0)	**19.45%**	0.30	**9.08%**	0.42
(4, 0)	**-138.18%**	-2.56**	**34.51%**	0.75
(3, 0)	**-52.63%**	-1.74*	**23.94%**	0.12
(2, 0)	**-19.96%**	-0.70	**-28.06%**	-0.60
(1, 0)	**36.97%**	0.21	**-13.88%**	-0.26
(0, 0)	**-0.36%**	**0.01**	**39.47%**	1.02
(-1, -5)	**37.38%**	2.07**	**77.55%**	2.22**
(-1, -15)	**37.15%**	1.7***	**14.81%**	0.96

, ** and * denote significance at the 1%, 5% and 10% significance levels, respectively*

The cumulative average abnormal trading volumes (CAAVs) show that, for both categories, average trading volumes decrease by the end of the hour. Analysed alongside the positive cumulative returns in Table 4, this could be an indicator that investors are bearish and anticipate a fall in Dogecoin's price to come soon. (Nickolas, 2022) We can see that the decrease in trading volume is nearly twice as strong for informative tweets (-190.97% as opposed to -96.19% for non-informative tweets). This could be due to the higher CAARs for informative tweets (43.19% > 1.15%), potentially signalling greater overvaluation to investors and resulting in even more bearish sentiment. Whether or not this is true, these results confirm again that Musk is able to significantly affect the Dogecoin with his tweets, rendering the semi-strong form of the EMH obsolete. Furthermore, the abnormal returns in the period preceding the event provide further evidence that Musk's tweets are a reaction and not a cause of abnormal trading activity.

Despite the small CAARs following the event of a non-informative tweet, we have witnessed massive returns following Musk's comedic tweets in the past (Appendix 1). To better understand this, below, this paper splits the sample of non-informative tweets into categories of those containing memes and those without.

6.4. AARs – Tweets with and without Memes

Table 7: Average Abnormal Returns for Dogecoin tweets based on their format (with or without memes)

AAR: Format of tweet	Tweets which contain memes (n=20)		Tweets which do not contain memes (n=16)	
	(1)		(2)	
Time (t)	AAR	t-stat	AAR	t-stat
15	3.82%	-5.98*	2.27%	-4.14*
14	0.79%	2.49**	-2.97%	-14.28*
13	-0.57%	1.14	-0.26%	-1.92
12	-4.35%	0.51	0.95%	13.66*
11	4.12%	-2.06**	-0.15%	-4.44*
10	-4.37%	5.72*	-0.56%	-6.35*
9	4.35%	0.61	-4.97%	12.89*
8	0.81%	-1.46	13.09%	0.65
7	-5.18%	3.74*	-13.27%	4.68*
6	4.77%	-1.04	4.97%	0.49
5	5.59%	-1.34	2.48%	1.72
4	-5.56%	-9.42*	-0.45%	-6.89*
3	0.18%	7.78*	3.02%	-3.94*
2	-0.07%	2.63*	-10.90%	5.03*
1	5.30%	11.22*	2.38%	-8*
0	-9.43%	-6.58*	11.41%	13.07*
-1	4.88%	15.24*	-7.13%	57.3*
-2	-4.60%	-1.98**	-5.74%	-6.95*
-3	9.35%	5.11*	5.24%	1.2
-4	0.43%	-1.46	-0.09%	0.09
-5	-4.83%	-1.42	-0.09%	0.16

, ** and * denote significance at the 1%, 5% and 10% significance levels, respectively*

The above table shows the AARs for all non-informative tweets, further categorised by their format. In Column 1 are all the non-informative tweets which also contain memes, while Column 2 lists all those which do not contain memes (but may contain links to videos or other media). Tweets are much more evenly distributed across these categories, with 20 in the first and 16 in the second. Excluding informative tweets from this section of the analyses is advantageous as it allows this paper to isolate the effects of the presence or absence of a meme. Indeed, this paper found that before informative tweets were removed, the average effect of a not containing a meme were considerably larger. For example, in the minute of an event, contaminated average returns were 2.58% higher while cumulative returns at the end of the hour were 7.45% higher. These results can be found in Appendix 8.

In the event minute ($t = 0$), we see that tweets containing memes have a strong, negative and statistically significant effect on Dogecoin's price of -9.43%. Considering that a vast majority of these memes were humorous and positive in nature, it is surprising that, on average, they would have such a large, negative effect. Just as interesting, is that tweets absent of memes and information generate abnormal returns of 11.41% during the event minute. These two contrasting reactions explain the near-neutral returns for non-informative tweets at $t = 0$ (-*0.17%*) and more generally, their smaller magnitudes throughout the rest of the event window.

6.5. *CAARs – Tweets with and without Memes*

Table 8: Cumulative Average Abnormal Returns for Dogecoin tweets based on their format (with or without memes)

CAAR: Format of tweet	Tweets which contain memes (n=20)		Tweets which do not contain memes (n=16)	
	(1)		(2)	
Event Window	**CAAR**	**t-stat**	**CAAR**	**t-stat**
(60, 0)	-2.70%	-6.94*	5.96%	20.21*
(45, 0)	-4.69%	-13.86*	8.79%	3.79*
(30, 0)	-5.46%	-18.4*	4.02%	8.7*
(15, 0)	0.21%	7.93*	7.02%	2.24**
(10, 0)	-3.61%	11.84*	7.18%	13.36*
(9, 0)	0.75%	6.13*	7.75%	19.71*
(8, 0)	-3.60%	5.51*	12.72%	6.82*
(7, 0)	-4.41%	6.98*	-0.38%	6.17*
(6, 0)	0.76%	3.24*	12.90%	1.49
(5, 0)	-4.01%	4.28*	7.93%	1.00
(4, 0)	-9.59%	5.63*	5.45%	-0.72
(3, 0)	-4.03%	15.05*	5.90%	6.17*
(2, 0)	-4.20%	7.27*	2.89%	10.1*
(1, 0)	-4.13%	4.64*	13.78%	5.07*
(0, 0)	-9.43%	-6.58*	11.41%	13.07*
(-1, -15)	5.15%	14.74*	-14.34%	42.51*

, ** and * denote significance at the 1%, 5% and 10% significance levels, respectively*

In the 15 minutes preceding the event, we find statistically significant returns for both groups at the 1% significance level. It is unlikely that these are due to insider trading as they are opposite in polarity to returns during the event and further along in the window. Instead, these tweets could simply be a reaction to abnormal returns in the market.

Further to this, it is possible that the returns in the event window are also a reaction to abnormal returns prior to the event. This idea assumes that these non-informative tweets simply bring investors' attention to Dogecoin, prompting them to observe the asset's current and recent price history. Investors may then interpret any positive, abnormal returns before the event as sign of the coin's overvaluation and proceed to sell, resulting in negative returns. Similarly, they may interpret negative, abnormal returns in the pre-event period as the coin's undervaluation and proceed to buy, resulting in positive returns. If this were true, it would indicate that even the weak form of the Efficient Market Hypothesis is invalid here, as even historical prices can generate abnormal returns.

Throughout the rest of the hour, we find that the majority of cumulative returns in Column (1) and (2) are negative and positive, respectively. In the 60th minute, the total return is 5.96% following tweets without memes and -2.7% following tweets with memes. If the ideas in the above paragraph are incorrect, these results may signify that non-informative tweets containing memes are perceived negatively by the market, while non-informative tweets without memes are perceived as positive.

Consistent with the results displayed throughout this section, these provide strong evidence that the semi-strong form of the EMH does not hold in the Dogecoin market.

6.6. *AAVs – Tweets with and without Memes*

Table 9: Average Abnormal Trading Volumes for Dogecoin tweets based on their format (with or without memes)

AAV: Format of tweet	Tweets which contain memes (n=20)		Tweets which do not contain memes (n=16)	
	(1)		(2)	
TIME (t)	AAV	t-stat	AAV	t-stat
15	46.01%	0.52	1.78%	0.34
14	-1.94%	-0.05	-42.18%	-1.08
13	-2.59%	-0.09	14.71%	0.17
12	6.46%	0.09	5.28%	0.23
11	-5.35%	-0.21	-6.83%	-0.03
10	-3.29%	-0.15	11.97%	0.27
9	-44.40%	-0.29	-14.11%	-0.45
8	1.26%	-0.02	10.50%	0.17
7	-22.48%	-0.41	7.42%	0.17
6	46.33%	0.36	-24.00%	-0.28
5	-25.03%	-0.12	-25.91%	-0.36
4	7.00%	0.52	15.04%	0.31
3	64.44%	0.41	36.44%	0.58
2	-18.01%	-0.17	-9.38%	-0.30
1	-66.20%	-0.90	-37.30%	-0.80
0	18.45%	0.40	65.75%	1.05
-1	24.17%	0.35	33.99%	1.26
-2	38.96%	0.74	-47.51%	-0.89
-3	-29.38%	-0.35	119.91%	1.46
-4	-33.12%	-0.75	-40.17%	-0.35
-5	71.13%	1.05	18.57%	0.54

, ** and * denote significance at the 1%, 5% and 10% significance levels, respectively*

Table 8 shows the average abnormal trading volumes for tweets present and absent of memes during a 21 minute period around each event. While the movement of abnormal trading volumes is interesting to watch, they are all statistically insignificant and very little can be inferred from them alone. The section below deals with cumulative abnormal trading volumes throughout the event window.

6.7. CAAVs – Tweets with and without Memes

Table 10: Cumulative Average Abnormal Trading Volumes for Dogecoin tweets based on their format (with or without memes)

CAAV: Format of tweet	Tweets which contain memes (n=20)		Tweets which do not contain memes (n=16)	
	(1)		(2)	
Event Window	CAAV	t-stat	CAAV	t-stat
(60, 0)	-94.74%	-1.35	-98.00%	-1.96***
(55, 0)	-127.78%	-1.74***	-123.14%	-2.57**
(50, 0)	-152.82%	-2.26**	-5.78%	-0.81
(35, 0)	-99.75%	-1.7***	-15.09%	-0.72
(30, 0)	-125.13%	-1.54	-15.23%	-0.56
(15, 0)	0.65%	-0.14	9.18%	-0.01
(10, 0)	-41.93%	-0.40	36.42%	0.35
(9, 0)	-38.65%	-0.25	24.45%	0.09
(8, 0)	5.75%	0.04	38.55%	0.54
(7, 0)	4.49%	0.06	28.06%	0.37
(6, 0)	26.97%	0.48	20.64%	0.20
(5, 0)	-19.36%	0.12	44.64%	0.48
(4, 0)	5.67%	0.24	70.55%	0.84
(3, 0)	-1.32%	-0.28	55.51%	0.52
(2, 0)	-65.77%	-0.68	19.07%	-0.05
(1, 0)	-47.75%	-0.51	28.45%	0.25
(0, 0)	18.45%	0.40	65.75%	1.05
(-1, -5)	71.75%	1.05	84.79%	2.03**
(-1, -15)	-4.13%	0.07	38.48%	1.35

, ** and * denote significance at the 1%, 5% and 10% significance levels, respectively*

In the minute of the event, the abnormal trading volumes for no-meme-tweets rise more than three times as high than for meme-tweets ($65.75\% \approx 3 * 18.45\%$). In fact, their cumulative trading volumes are much higher throughout the event window. That being said, only very few results towards the end of the window are statistically significant, meaning that the majority cannot be considered as reactionary behaviour. Although this may seem rational, it is contrary to this paper's prediction that Dogecoin will behave irrationally.

By the end of the window, there is a decrease of nearly 100% for both categories. During the same period, there is a positive return of 5.96% for no-meme-tweets and -2.70% for meme-tweets. While this may be an indicator of bearish sentiment for the first group, it could also indicate investors' lack of interest in further selling following meme-tweets (Nickolas, 2022). Despite very few results being statistically significant, they show that for at least 55 minutes, even Musk's non-informative tweets are seen by investors as worthy of action.

7. Discussion

This study is conclusive in its findings that Elon Musk's Twitter activity can move the Dogecoin market. The results displayed put the semi-strong, and the weak form of the EMH under serious question. For at least 60 minutes, his informative, non-informative, meme- and no-meme-tweets induce significant abnormal trading volumes and prices.

In response to this paper's research questions, investors were found to be much more sensitive to Musk's informative tweets than his non-informative tweets. This was not anticipated. At the end of and at several points during the event window, cumulative returns were more than 35x higher for informative tweets. At a glance, this shows at least a partial consistency with what we already know about the EMH: the market does not adjust quickly following informative tweets and is affected to a much lesser extent by non-informative tweets. However, the aim of this study was to extend on the current literature, specifically by exploring the financial effects of 'non-information'. Stopping the analysis at the primary would therefore not suffice, and this paper's investigation was continued by further partitioning the sample of non-informative tweets.

Once this group was separated into tweets containing memes and those which didn't, the reason for their small financial effect became clearer. Generally, meme-tweets produced negative returns while no-meme-tweets produced positive returns, resulting in averages of smaller, absolute magnitudes. While the separate results here were still smaller than for informative tweets, they were much greater and more meaningful than those for non-informative tweets.

Additionally, we now know that, on average and despite both not containing any information, the market perceives meme-tweets negatively and no-meme-tweets positively.

The reason for this is not clear. It cannot be attributed to the ambiguous nature of Musk's meme-tweets because some of his no-meme-tweets are equally ambiguous. Furthermore, though one could argue that memes prevent investors from taking a tweet seriously, this does not explain why they produced *negative* returns. Perhaps these tweets have another role besides being a conduit of information… This paper presents the following idea:

> *For both groups, cumulative returns following the event are opposite in polarity to the returns in the period leading up to the event. Following a non-informative tweet, it is likely that investors immediately analyse Dogecoin's recent prices and speculate that negative ARs are a sign of undervaluation, while positive ARs are a sign of overvaluation. They then buy or sell accordingly.*

The logic behind this is that Dogecoin's value is derived mostly from the interaction between supply and demand forces. A history of these interactions may therefore be integral to investor decisions and profits, suggesting that the weak-form efficiency of the EMH does not hold.

Finally, this analysis concludes with a short discussion on Events 24 and 38 in Appendix 7. These are the two tweets referred to at the end of Section 3 which contain Musk's poll and his announcement of its outcome. The data, in Appendix 11, shows that in the minute of the poll, there was an abnormal return of 84.74%. By the end of the hour, cumulative returns had decreased slightly to 71.69%. During the minute of the announcement, Musk's announcement abnormal returns were much lower at -0.10%. By the end of the event's window, returns had decreased further to -3.80%. Although the first event's returns are consistent with the thoughts outlined earlier, the returns during the announcement tweet are not. This could be because Musk's poll suggested that Tesla would accept Dogecoin as payment for its vehicles. When he later announced that it would only be used for Tesla's merchandise (clothing, accessories, etc…), investors may have been heavily disappointed.

It is also worth noting that the poll was posted to Twitter during a period of high, negative abnormal returns (-91.52% and -94.91% in the 15 and 60 minutes before the event, respectively). It seems that Musk's tweet was able to reverse the direction of this volatility, producing mostly positive tweets in the period afterwards (with 84.72% in the minute following the event and a total of 71.69% at the end of the window).

8. Limitations

The impact of social media on cryptocurrency markets is a young area of study. As such, there are many ways in which this particular study can be taken further, allowing for more comprehensive, reliable and powerful inferences. The first is that the event window could be extended far beyond 120 minutes. This would allow for a better understanding of how long abnormal returns persist in the market. Also, Google search activity, or data on social media mentions (how many times a term/phrase is mentioned on social media) could complement this study to specifically discern retail investor reactions. One would have to take care with social media mentions, though, as there are many bots which simulate human behaviour through automated posts. (Simpson, 2021) In fact, Elon Musk is now re-considering his acquisition of Twitter due to fears that bots constitute more of Twitter's user base than expected (see Appendix 12).

More technically, some studies have found that nonparametric sign and rank tests are more effective than parametric tests in identifying abnormal performance. (Dutta 2014) This could be because nonparametric tests do not rely on the assumption that abnormal returns are normally distributed. They therefore remain unimpacted by outliers, which more commonly affect the results of parametric tests (Schipper and Smith, 1983). A more robust methodology may make use of both forms of significance testing, such as in Ante (2022).

Furthermore, due to its use of high frequency data, this event study may have been exposed to microstructure bias (Mashall et al., 2017): a bias generated by the technical mechanisms through which exchanges facilitate trading. Although this study needed high frequency data to capture abnormal effects with precision, future researchers could find a balance between the two, or better yet, develop methods to account for the bias.

Although a variety of methods were used, the collection of Dogecoin-related tweets was still prone to human error; some may not have been identified, especially those which were more obscure in their relevance. Also, a new definition of 'informative' was established within the context of this study, making any consequent classification of tweets a subjective matter. A better study may have gathered a panel of 'judges' or 'experts' to assess each one, reducing any human bias. Further, the use of a panel could have allowed this paper to focus its research on a smaller subset of unambiguous tweets and generate more powerful results.

Finally, the main focus of any future study should be to more intricately understand and explain any observed abnormal activity. Ways in which this could be done include analysing more cryptocurrencies; undertaking cross-sectional regressions; further partitioning samples and constructing a reliable and robust proxy for market returns.

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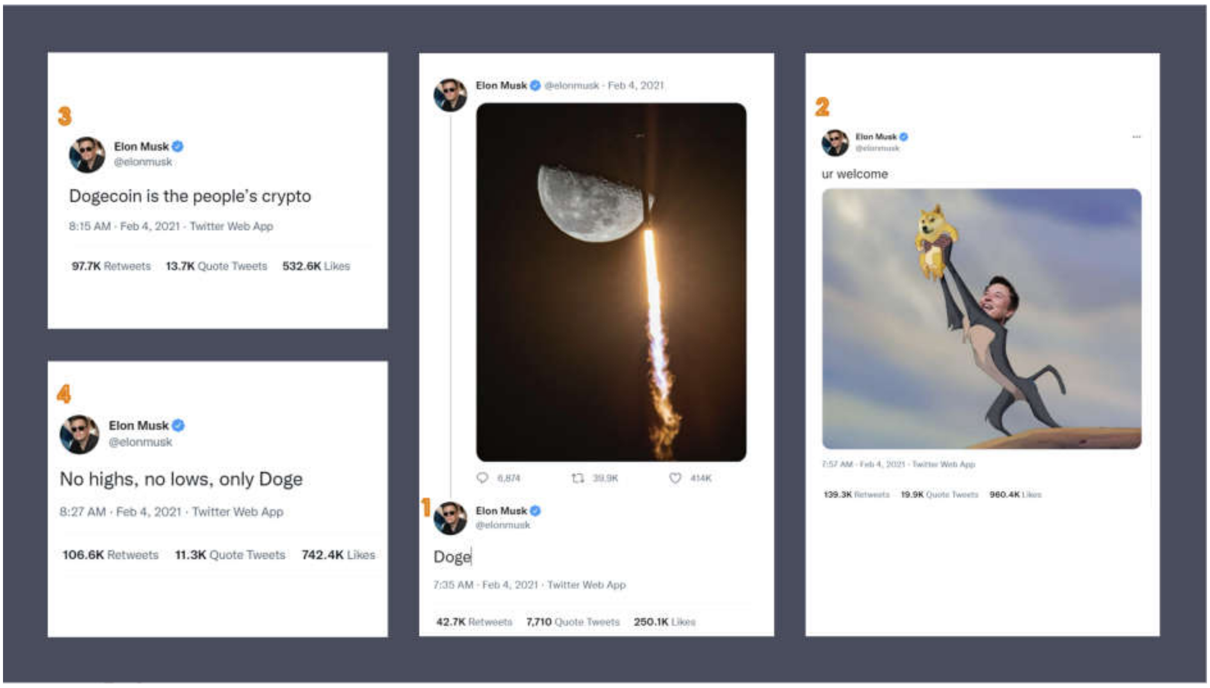
10. Appendix

Appendix 1)



Appendix 2)

```
In [1]: pip install VaderSentiment

Requirement already satisfied: VaderSentiment in c:\users\adeye\.julia\conda\3\lib\site-packages (3.3.2)Note: you may need to restart the kernel
to use updated packages.
Requirement already satisfied: requests in c:\users\adeye\.julia\conda\3\lib\site-packages (from VaderSentiment) (2.25.1)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in c:\users\adeye\.julia\conda\3\lib\site-packages (from requests->VaderSentiment) (1.26.6)
Requirement already satisfied: chardet<5,>=3.0.2 in c:\users\adeye\.julia\conda\3\lib\site-packages (from requests->VaderSentiment) (4.0.0)
Requirement already satisfied: idna<3,>=2.5 in c:\users\adeye\.julia\conda\3\lib\site-packages (from requests->VaderSentiment) (2.10)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\adeye\.julia\conda\3\lib\site-packages (from requests->VaderSentiment) (2021.10.8)

In [2]: from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer

In [8]: obj = SentimentIntensityAnalyzer()

In [12]: sentence = "Tesla merch buyable with Dogecoin"
         sentiment_dict = obj.polarity_scores(sentence)
         print(sentiment_dict)

{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}

In [13]: sentence = "It's inevitable"
         sentiment_dict = obj.polarity_scores(sentence)
         print(sentiment_dict)

{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
```

http://localhost:8888/notebooks/VADER%20analysis.ipynb

Appendix 3) Jarque Bera Statistics for Average Abnormal Returns and Average Abnormal Trading Volumes by Category

	AARs	AAVs
Non-informative	0.300	1.102
No-meme	0.895	2.249
Meme	2.241	1.867
Informative	1.411	1.314

Appendix 4)


Elon Musk
@elonmusk
If major Dogecoin holders sell most of their coins, it will get my full support. Too much concentration is the only real issue imo.
11:25 pm · 14 Feb 2021 · Twitter for iPhone
32.5K Retweets 5,875 Quote Tweets 315.7K Likes

Figure 6 States an issue currently faced by Dogecoin and an appropriate action


Elon Musk
@elonmusk
If you'd like to help develop Doge, please submit ideas on GitHub & reddit.com/r/dogecoin/ @dogecoin_devs
reddit.com
Dogecoin • r/dogecoin
The most amazing place on reddit! A subreddit for sharing, discussing, hoarding and wow'ing about Dogecoins. The ...
8:49 pm · 24 May 2021 · Twitter for iPhone
31.4K Retweets 3,105 Quote Tweets 187.1K Likes

Figure 7 Implies that the digital construction of Dogecoin will be improved, hence increasing its future value


Elon Musk
@elonmusk
Tesla merch buyable with Dogecoin
6:18 am · 14 Jan 2022 · Twitter for iPhone
50.8K Retweets 7,619 Quote Tweets 330.3K Likes

Figure 9 States his company's acceptance of Dogecoin as a method of payment, indicating an increase in its utility and, consequently, its value


Elon Musk
@elonmusk
Working with Doge devs to improve system transaction efficiency. Potentially promising.
11:45 pm · 13 May 2021 · Twitter for iPhone
81.4K Retweets 21K Quote Tweets 530.7K Likes

Figure 8 Implies that the digital construction of Dogecoin will be improved, hence increasing its future value

Appendix 5) Dogecoin Calculations – Trading Volumes

AVs, AAVs and CAAVs

$$EV_{i,t} = \overline{V_{i,t}} + e_{i,t}$$

$$\boldsymbol{AV_{i,t}} = V_{i,t} - EV_{i,t}$$

$$\boldsymbol{AAV_{i,t}} = \frac{1}{N}\sum_{i=1}^{N} AV_{i,t}$$

$$\boldsymbol{CAAV_{i,t}} = \sum_{i=t_1}^{t_2} AAV_{i,t}$$

t-statistic (using ADJ-BMP) for AAV

$$SAV_{i,t} = \frac{AV_{i,t}}{\sigma_{AV_i}}$$

$$ASAV_t = \frac{1}{N}\sum_{i=1}^{N} SAV_{i,t}$$

$$\boldsymbol{t_{AAV}} = \frac{ASAV_t\sqrt{N}}{S} * \sqrt{\frac{1+\bar{r}}{1+(N-1)\bar{r}}}$$

$$S = \sqrt{S^2} \qquad , \qquad S^2 = \tfrac{1}{N-1}\textstyle\sum_{i=1}^{N}(SAV_{i,t} - AAV_t$$

$\bar{r}$ = average cross-correlation, calculated using Excel's Data Analysis tool

t-statistic (using ADJ-BMP) for CAAV

$$SCAR_{i,t} = \sum_{i=t_1}^{t_2} SAR_{i,t}$$

$$ASCAR_t = \frac{1}{N}\sum_{i=1}^{N} SCAR_{i,t}$$

$$\boldsymbol{t_{CAAR}} = \frac{ASCAR_t\sqrt{N}}{S} * \sqrt{\frac{1+\bar{r}}{1+(N-1)\bar{r}}}$$

Use the same values as in the above section for S and $\bar{r}$

Appendix 7 Full sample of tweets

Event	Date and Time	Tweet	Content (information)	Format (Meme)	Sentiment	Coin	Link
1	18/07/20 01:58	It's inevitable [*picture of a "dogecoin standard" flooding the "global financial system"*]	Non-informative	Meme	Positive	DOGE	Link
2	20/12/20 09:30	One word: Doge	Non-informative	No-meme	Positive	DOGE	Link
3	25/12/20 16:47	Merry Christmas & happy holidays! [*picture of doge underwear*]	Non-informative	Meme	Positive	DOGE	Link
4	28/01/21 22:47	[*Picture of a "Dogue" magazine cover (as in Vogue)*]	Non-informative	Meme	Positive	DOGE	Link
5	04/02/21 08:35	Doge	Non-informative	No-meme	Positive	DOGE	Link
6	06/02/21 04:02	Much wow!	Non-informative	No-meme	Positive	DOGE	Link
7	07/02/21 07:41	So … it's finally come to this … [*even more edited photo from Disney's Lion King where Musk holds Gene Simmons, who holds Snoop Dogg, who holds a "baby Simba" doge*]	Non-informative	Meme	Positive	DOGE	Link
8	07/02/21 22:25	Who let the Doge out	Non-informative	No-meme	Positive	DOGE	Link
9	10/02/21 15:08	Bought some Dogecoin for lil X, so he can be a toddler hodler	Non-informative	No-meme	Positive	DOGE	Link
10	11/02/21 09:08	Frodo was the underdoge, All thought he would fail, Himself most of all. [*picture with pricing of different altcoin/BTC pairs that underperform against BTC; large ring with the Bitcoin logo and the phrase "One coin to rule them all"*]	Non-informative	Meme	Positive	DOGE	Link
11	14/02/21 23:25	If major Dogecoin holders sell most of their coins, it will get my full support. Too much concentration is the only real issue imo.	Informative	No-meme	Negative	DOGE	Link
12	21/02/21 21:27	Dojo 4 Doge	Non-informative	No-meme	Positive	DOGE	Link
13	24/02/21 13:00	Literally [*picture of a doge holding a doge flag on the moon*]	Non-informative	Meme	Positive	DOGE	Link
14	01/03/21 19:57	Doge meme shield (legendary item) [*picture showing a man in camouflage shielding Dogecoin. The picture features the words "Dogecoin vaule dropping", "memes" and "Dogecoin".*]	Non-informative	Meme	Positive	DOGE	Link
15	06/03/21 04:40	Doge spelled backwards is Egod	Non-informative	No-meme	Positive	DOGE	Link

16	13/03/21 23:40	Doge day afternoon	Non-informative	No-meme	Positive	DOGE	Link
17	01/04/21 11:25	SpaceX is going to put a literal Dogecoin on the literal moon	Non-informative	No-meme	Positive	DOGE	Link
18	09/04/21 08:32	[*picture comparing bacteria in nature to bacteria in the lab using two doges for illustration*]	Non-informative	Meme	Positive	DOGE	Link
19	15/04/21 05:33	Doge Barking at the Moon [*picture of a dog barking at the moon*]	Non-informative	Meme	Positive	DOGE	Link
20	15/04/21 18:01	Eyes emoji [*referencing his own tweet from July 2020 with a picture of a "dogecoin standard" flooding the "global financial system"*]	Non-informative	Meme	Positive	DOGE	Link
21	28/04/21 07:20	The Dogefather SNL May 8	Non-informative	No-meme	Positive	DOGE	Link
22	07/05/21 17:24	Cryptocurrency is promising, but please invest with caution! [*link to a video entitled "Elon Musk Says Dogecoin Could Be the Future of Cryptocurrency | TMZ" - an interview in which he comments on the future of cryptocurrency, speculation and risks for investors*]	Non-informative	No-meme	Positive	DOGE	Link
23	09/05/21 23:41	SpaceX launching satellite Doge-1 to the moon next year – Mission paid for in Doge – 1st crypto in space – 1st meme in space To the mooooonnn!! [*link to a video entitled "Dogecoin Song - To the Moon"*]	Non-informative	No-meme	Positive	DOGE	Link
24	11/05/21 09:13	Do you want Tesla to accept Doge? [*Twitter poll with "Yes" and "No" as choices*]	Non-informative	No-meme	Positive	DOGE	Link
25	13/05/21 23:45	Working with Doge devs to improve system transaction efficiency. Potentially promising.	Informative	No-meme	Positive	DOGE	Link
26	20/05/21 11:41	How much is that Doge in the window? [*picture showing the word "Cyberviking" and a dollar bill with a doge logo on a laptop*]	Non-informative	Meme	Positive	DOGE	Link
27	24/05/21 20:49	If you'd like to help develop Doge, please submit ideas on GitHub & http://reddit.com/r/dogecoin/ @dogecoin_devs	Informative	No-meme	Positive	DOGE	Link
28	02/06/21 08:05	Found this pic of me as a child [*picture of a doge in front of a computer stating "1980: I have to keep my passen hidden from the public or I'll be socially ostracized"*.]	Non-informative	Meme	Positive	DOGE	Link
29	25/06/21 12:03	My Shiba Inu will be named Floki	Non-informative	No-meme	Negative	DOGE	Link

30	01/07/21 09:43	Release the Doge! [*picture from the movie The Godfather with the caption "You come to me at runtime to tell me the code you are executing does not compile"*.]	Non-informative	Meme	Positive	DOGE	Link
31	02/07/21 14:20	[*picture of a male solely focusing on his laptop with a dogecoin price charts stating "Polytopia", while women are kissing around him.*]	Non-informative	Meme	Positive	DOGE	Link
32	25/07/21 05:23	[*picture from the movie Matrix where Neo asks: "What are you trying to tell me, that I can make a lot of money with Dogecoin?" A doge resembling Morpheus answers: "No, Neo. I'm trying to tell you that Dogecoin is money."*]	Non-informative	Meme	Positive	DOGE	Link
33	12/09/21 11:22	Floki has arrived [picture of Shiba Inu dog laying down on floor]	Non-informative	Meme	Negative	DOGE	Link
34	04/10/21 02:41	Floki Frunkpuppy [picture of Shiba Inu dog]	Non-informative	Meme	Negative	DOGE	Link
35	17/10/21 23:20	(_/) (•_•) / >🚀	Non-informative	Meme	Positive	DOGE	Link
36	31/10/21 18:20	Tuition is in Dogecoin & u get a discount if u have a dog	Non-informative	No-meme	Positive	DOGE	Link
37	25/12/21 21:53	Floki Santa [Shiba inu dog in a Santa costume]	Non-informative	Meme	Negative	DOGE	Link
38	14/01/22 06:18	Tesla merch buyable with Dogecoin	Informative	No-meme	Positive	DOGE	Link
39	25/01/22 12:30	I will eat a happy meal on tv if @McDonalds accepts Dogecoin	Non-informative	No-meme	Positive	DOGE	Link
40	02/04/19 21:16	Dogecoin rulz [*picture of a doge with the caption "*draws cigarette* Doge? I haven't heard that name in years"*]	Non-informative	Meme	Positive	DOGE	Link

Appendix 8) Table of AARs and CAARs for meme-tweets and no-meme-tweets contaminated by effects of informative tweets

AAR: Format of tweet	Tweets which contain memes (n=20)		Tweets which do not contain memes (n=20)	
	(1)		(2)	
Event Time (t)	AAR	t-stat	AAR	t-stat
15	3.82%	-5.98*	6.55%	-3.34*
14	0.79%	2.49**	-7.21%	-11.04*
13	-0.57%	1.14	4.58%	-0.93
12	-4.35%	0.51	0.67%	8.86*
11	4.12%	-2.06**	-0.09%	-2.78*
10	-4.37%	5.72*	-5.08%	-3.48*
9	4.35%	0.61	0.74%	8.78*
8	0.81%	-1.46	10.35%	-0.61
7	-5.18%	3.74*	-15.30%	3.82*
6	4.77%	-1.04	3.82%	-0.89
5	5.59%	-1.34	6.46%	-1.25
4	-5.56%	-9.42*	-5.04%	-4.94*
3	0.18%	7.78*	2.37%	-3.51*
2	-0.07%	2.63*	-3.91%	1.68
1	5.30%	11.22*	1.73%	-4.81*
0	-9.43%	-6.58*	13.99%	10.04*
-1	4.88%	15.24*	-14.88%	48.71*
-2	-4.60%	-1.98**	-4.55%	-4.24*
-3	9.35%	5.11*	4.17%	0.93
-4	0.43%	-1.46	4.64%	0.84
-5	-4.83%	-1.42	-4.82%	-1.19

CAAR: Format of tweet	Tweets which contain memes (n=20)		Tweets which do not contain memes (n=20)	
	(1)		(2)	
Event Time (t)	AAR	t-stat	AAR	t-stat
(60, 0)	-2.70%	-6.94*	13.41%	11.36*
(45, 0)	-4.69%	-13.86*	11.06%	-2.68*
(30, 0)	-5.46%	-18.4*	7.55%	0.76
(15, 0)	0.21%	7.93*	14.64%	-4.4*
(10, 0)	-3.61%	11.84*	10.14%	4.82*
(9, 0)	0.75%	6.13*	15.22%	8.3*
(8, 0)	-3.60%	5.51*	14.48%	-0.47
(7, 0)	-4.41%	6.98*	4.13%	0.14
(6, 0)	0.76%	3.24*	19.43%	-3.68*
(5, 0)	-4.01%	4.28*	15.60%	-2.79*
(4, 0)	-9.59%	5.63*	9.14%	-1.54
(3, 0)	-4.03%	15.05*	14.18%	3.4*
(2, 0)	-4.20%	7.27*	11.80%	6.92*
(1, 0)	-4.13%	4.64*	15.71%	5.24*
(0, 0)	-9.43%	-6.58*	13.99%	10.04*
(-1, -15)	5.15%	14.74*	-15.98%	37.49*

Appendix 9) Ambiguous meme-tweet

Elon Musk
@elonmusk

Doge Barking at the Moon

5:33 am · 15 Apr 2021 · Twitter for iPhone

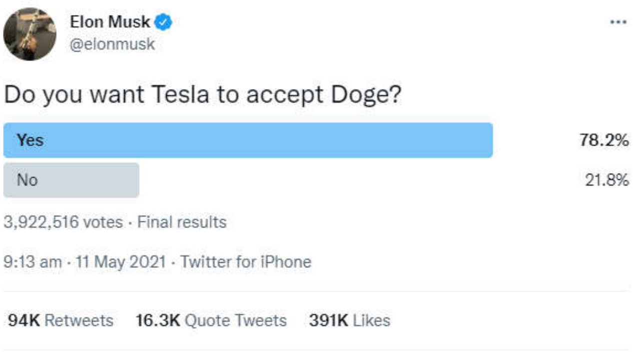
47.1K Retweets **5,203** Quote Tweets **321.6K** Likes

Elon Musk
@elonmusk

How much is that Doge in the window?

11:41 am · 20 May 2021 · Twitter for iPhone

Appendix 10) Poll Tweet and Answer



Appendix 11) Event 24 and 38 Cumulative Average Abnormal Returns

CAAR	**Event 24**	**Event 38**
	Link	Link
Event Window	**CAAR**	**CAAR**
(60, 0)	**71.69%**	**-3.18%**
(45, 0)	**75.94%**	**-4.50%**
(30, 0)	**80.70%**	**-4.74%**
(15, 0)	**-3.69%**	**-4.33%**
(10, 0)	**84.03%**	**-3.33%**
(9, 0)	**83.71%**	**-3.89%**
(8, 0)	**83.98%**	**-3.41%**
(7, 0)	**-1.74%**	**-3.02%**
(6, 0)	**83.72%**	**-3.98%**
(5, 0)	**84.76%**	**-3.46%**
(4, 0)	**83.92%**	**-1.30%**
(3, 0)	**83.59%**	**-1.71%**
(2, 0)	**83.54%**	**-1.33%**
(1, 0)	**84.72%**	**1.03%**
(0, 0)	**84.74%**	**-0.10%**
(-1, -15)	**-91.52%**	**7.43%**

Appendix 12) Elon Musk Reconsidering Twitter Deal

Elon Musk
@elonmusk

Twitter deal temporarily on hold pending details supporting calculation that spam/fake accounts do indeed represent less than 5% of users

reuters.com
Twitter estimates spam, fake accounts comprise less than 5% of users -filing
Twitter Incestimated in a filing on Monday that false or spam accounts represented fewer than 5% of its monetizable daily active users during the first ...

10:44 am · 13 May 2022 · Twitter for iPhone

28.4K Retweets **11K** Quote Tweets **233.2K** Likes