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## CEO's tweets and firm stock returns: A case study of Elon Musk and Tesla

Jauron Gunther Dam  
*Georgia Southern University*

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# **CEO's tweets and firm stock returns:**

## **A case study of Elon Musk and Tesla**

An Honors Thesis submitted in partial fulfillment of the requirements for Honors in  
the *Department of Finance*

By  
*Jauron Dam*

Under the mentorship of *Dr. Nicholas Mangee*

### **ABSTRACT**

This research study explores the relationship between a CEO's public statements and a firm's abnormal stock returns by focusing on the case study of Elon Musk's tweets and Tesla's stock price over the course of 2021. A longitudinal dataset is constructed by analyzing how the information contained in tweets affected Tesla's short-run stock price. The textual data is analyzed based on CEO tweets, the daily frequency of tweets, explicit and implied fundamentals, and sentiment. The content of Elon Musk's publications may lead TSLA to have abnormal returns. The tweets are able to capture influences from fundamentals and psychology. When Elon Musk's tweets are Tesla-related the abnormal returns increase, but more tweets per day reduce the absolute magnitude of returns. Though, findings suggest that a higher frequency of all tweets corresponds with regimes of negative abnormal returns. Greater social media pessimism is connected to negative abnormal returns, fewer CEO tweets, and greater internet search interest for Musk-Tesla-Twitter terms.

Thesis Mentor: \_\_\_\_\_

Dr. Nicholas Mangee

Honors Director: \_\_\_\_\_

Dr. Steven Engel

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*Department of Finance*  
Honors College  
**Georgia Southern University**

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## **I. Introduction**

Elon Musk often communicates information about his companies, such as Tesla and Twitter, and his broader financial aspirations through the social media giant. In fact, his staggering offer made in April 2022 to purchase all outstanding shares of Twitter for \$46.5B (Hoffman et al. 2022) speaks to his desire to meld his Tesla endeavors with the potential he sees in the social media platform. Even the most cursory observer can attest to the impact his tweets have on not only Tesla stock but on Twitter's overall prospects and his EV industry rivals. Thus, understanding the informational content of his tweets offers a poignant lens through which to investigate which information matters from CEO tweets on their company's stock returns, in which ways, and if the relationship remains stable over time. This introduces a completely new perspective on the CEO-firm share price relationship due to the unique nature of Musk's relationship with Twitter.

Traditionally, publicly-traded stocks are evaluated by fundamental analysis – a method of determining a stock's intrinsic or “fair market” value by examining the company's financial statements and considering broader economic circumstances (Li et al, 2018). Over time, stocks tend to perform similarly to the market, which depends on the state of the US economy, current fiscal and monetary policies, and so on. However, certain companies' stocks experience significantly higher volatility due to reasons not directly correlated to systematic, or market, risk, the company's related sector, or even a company's financials.

For example, as of April 5, 2022, Tesla is trading at a 5-month Beta of 2.193 (Bloomberg Terminal, 2022), more than twice the Beta of the market and significantly higher than other EV-competing firms, suggesting that outside factors independent of the firm size and age may also influence a specific stock's volatility.

Such outside factors could include information from various publications, ranging from executive comments to financial analyst reports to celebrities posting sentiment-evoking tweets driving retail investors' appetite for risk.

The goal of this research paper is to investigate the nature of CEO tweets and assess if there is a connection between executive communications and their affiliated company's equity price movements. Specifically, the study explores the informational content of Elon Musk's tweets and the short-run responsiveness of Tesla's stock price from January 1, 2021, to December 31, 2021. This study serves as a current and relevant interconnection between financial markets, executive communication and the scope and impacts of social media.

Financial markets play a vital role in facilitating growth of capitalist economies by allocating scarce capital and creating liquidity for the most productive businesses. The prices financial markets produce are informational signals that help investors better understand this allocation process given estimates of risk and return. Investors all across the world have tried to evaluate stocks using different approaches, all hoping to most accurately predict a stock's intrinsic value.

The most widely used valuation approach is called fundamental analysis. This includes comparing specific figures of a company from financial statements, such as income statements and balance sheets, by using metrics like the price-to-earnings, return-on-equity, earnings per share, or dividend yields, but also utilizing models such as a discounted cash flow model. One stylized fact in the literature is that assets have seemingly not been fairly priced in the market when compared to their value-based predictions; that is, prices move too much to be justified by fundamentals alone. The Efficient Markets Hypothesis (EMH) implies that all fundamental information is

instantly reflected in a stock's price (Fama, 1970) which begs the question: which information matters for individual stock prices and in which ways over time?

The finding of excess volatility might be due to behavioral considerations or uncertainty. It might be due to narrative information in publications posted by famous and influential people, with a certain prominence that influences other people's perception of the asset's value in the short run. This is a valid assumption, considering that famous people with a large following often determine what is perceived as “cool” and “trendy” at the moment in influencing consumer demand, no matter whether it relates to fashion or technology. Cristiano Ronaldo exemplified this on June 16, 2021 when Coca-Cola's market capitalization decreased by \$4B as shares dropped by 1.6% percent due to a TV appearance in which the soccer superstar saw two bottles of Coca-Cola and proceeded to move them out of the camera frame and held up a bottle of water instead while saying “Water!” in Portuguese (Garcia, 2021).

So why shouldn't this also apply to stock valuation? If so, speculators who are aware of this effect could create trading rules that predict short-term stock price fluctuations on a certain stock. Within such a framework, they could buy and sell publicly traded equities based on publications by certain people, and the nature of the content within those publications, to profit from short-term price increases or decreases. This assumption of CEO tweets potentially impacting short-run firm returns may help shed light on which information matters and in which ways, implying that contextualized information is useful when analyzing a stock's price movements.

This study investigates whether contextualized information from CEO tweets influences Tesla's stock returns. Because markets are inherently unstable, the interaction of fundamentals and psychology may have nuanced effects on Tesla returns that vary over time. More specifically, the analysis assesses, first, the content of

Musk's tweets and, second, whether the decomposition of tweeted information into direct fundamentals, implied fundamentals, and psychological factors offers any explanatory power for returns.

When Elon Musk's tweets are Tesla-related the abnormal returns increase, but more tweets per day reduce the absolute magnitude of returns. Though, findings suggest that a higher frequency of all tweets corresponds with regimes of negative abnormal returns. Greater social media pessimism is connected to negative abnormal returns, fewer CEO tweets, and greater internet search interest for Musk-Tesla-Twitter terms.

## **II. Literature Review**

Stock prices are thought to reflect the market's evaluation of a company based on its discounted cash flow stream and profit margins. This relates to EMH, which states that market prices fully reflect all essential information about the company at every point in time (Fama, 1970). This process is based on a fundamental evaluation of an asset from financial statements. But other aspects can temporarily influence a stock's price, implying that the EMH theory also extends to the information contained in tweets and other news media content. The seminal study of Tetlock (2007), for example, finds a statistically significant relationship between the negative tone of *Wall Street Journal* media content and lower future stock returns. Social media content, too, has displayed a connection to stock price volatility.

In October 2015 Oprah Winfrey tweeted that she was joining the board of Weight Watchers, as well as announced that she was buying a 10% stake in it, by investing \$43 million in newly issued shares. This acquisition and her related publication on Twitter caused the share price to increase by 105% within one day (Bomey, 2015). This dramatic increase in such a short period can arguably not be due



to the increased demand of Oprah Winfrey alone since, after all, she bought newly issued shares which are not exposed to the waves of supply and demand like existing shares traded in secondary markets. Furthermore, the increase in price could not reflect a comparable increase in earnings-per-share, as the newly gained cash could not have been distributed and used to increase sales to this extent within just a couple of hours. Another instance occurred when she tweeted “Eat bread. Lose Weight. Whaaatttt? #ComeJoinMe weightwtch.rs/oprah” (Winfrey, 2016), increasing Weight Watchers stock price by more than 16% within just one hour (Witkowski, 2016) and on the 23rd of January when the stock’s price increased 20% after another tweet (Bryan, 2017).

Sul, Dennis, and Yuan (2017) researched postings on Twitter and whether social media sentiment could predict stock returns. Their study is similar to the present study since the authors also try to identify how contextualized sentiment influences stock returns. A key difference though, is that the present study additionally looks at fundamentals and both the absolute and relative returns that follow such publications. Their study researched how gross sentiment evoked by social media can influence a stock’s price. They “analyzed the cumulative sentiment (positive and negative) in 2.5 million Twitter postings about individual S&P 500 firms and compared this to the stock returns of those firms” (Sul et al., 2017, p 454). Their research showed that sentiment in social media postings can predict stock returns, which is similar in spirit to this thesis.

In another related study, Ante (2007) researched whether Elon Musk’s social media presence on Twitter and his tweets influence cryptocurrency markets. Their paper investigated similar hypotheses to other literature but in application to the cryptocurrency market and across a range of different equities. Throughout the analysis, Ante (2007) was able to identify “significant positive abnormal returns and

trading volume” (Ante, 2022, p. 1) related to tweets. This finding could hint at a possibly similar relationship between Elon Musk’s tweets and Tesla Stock, though cryptocurrencies and publicly traded stocks are evaluated differently.<sup>1</sup>

In a recent study, Knipmeijer (2020) examines the effect of Twitter use on stock market outcomes, such as volatility, returns, and trading volume. Similar to the present study, Knipmeijer also conducts a textual analysis of published tweets, though only considering whether a tweet is fully sentiment-based (Knipmeijer, 2020, p. 4) whereas subsequent analysis here also considers whether the tweet includes fundamentals. This nuance of the present study is similar in spirit to Tetlock et al. (2008) who shows that stock returns are amplified when there are mentions of fundamentals in news articles. Knipmeijer’s research concludes that “the sentiment of a tweet plays no role in explaining the effect on the stock market activity” (Knipmeijer, 2020, p. iii).

However, the authors do not assess the interaction of fundamentals and sentiment in the tweets, nor do they consider whether the explicit versus implied fundamentals within the text play a role. The study of Knipmeijer (2020) shows that “there is a positive effect of tweeting on the return and a positive effect of tweeting of CEOs with a large audience on the trading volume” (Knipmeijer, 2020, p. iii), which would suggest that Elon Musk’s tweets would produce similar effects. This may be especially true considering that Elon Musk started 2021 with a following of approximately 41M subscribers on Twitter, which over the year increased to around 65M subscribers, making it the second most followed account on Twitter with a current following of 132M.

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<sup>1</sup> Cryptocurrencies traditionally don’t have “intrinsic” values, since they are not linked to a company producing revenue or cash flows, but are decentralized networks based on blockchain technology (Frankenfield, 2022).

### **III. Research Approach**

The present paper's main research topic is investigating the content of CEO Elon Musk's tweets and the potential impacts on Tesla's short-run stock return responsiveness. When referring to Tesla's stock in this paper, only reference to Tesla's common stock is taken; which for the sake of readability will also only be referred to as Tesla's stock.

Elon Musk's tweets will be examined following a manual textual analysis that decomposes the content into explicit fundamentals (e.g. sales, earnings), implied fundamentals (e.g. PP&E, products and financial), and psychology (optimistic versus pessimistic tone). To assess the impact of a tweet on Tesla's stock, analysis of a precise timestamp of each publication is combined with high-frequency financial data. To determine how a tweet affects Tesla's price, an event study will be conducted, and end-of-day returns will be evaluated. As the overall analysis is comprised of various types of content and categories, it will include multiple steps to assess how each affects the direction of the price change and its absolute magnitude. Subsequently, only the return will be analyzed at first, irrespective of the publication's content, followed by a detailed analysis comprised of testing sub-theses across factor categories. Frequency and proportion data will then be generated for each category. Binary data is also generated to identify which types of content are included in a tweet.

A Capital Asset Pricing Model, based on a stock's 5-year-monthly beta, will be used to compare Tesla's nominal and absolute return to its expected return to identify abnormal returns over the sample period.

The empirical analysis will help assess whether there are overall positive or negative correlations between the nature of informational content contained in Musk's tweets about Tesla and the behavior of the corresponding firm's stock return.

Once these relations are sorted, more specified dimensions can be assessed, such as whether Tesla's abnormal return is positive or negative on days when Musk tweets; Tesla's abnormal return is higher in absolute magnitude on days when Musk tweets, or social media posts, contain sentiment; or that Tesla's abnormal return may be simply different on days when Musk tweets.

The following hypotheses are assessed:

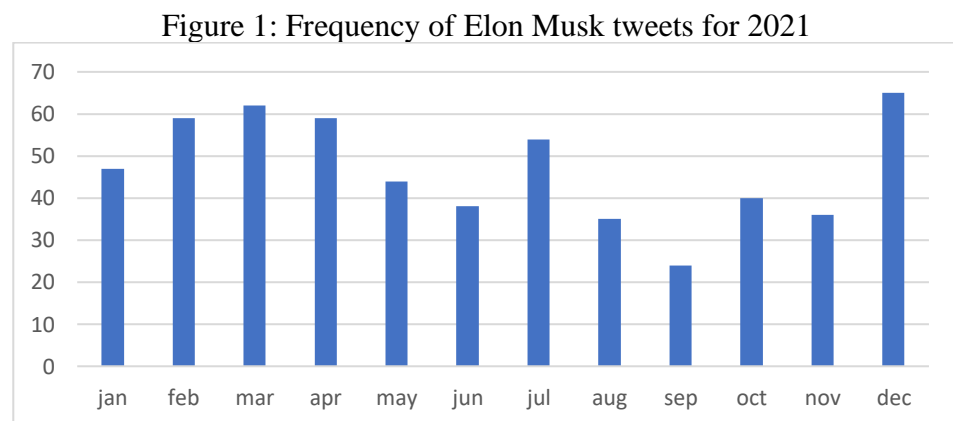
H1: Elon Musk tweets are correlated with TSLA abnormal returns

H2: Elon Musk tweet sentiment is related to abnormal TSLA returns

H3: Elon Musk's tweets about different types of fundamentals are related to abnormal TSLA returns

#### **IV. Data**

This paper produces a time-series dataset by collecting information about CEO Elon Musk's tweets, between 01/01/2021 and 12/31/2021. The data was extracted from Elon Musk's Twitter "@elonmusk" via a Twitter Media Downloader Chrome Extension Tool. While Elon Musk's Twitter activity reaches far beyond just his tweets – his activity involves retweets and replies to other tweets, and his interactive replies to his posts - the sample consists of only tweets originating from Elon Musk "@elonmusk", which totaled 563 in 2021.



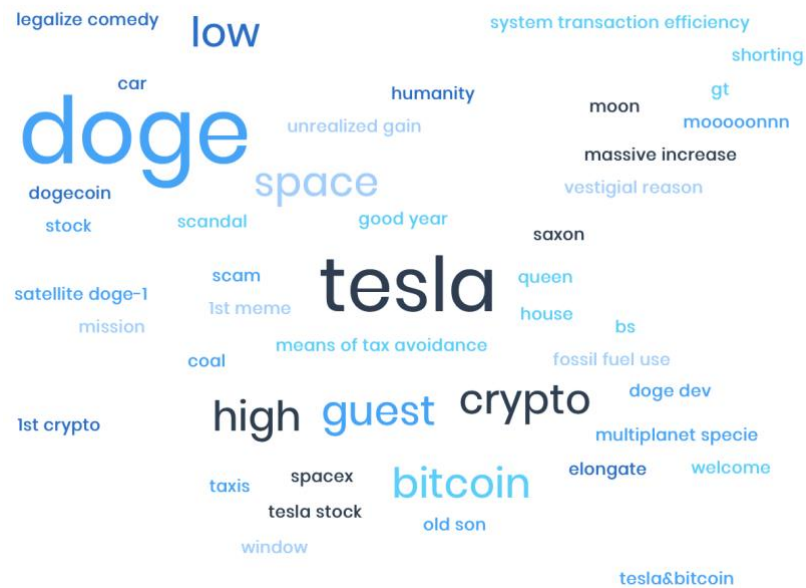
Notes: The figure reports the frequency of Elon Musk tweets per month for 2021.

The chart above shows how many tweets Elon Musk published in each month of the year 2021. Averaging around 47 per month, it is clear to see that more tweets were published in the first quarter of the year and that there, in general, was a declining trend from March to September, with July being an outlier. While Q4 still did not have as many tweets as Q1 on average, December is the month in which Elon Musk released the most tweets, totaling 65.

The sample is then further broken down into three subsamples which are “Top tweets sorted”, “Top Tesla tweets sorted” and “Tesla-related tweets only”. Both “Top tweets sorted” and “Top Tesla tweets sorted” are also further categorized by “Top 10 tweets by likes”, “Top 10 tweets by retweets” and “Top 10 tweets by replies”.

Consistent with the previous bar chart, tweets in “Top 10 tweets by likes” and “Top 10 tweets by retweets” within the sub-sample “Top tweets sorted” are only within the first half of the year and also concentrated around Q1. Tweets within “Top 10 tweets by replies” surprisingly have a different spread, as three of them are within Q4 as well as 7 of them are all in May. Similarly, tweets in “Top 10 tweets by likes” and “Top 10 tweets by retweets” within the sub-sample “Top Tesla tweets sorted” are mainly in the first half of the year, though they are more evenly spread. Tweets within “Top 10 tweets by replies” are relatively evenly spread across the year, though most of them are in the first half of the year, especially in May.

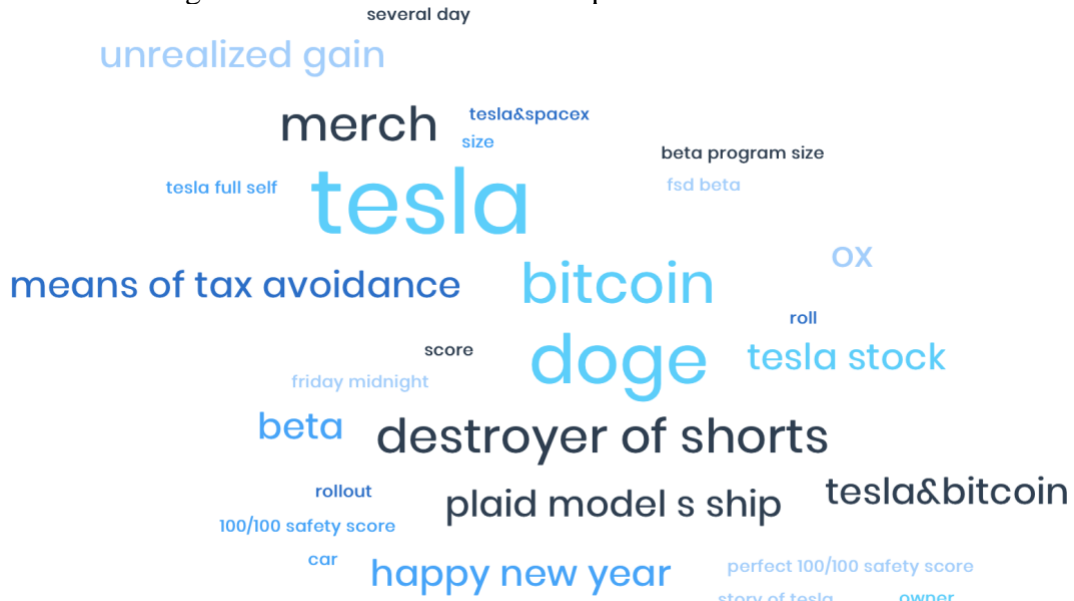
Figure 2: Wordcloud based on Top Elon Musk tweets for 2021



Notes: The figure plots a wordcloud for Elon Musk’s top tweeted posts for 2021.

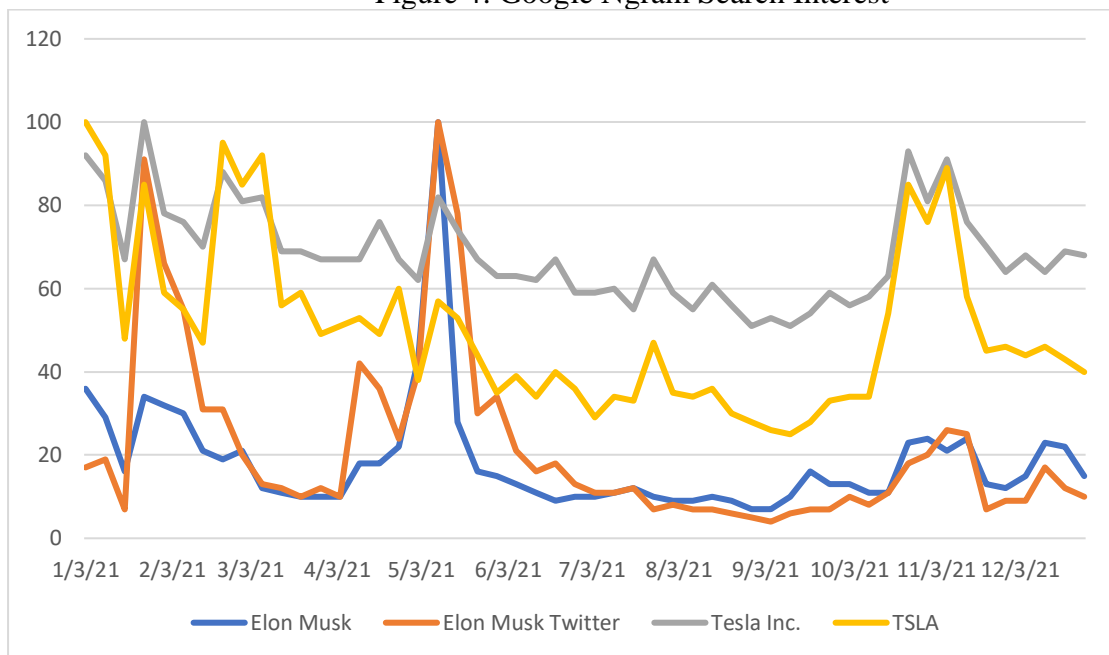
Figure 2 produces a wordcloud from “Top tweets sorted”, for all three subcategories without adjusting for double entries. The most frequently occurring words are “doge” and “tesla.” Figure 3 shows a wordcloud from “Top Tesla tweets sorted”, for all three subcategories without adjusting for double entries. The most frequently occurring words are “doge” and “tesla”. A visible difference compared to the first word cloud in Figure 2 is that “tesla” now has surpassed “doge” by being the most frequently used word or phrase, and there now is a number of words or phrases like “destroyer of shorts”, “means of tax avoidance” and “plaid model S ship” that are also more frequently used.

Figure 3: Wordcloud based on Top Elon Musk Tesla tweets



Notes: The figure plots a wordcloud for Elon Musk’s top Tesla tweeted posts for 2021.

Figure 4: Google Ngram Search Interest



Notes: The figure plots the Google Ngram search interest for particular terms related to Elon Musk, Twitter and Tesla for the period 2021.

Figure 4 shows the search interest over the year 2021 for the key terms “Elon Musk”, “Elon Musk Twitter”, “Tesla Inc.” and “TSLA”. Visible news spikes include “Elon Musk Twitter” from January to February, “Elon Musk Twitter” and

“Elon Musk” from April to May, and “Tesla Inc” and “TSLA” in January, March, and November.

To determine TSLA abnormal returns, the Capital Asset Pricing Model – “CAPM” – is used. Market returns  $R^M$  are proxied by the Standards & Poor 500 – “SPY”, a time-varying risk-free rate  $r_t^f$  was based on the 3-month treasury bill yield and Tesla’s returns were based on “TSLA” common stock during 2021. Beta calculations  $\beta^{TSLA}$  were based on a 5-year monthly lookback. The analysis is based on daily trading days, yielding 252 observations in 2021.<sup>2</sup> The average SP500 return of around 11.88% is based on historic annualized average returns since from 1957 through 2021. All data is broken down to daily trading intervals. To determine abnormal returns, expected returns are needed, which are calculated via the Capital Asset Pricing Model – CAPM.<sup>3</sup> The following formulas were used to get the expected returns “E(R)” and abnormal returns “AR” from the raw data:

$$E(R_t^{TSLA}) = r_t^f + \beta^{TSLA}(R^M - r_t^f) \quad (1)$$

$$AR_t^{TSLA} = R_t^{TSLA} - E(R_t^{TSLA}) \quad (2)$$

## **V. Results**

This first stage of analysis considers H1 and the correlations between different categories of Elon Musk tweets and abnormal returns (nominal and absolute value) for Tesla. To calculate the correlation of the number of tweets published per day with a) the abnormal returns of TSLA and b) the absolute abnormal return of TSLA, frequency count variables are created. The numerical number then represents the number of tweets published per day. The correlation of tweets per day with Tesla

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<sup>2</sup> SPY and TSLA data originate from Eikon, 3-month treasury bond bill data originates from Federal Reserve Economic Data – FRED and the Beta data originates from ycharts

<sup>3</sup> For a survey of CAPM literature see Fama French 2004



abnormal returns equaled -0.02 and the correlation of tweets per day with the absolute value of abnormal returns equaled 0.11. From this, it can be inferred that the number of tweets published per day shares no correlation with TSLA abnormal returns, but that the number of tweets positively correlates (and is relatively stronger) with the absolute magnitude of TSLA returns.

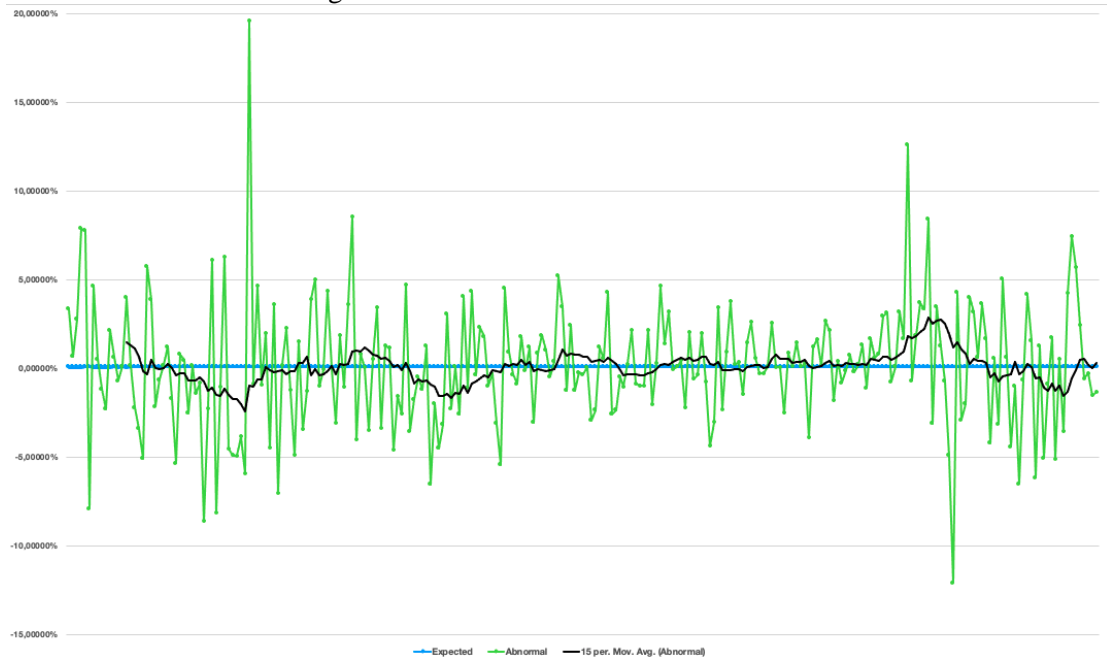
To assess whether a Tesla-related tweet is correlated or not with a) the abnormal returns of TSLA and b) the absolute abnormal return of TSLA, dummy variables had to be created. The value 1 represents that the tweet is Tesla-related and 0 represents that the tweet is not Tesla-related. The correlation between Tesla-related tweets and abnormal returns is 0.062, and the correlation between Tesla-related tweets and the absolute value equaled -0.008. From this, it can be inferred that there are small positive correlations if a tweet is Tesla-related with Tesla's abnormal and absolute value of returns and that the correlation is negligible for the absolute magnitude of abnormal Tesla returns.

The next statistics calculate the correlation of the frequency of Tesla-related tweets published per day with a) the abnormal returns of TSLA and b) the absolute abnormal return of TSLA. The numerical value then represents the number of Tesla-related tweets published per day. The correlation of Tesla-related tweets per day with the abnormal return is 0.041 and the correlation of Tesla-related tweets per day with the absolute value equaled -0.016. From this, it can be inferred that the number of Tesla-related tweets published per day positively correlates with TSLA abnormal returns and that the number of Tesla-related tweets negatively correlates weaker with the absolute magnitude of TSLA returns.

The next stage of the analysis considers H2 and whether the sentiment of Elon Musk's tweets is related to abnormal TSLA returns. Figure 5 plots TSLA abnormal

returns with a 15-day moving average to demarcate different regions based on the sign of the series.

Figure 5: Tesla Abnormal Returns for 2021



Notes: The figure plots the abnormal returns for Tesla (green) with the 15-day moving average (black) for the year 2021.

Table 1 reports the findings from Figure 5 compared to tweet data in columns 4 and 5 and sentiment data based on manual scoring in column 6. Column 3 shows that the sign of abnormal returns switched many times over the year 2021. Interestingly, when compared to the number of total tweets and Tesla-related tweets, the lower the frequency of posts, the more neutral or negative the abnormal returns.

The sentiment column is virtually always positive except for regions of July and November. Since there is not enough data on pessimistic sentiment, a graph from Eikon plotting Tesla's social media sentiment (presented in Figure 6) is used as a proxy. The variation in the social media sentiment connected to TSLA helps to assess H2. The figure suggests that when social media posts about TSLA are pessimistic in sentiment there are negative abnormal returns, such as in May. This is also the month in Figure 4 where the Google Ngram search interest for all Musk-TSLA-Twitter

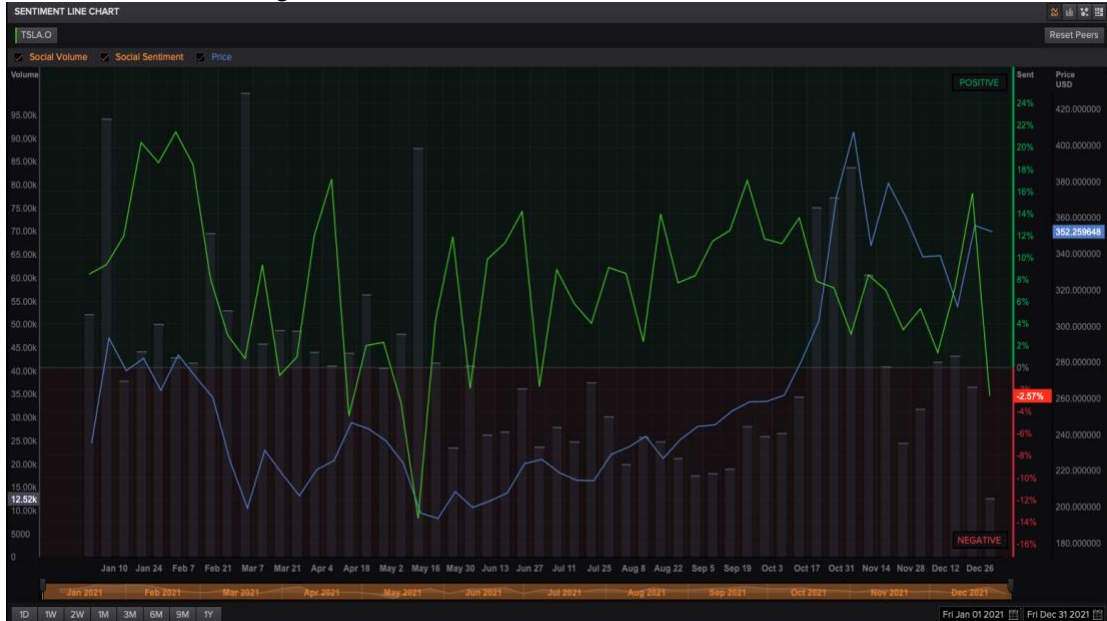
keywords spiked to their highest values. The findings suggest that negative abnormal returns for TSLA are connected to infrequent CEO tweets, high internet search interest, and social media pessimism.

Table 1: Tesla Abnormal Returns

region	date	MA	tweets total	Tesla tweets	sentiment to tesla
1	Feb 08	neutral	74	11	+
2	Mar 24	negative	82	6	+
3	Apr 11	neutral	42	1	+
4	Apr 24	positive	25	4	+
5	May 01	neutral	9	0	+
6	Jun 04	negative	43	6	+
7	Jun 22	neutral	24	3	+
8	Jul 15	positive	40	3	+
9	Jul 28	negative	16	0	neutral
10	Aug 19	positive	26	1	+
11	Oct 07	neutral	50	3	+
12	Nov 20	positive	52	1	-
13	Dec 06	neutral	26	2	+
14	Dec 23	negative	44	5	+
15	Dec 31	neutral	10	1	+

Notes: The table reports regions of abnormal returns classified by sign along with tweet data and sentiment from manual analysis.

Figure 6: Social Media Sentiment for TSLA in 2021



The next stage of the analysis considers H3 and asks whether explicit and implied fundamentals within tweets are connected to TSLA’s abnormal returns. The average abnormal return for all of 2021 is 0.1367%, the average abnormal return for days when Tesla-related tweets were posted is -0.39%, and the average abnormal return for days when tweets included explicit fundamentals is -2.43%. This is a striking difference in the magnitude of abnormal returns on days where explicit fundamentals are mentioned in Elon Musk's tweets.

To further deepen the analysis of fundamentals a new classification of implied fundamentals is considered, with subdivisions into the two most common types, “Production” or “Financial” related. The average abnormal return for tweets that include implied fundamentals is 0.29%, the average abnormal return for tweets that include implied fundamentals and are production related is -0.34% and the average abnormal return for tweets that include implied fundamentals and are financially related is -3.51%. While the sample size is rather small to be fully conclusive, it seems

like tweets that have implied fundamentals and that are financially related have a stronger negative impact on TSLA price fluctuations.

## **VI. Conclusion**

This thesis explores CEO tweets and their impact on stocks. More specifically, the thesis investigates whether contextualized information in tweets from Tesla CEO Elon Musk influences TSLA stock returns. While stocks often perform similarly to the market, the interaction of fundamentals and psychology may have nuanced effects on Tesla returns that vary over time. The content of Elon Musk's publications may lead TSLA to have abnormal returns. The tweets are able to capture influences from fundamentals and psychology. When Elon Musk's tweets are Tesla-related the abnormal returns increase, but more tweets per day reduce the absolute magnitude of returns. Though, findings suggest that a higher frequency of all tweets corresponds with regimes of negative abnormal returns. Greater social media pessimism is connected to negative abnormal returns, fewer CEO tweets, and greater internet search interest for Musk-Tesla-Twitter terms.

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