SOCIAL MEDIA, MARKET REGULATION AND CEO INFLUENCE: LESSONS FOR MARKET EFFICIENCY

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ABSTRACT: *Social media communication has become increasingly influential in the stock market. Platforms such as X (formerly known as Twitter), Facebook, and Reddit serve as channels for corporate CEOs to share information, analysis, and opinions that can influence the stock prices of the companies they manage. The research this paper is based on tested whether it is possible to obtain abnormal stock trading returns by following Elon Musk's tweets about Tesla. We studied ten years of Elon Musk's tweets about Tesla, collecting data on 3,158 tweets and 2,420 stock trading days and identifying 33 events. We employed an event study methodology, utilizing the Five-Factor Model and the Capital Asset Pricing Model to estimate Tesla's daily expected returns and assess the statistical significance of Tesla's abnormal stock returns following Elon Musk's tweets. We estimated abnormal returns over the event window and on the event day. We also estimated a logit regression on the ten-year sample period to assess whether the tweets caused aggregate abnormal returns. We conclude that Elon Musk's tweets did not significantly impact Tesla's stock price, suggesting that the market is informationally efficient and that, in recent years, it has not been possible to obtain abnormal returns by trading based on these tweets. Our methodological contribution is isolating tweet-related price reactions by excluding pre-event days, which are usually contaminated by fundamental information, and focusing exclusively on the effects of social media on stock price returns. We contribute to the literature on the relationship between social media and market efficiency, offering valuable insights for investors, regulators, and policymakers.*

KEYWORDS: *social media, event study, Elon Musk, stock price returns, efficient market hypothesis*

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INTRODUCTION

The debate over the efficiency of financial markets is a primary theme in economic sociology (Fligstein 2018; MacKenzie 2008). The Efficient Market Hypothesis (Fama 1970) suggests that all available information is immediately reflected in asset prices. However, sociological studies have long challenged this assumption, arguing that investor behavior is influenced by social factors, narratives, and regulatory frameworks (Enriques–Gilotta 2014; Jiao et al. 2020). The rise of social media adds complexity to this debate: platforms like X (formerly known as Twitter) allow CEOs to communicate directly with investors, potentially bypassing formal disclosure channels. This study is situated at the intersection of these themes, contributing to the sociological debate on whether social media introduces new inefficiencies in financial markets and how regulation may mitigate these effects.

Social media platforms such as X, Facebook, Instagram, and others have become globally pervasive tools for communication and information dissemination. Empirical literature tries to understand whether they substitute or complement traditional information communication channels, such as economics and finance magazines and newspapers (Jerit–Gaskins 2012). In social media, the dissemination of public information is no longer restricted to traditional means of communication, such as print media. Users of social media accounts can be individuals, companies, and the leading representatives of publicly listed companies, who also maintain individual social media accounts. It has been demonstrated that corporate Chief Executive Officers (CEOs) engage in CEO activism (Rumstadt et al. 2024) on various themes, including climate change, economic visions, technological innovations, and other related topics. Given their relevance within organizations, those who repeatedly address business themes often end up seeing their accounts converted into professional accounts, in which a simple emoji can make a significant impact among investors, as exemplified by Elon Musk.

Daily news reports emerged that Elon Musk's activity on X had an immediate impact on Tesla's share price (Root 2022). In this sense, the empirical literature has intensified its research on this subject to obtain more concrete data regarding the potential correlation between social network publications and financial market movements (Ranco et al. 2015). The hypothesis of efficient markets postulates that, in its semi-strong form, all publicly available information is immediately reflected in asset prices (Fama 1970). However, frequent price abnormalities in the financial markets cause questions about their efficiency (De Bondt – Thaler 1985; Vega 2006). One line of research has focused on the impact of social media sentiment on stock prices (Nguyen et al. 2015;

Tan–Tas 2021; García 2022). These studies analyze the sentiment expressed in social media posts about specific stocks or companies and then compare this sentiment to stock prices. The findings suggest a significant correlation between social media sentiment and stock prices, with positive sentiment associated with higher stock prices and negative sentiment with lower prices. Another area of research has focused on the impact of social media news and rumors on stock prices. Studies have shown that social media can provide information about breaking news, mergers and acquisitions, and other market-moving events. Social media has also been implicated in spreading false information and rumors that can lead to market volatility (Jia et al. 2020). It has been found that investors are more attracted by news stories than by corporate disclosures of fundamental information (Eachempati–Srivastava 2022).

We are interested in whether corporate managers of publicly listed companies use social media to communicate about their companies, and whether this can lead to financial markets becoming informationally inefficient. If true, this hypothesis would enable us to design an investment strategy for generating abnormal returns by trading on corporate managers' communications on social media platforms. To test this hypothesis and as a pilot study for future replication, we analyzed 3,158 tweets by Elon Musk, one of the most famous and active corporate managers on social media (through X), and 2,420 trading days of his company's stock. Using the event study methodology, this research tests the impact of Elon Musk's frequent interactions on Tesla's stock prices. We designed a study to measure the effect of communications through X on Tesla's stock prices, controlling for fundamental changes in value already known to investors by excluding changes in stock prices in the days preceding the analyzed tweets. If the market is efficient, there should be no abnormal returns, and these tweets should only generate noise trading, as Black (1986) explained.

Our study contributes to the literature by systematically analyzing the impact of Elon Musk's tweets on Tesla's stock prices, utilizing a large sample and controlling for potential confounding effects. In this regard, our research adds to the understanding of the role of social media as a channel for transmitting corporate information to stock markets, particularly when upper echelons of the corporate world use social media tools. Our findings are relevant to the efficient market hypothesis and offer valuable insights for investors, regulators, and policymakers when analyzing the impact of social media communications.

The remainder of the article is structured as follows: the next section reviews the relevant literature, while the subsequent section presents the methodology and data. This is followed by the sections presenting the results and the robustness tests. The last two sections contain the discussion of the results and the conclusion.

LITERATURE REVIEW

The influence of social media communications on stock markets is a complex and dynamic phenomenon that requires further research. Davis (2005) showed that while social media can be a source of valuable information and insights for investors, it can also be a source of misinformation and hype that can lead to market instability. According to Milbourn (2003), how information is disclosed significantly impacts a Chief Executive Officer's (CEO) career, as stock prices are the central measure for evaluating their performance in the market. Managers are encouraged to maximize the dissemination of good news and, conversely, limit bad news, considering the increase in their reputation and career prospects and protection against possible criticism from stakeholders (deHaan et al. 2015). Ahern and Sosyura (2014) studied whether companies can manipulate the relationship between prices and information through media coverage. Thus, these authors concluded that companies sometimes turn to the press to promote their interests, emerging evidence that this affects numerous corporate actions and some merger negotiations.

The constant changes in and complexity of financial markets have required the monitoring and consequent evolution of various associated technological tools (Brown 2012; Holub–Némethová 2015). Globalization and the use of the internet have accelerated and facilitated this process. All this has led to a change in the way investors trade and their information collection patterns (Brown 2012). Social networks are increasingly essential in this context, as accessing and sharing information is straightforward and continuous. Chen et al. (2011) refer to the fact that most financial market professionals and clients use social networks for professional reasons. Thus, evidence emerges that financial professionals negotiate based on the information provided by this data dissemination channel, which has aroused much interest from academics and researchers (Bukovina 2016). According to Shiva and Singh (2020), X is the social media platform that stock market investors most commonly use to select investment portfolios.

Mazboudi and Khalil (2017) concluded that X is an important information channel, so it should be considered when assessing the context of company information and fluctuations in stock prices. Regarding the sentiment, Bollen et al. (2011) found that the collective humor verified in tweets can contribute favorably to a correct calculation of the Dow-Jones Industrial Average index, and there is evidence that there is a significant relationship between the level of emotionality of the tweet (hope or fear) and stock market indices such as Dow Jones, NASDAQ, and S&P 500 (Zhang et al. 2011). It has been shown that investor sentiments are the major driving forces that positively influence portfolio stock returns (Solanki–Seetharam 2018; Bhaskaran–Sukumaran 2022), that investors tend to react to feelings of risk (Cunha–Lobão 2022) and are more interested in news about the stock-listed companies than in corporate disclosures of information (Eachempati–Srivastava 2022). Sprenger and Welpe (2011) investigated the relationship between company-specific news events and the S&P 500 stock price, showing that companies mentioned together in tweets tend to exhibit correlated stock price movement. There is also evidence that unusual interactions with a particular company on X cause a sudden increase in the trading of its shares; however, the forecast points out that such a move may not be enough to result in gains (Tafti et al. 2016). In a study of analysts' tweets about individual S&P500 firms, Sul et al. (2017) showed that the sentiment in tweets had a significant impact on the stock's return on the next trading day, the next ten days, and the next twenty days, suggesting that a trading strategy based on these findings could deliver 11% to 15% annual return. Machus et al. (2022), using intraday (minute-by-minute) data, further found that Donald Trump's tweets affected the trading volumes of a sample of individual stock-listed companies but did not have lasting effects on stock prices. These authors also found evidence of abnormal returns before Donald Trump's tweets, concluding that the tweets did not provide new information but rather comments on events that had already occurred.

Aware of the size and reach of X as a means of disseminating information, several CEOs often utilize this platform to advertise their company's profits, launch new products, and share news from their organizations (Kubowicz Malhotra – Malhotra 2016). Elon Musk, Tesla's CEO, is a strong example of this social media presence, frequently tweeting. Seigner et al. (2023) demonstrated that high-status entrepreneurs, such as Elon Musk, can enhance followers' engagement by using provocative language in their tweets. Elon Musk has notoriously excelled in tweeting about the cryptocurrency markets. Ante (2023) observed Elon Musk's activities regarding six cryptocurrencies, finding highly significant abnormal trading volumes after the events. Nevertheless, not all events caused abnormal returns. Zaman et al. (2023) also found that when Elon Musk changed his X bio to address Bitcoin, there was an increase in tweets mentioning this cryptocurrency, accompanied by a correlated increase in the Bitcoin price. Šević et al. (2023) studied three years of Tesla stock prices and Elon Musk's tweets, finding a strong correlation between both. Strauss and Smith (2019) addressed the market's reaction to Tesla's release and introduction of a battery for the S and X Models. Although the study focused on only four days, it was possible to conclude that investors react based on speculation, as they react to Elon Musk's tweets virtually immediately, given that Tesla's stock price rose mainly after the tweet. However, those beliefs led to a surplus of expectations that culminated in investor dismay and the subsequent sale of shares acquired shortly after the company's official announcement. The investigation also concluded that X accounts of high-profile companies or personalities, such as Tesla and its CEO, Elon Musk, were recognized as valuable sources of market information for day traders and shareholders to trade profitably (Strauss–Smith 2019).

In fact, on September 27, 2018, the Securities and Exchange Commission (SEC 2018), the North American entity responsible for protecting capital market investors and ensuring the proper functioning of securities markets, charged Elon Musk with securities fraud for a series of false and misleading tweets about a potential transaction to take Tesla private. Elon Musk's tweets caused a significant fluctuation in Tesla's stock prices, resulting in a rise of approximately 6%, indicating that the use of X for corporate communications may affect stock prices in the short term. In this case, a piece of erroneous fundamental information was communicated to the market, which is uncommon for CEOs of stock-listed companies.

Agrrawal and Agarwal (2023) evaluated the long-term cumulative abnormal returns based on tweets to assess whether markets are semi-strongly efficient and whether returns can be derived from strategies based on tweets. In the case of Elon Musk's tweets, they found cumulative abnormal returns in the event window (ten-day event window) and in the long term (two hundred days). Nevertheless, they did not control the emergence of new fundamental information that affected stock prices in the days leading up to the event.

From a broader perspective, Kim et al. (2021) took a sample of Elon Musk's tweets between 2015 and 2020 to understand the relationship between the CEO's tweets and the value of Tesla's shares. The study showed evidence of a correlation in the short term; however, this becomes more evident when the analysis focuses on the long term.

Although it seems that Elon Musk's tweets affect Tesla stock prices, the reviewed studies included several days (or minutes) of stock returns before the tweet, as is the standard procedure in corporate finance research to incorporate trading activity executed by insiders, or some time before the tweet. Stock-listed companies must inform the market before tweeting about information that affects their fundamental value, as the SEC (2018) ruling showed. This means that these studies did not measure the effect of the tweet, but the effect of the information, as Machus et al. (2022) explained.

There is a gap in the literature regarding the effects of Elon Musk's random tweeting about Tesla's stock price, controlling for the changes in Tesla's fundamental value. We are interested in filling this gap by testing if it is possible to obtain abnormal returns based on Elon Musk's tweets about Tesla, regardless of changes in the company's fundamental value. While many prior studies, such as Sul et al. (2017), Šević et al. (2023), and Kim et al. (2021), have investigated the link between tweets and stock prices, few have used robust models, such as the CAPM or the Five-Factor Model, for estimating expected returns. For example, Strauss and Smith (2019) focused on intraday price reactions using the market model to compute the expected returns. Our study distinguishes itself by using these established models to adjust for systematic risk and by removing the pre-event window to isolate the pure effect of tweet-related information.

METHODOLOGY AND DATA

Event study models

The event study methodology enables the measurement of an event's impact on the value of a company's stock price return (McWilliams–Siegel 1997). At an early stage, it is necessary to adjust returns to determine whether returns are abnormal, as it is essential to control for market-wide movements on the same day. Starting from the assumptions presented by Kothari and Warner (2007), the return of a security is obtained according to the following equation:

$$R_{it} = E_{it} + AR_{it} \tag{1}$$

Where is the observed return of security *i* on the date of event *t*, is the expected return of security *i* on the date of event *t*, and is the abnormal return of security *i* on the date of event *t*. It is assumed that the abnormal return results from the difference between the observed and expected return:

$$AR_{it} = R_{it} - E_{it} \tag{2}$$

The determination of the expected return is conditioned by the estimation period, which consists of a time interval not encompassed in the event period, to ensure unbiased results. As a rule, this interval precedes the event, and the expected return (E_{it}) is estimated by regressing historical returns of the security (R_{it}) against the historical returns of the stock market in which the security is traded (for Tesla, this corresponds to the Nasdaq Composite Index).

MacKinlay (1997) describes this as the market model, noting that more recent models incorporate additional stock return factors, such as the industry index, which might improve estimates by reducing variance. The Capital Asset Pricing

Model (CAPM) by Sharpe (1964), Lintner (1965), Mossin (1966), and Black et al. (1972) introduces a risk premium through the beta coefficient, measuring the asset's sensitivity to market movements, and it can be described with the following equation:

$$Eit = Rft + \beta t(Rmt - Rft) \tag{3}$$

Where *Ei* is the expected return of security *i* in period *t, Rft* is the risk-free rate in the period (usually the treasuries yield), *β* is the industry *j* index measured by the ratio between the covariance of the industry returns with the total market return, and the market variance, and *Rmt* is market return in the period.

Fama and French (1992) added two additional factors (size and book-to-market equity), demonstrating that this model provided a more accurate explanation of returns. This model has been improved several times over the years, with Fama and French (2015) concluding that the following Five-Factor Model demonstrates superior performance:

$$Eit - Rft = \alpha t + \beta t(Rmt - Rft) + sSMBt + hHMLt + rRMWt + cCMAt \tag{4}$$

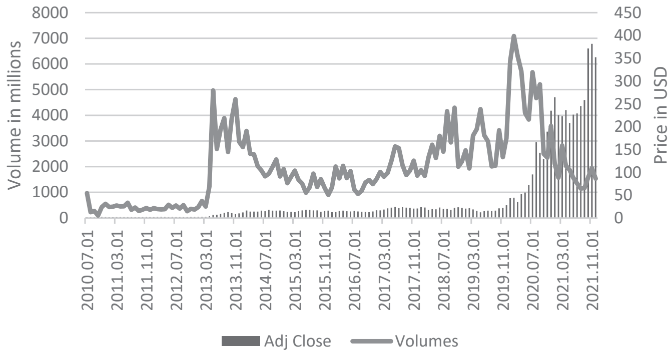
Where, adding to the CAPM factors, *SMB* is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, *HML* is the difference between the returns of diversified portfolios of high and low book-to-market equity stocks, *RMW* is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and *CMA* is the difference between the returns on diversified portfolios of the stocks of low and high investment firms. If all the variation in expected returns is captured by *β*, *s*, *h*, *r*, and *c*, the intercept *αt* is zero.

Given the numerous models that can be used, we chose the canonical CAPM and the more recent Fama and French (2015) Five-Factor Model as an alternative estimation for results validation.

Data

The sample for this study comprises Tesla stock price returns from January 1, 2012, to December 31, 2021. The historical prices of Tesla shares were collected from Yahoo Finance. Figure 1 illustrates the evolution of Tesla's stock price and trading volumes.

Figure 1. *Stock prices and trading volumes of Tesla stocks*



Source: Compiled by the authors, based on Yahoo Finance.

It can be observed that during the sample period, Tesla's stock experienced a substantial price increase, accompanied by high trading volumes that varied significantly over time.

The five factors' data were extracted directly from Professor Kenneth French's website,[2] which includes all market data for the estimations. The market factor results from the weighted return of all CRSP (Center for Research in Security Prices) companies incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ.

As a proxy for the risk-free rate, the U.S. one-month treasury bill rate is used and obtained in conjunction with the remaining data from the website mentioned above.

Events

The content categorization of tweets followed a systematic approach based on established frameworks for analyzing CEO social media communication (Tafesse–Wien 2017). The tweets were collected by exporting all tweets posted by Elon Musk from the X Search API, excluding retweets and replies. This data was stored, indicating the content of the tweet and its publication date, totaling 3,158 tweets.

Four categories were created to categorize the content of each tweet. This distinction was based on the information expressed in the tweet and on the news

2 https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

related to each. The Tesla subcategory is the subject of this research. Regarding the "Other companies founded by Elon Musk" and "Cryptocurrencies," we opted to group them since the research focus is unrelated to these themes. Finally, we designated "Other" tweets whose content proved indecipherable or did not fall into any other category. Two authors performed the initial classification, with disagreements resolved through discussion and consultation with the third author to ensure reliability and consistency in the categorization process. Table 1 details this division.

Table 1. *Content categories and frequency of Elon Musk's tweets*

Category	Content	Number of tweets
Tesla	Congratulations to the team, launch and dissemination of products, public announcements, account reports presentation, and SolarCity.	943
Other companies founded by Elon Musk	SpaceX, Starlink, Neuralink, and The Boring Company, among others.	983
Cryptocurrencies	Exhibition of images and text content related to cryptocurrencies, highlighting Dogecoin, Bitcoin, and tokens.	80
Other	Elon Musk's quotes, current or older facts, cartoons, moments of personal life, and comments on specific events unrelated to the three previous categories.	1,152

Source: Compiled by the authors.

We are only interested in the 943 tweets about Tesla, with several posted on the same day. After eliminating the daily repetition of tweets about Tesla (keeping the first tweet of the day), we have 621 daily tweets for analysis. As Elon Musk frequently posts about Tesla for several consecutive days, we designated the first tweet of each month, provided it was isolated, as an event day. This means we only considered those tweets without interference in the event window, five days before and after a tweet was posted. This was designed to avoid overlapping tweet effects that could have determined stock price returns from previous days. This procedure identified 33 events to which the event study methodology was applied.

We were not interested in classifying the tweets regarding market sentiment, as this research aims to measure the statistical significance of abnormal returns, whether positive or negative, rather than to measure market sentiment. We will assume that the investor will buy Tesla's stocks if the tweet has a positive sentiment and sell them if it is associated with a negative sentiment.

After the tweets were gathered, the historical adjusted closing prices and traded volumes were extracted for each transaction date in *Yahoo Finance.*

There are 2,420 historical price quotes from 2012 to 2021. Tweets posted on days when the market was closed were associated with the following trading day. The estimation period was defined by the ninety trading days before the event.

Regarding the event window, we first estimate abnormal returns using a ten-day window. The first five trading days constitute the pre-event window, and the second five trading days encompass the day of the tweet and the subsequent four trading days. Then, we perform a second estimation with a five-day event window, including the event day and the next four trading days, to verify whether there are abnormal returns that the tweets could have caused beyond any fundamental changes already incorporated into the stock price. The pre-event window is typically applied in corporate finance event studies, where the event day is positioned between the pre-event and post-event windows. These pre-event windows are included to consider any potential information that leaks before the tweet or that the tweet comments on events that have already occurred. With a pre-event window, the event study methodology measures the impact on stock prices of fundamental events that alter the stock's value. Such information must be disclosed to the stock market by Tesla's investor relations departments before being published on Elon Musk's private social media accounts. Our study aims to measure changes in stock prices caused by Elon Musk's communications, excluding any fundamental changes that may already be known to insiders or the stock market prior to the tweet. By excluding the pre-event window, we are controlling for stock price changes that incorporate fundamental information about Tesla's value. Thus, we expect to measure the effects of tweets exclusively, not the effects of the information itself.

Hypothesis testing

We are interested in testing the null hypothesis that the event does not impact returns by statistical inference within the event window. It is necessary to accumulate abnormal returns over time to infer events of the most significant interest. Such accumulation over time is only possible by accepting the premise that there is no correlation between abnormal returns. Acceptance of this assumption predicts that abnormal returns and accumulated abnormal returns are independent. As a general rule, this applies when no overlap record exists in the event windows of the securities under analysis (Campbell et al. 1997). Such accumulation, for N days of events, results from the following expression (Fama 1970):

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

Where is the mean daily abnormal return of security i, and whose variance is:

$$var(\overline{AR_t}) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma^2_{\varepsilon_i^2} \qquad (6)$$

Analyzing the mean daily abnormal returns for any event window period is possible using the two estimates. Given the assumption that abnormal returns follow a normal distribution of zero mean and conditional variance, the calculation of the variance of the mean daily absolute return is obtained from the following equation (Mackinlay 1997):

$$var\ (\overline{AR}(t_{-5}, t_4)) = (1\ /\ N^2)\sum_{i=1}^{N} \sigma^2_{\varepsilon_i}\ (t_{-15} - t_{-5}) \qquad (7)$$

The standard deviation is relative to the period before the event, improving the estimation of the results. Based on the null hypothesis, which considers that the event has no impact on the behavior of returns, we use hypothesis testing to determine the significance level of differences between means. Considering that the objective is to draw conclusions from small samples, the statistical test is based on the t-Student test, often referred to as the t-test. The test is parametric as it uses mean sample data to estimate the population average according to the following equation:

$$\frac{\overline{AR}(t_{-5}, t_4)}{\frac{\sqrt{var\ (\overline{AR}(t_{-5}, t_4))}}{\sqrt{10}}} = \hat{\theta} \sim N(0{,}1) \qquad (8)$$

Where t_{-5} to t_4 is the total duration of the event window (ten days).

One methodological limitation of our approach lies in the number of observations used per event. For each of the 33 events, we used only 10 observations (five days before and five days after) to estimate abnormal returns. This small sample size per event increases the likelihood of Type II errors, reducing the statistical power of our tests. However, this design choice was intentional: our primary aim was not to aggregate abnormal returns across events, which would assume homogeneous event effects, but to isolate the reaction to each tweet while excluding prior known information. We acknowledge that this may limit our ability to detect weak effects. To mitigate this limitation, we supplement our analysis (see the discussion of logit regressions in the section on "Robustness tests") with a pooled model that incorporates all trading days and examines the aggregate effect of tweets using logistic regression.

RESULTS

After determining the daily abnormal returns for each event day, we obtained the mean abnormal returns for each event (Equation 5), estimated using both the Five-Factor Model and the CAPM, with and without a pre-event window in the estimation process. Table 2 presents the selected events and the results of the models defined for the present study, reporting the t-tests (Equation 8) *p*-values that show statistical significance at the 10% level. These results must be interpreted with caution, as the small number of observations per event reduces statistical power and may lead the tests to fail to reject the null hypothesis of no abnormal returns.

Table 2. *Abnormal returns around Elon Musk's tweets*

Dates	Events	With the pre-event window		Without a pre-event window	
		Five-Factor Model	CAPM	Five-Factor Model	CAPM
May 22, 2012	1	0.005	0.006	0.0136*	0.0135*
June 22, 2012	2	0.007	0.006	–0.0042	–0.0065
July 02, 2012	3	–0.010	–0.010	0.0040	0.0037
Sep 06, 2012	4	–0.004	–0.004	–0.0004	–0.0034
July 02, 2013	5	0.005	0.001	0.0019	–0.0080
Aug 20, 2013	6	–0.010	–0.000	–0.0110	0.0089
Sep 06, 2013	7	–0.028**	–0.018**	–0.0241*	–0.0231**
Oct 04, 2013	8	–0.009	–0.015	0.0031	–0.0078
Nov 19, 2013	9	–0.019	–0.012	–0.0059	–0.0025
Dec 19, 2013	10	0.007	0.008	0.0043	0.0074
Feb 25, 2014	11	0.021**	0.022**	0.0338	0.0278
Apr 25, 2014	12	0.001	–0.001	–0.0012	–0.0029
July 01, 2014	13	–0.008	–0.008	–0.0118*	–0.0165***
Aug 04, 2014	14	0.009	0.016**	0.0065	0.0092
Sep 08, 2014	15	0.003	0.004	–0.0033	0.0009

Table 2. *(continued)*

Dates	Events	With the pre-event window		Without a pre-event window	
		Five-Factor Model	CAPM	Five-Factor Model	CAPM
Oct 02, 2014	16	–0.000	0.003	0.0126*	0.0110**
Feb 24, 2015	17	–0.003	–0.002	–0.0068	–0.0081
May 12, 2015	18	0.007	0.006	0.0047	0.0040
Aug 24, 2015	19	0.004	0.006	0.0064	0.0105
Nov 20, 2015	20	0.007	0.007	0.0098	0.0086
Jan 11, 2016	21	–0.002	–0.005	0.0028	0.0011
Mar 07, 2016	22	0.007	0.003	0.0076	0.0028
Dec 01, 2016	23	0.005	0.002	0.0076	0.0034
Sep 14, 2017	24	0.007	0.004	0.0037	0.0010
Oct 26, 2017	25	–0.011	–0.010	–0.0091	–0.0033
Jan 29, 2018	26	–0.000	0.003	0.0111*	0.0126*
Mar 22, 2018	27	–0.013	–0.017	–0.0272**	–0.0300***
Apr 04, 2018	28	0.003	0.003	0.0209	0.0235
Apr 16, 2020	29	0.004	0.014	–0.0229	–0.0123
Oct 14, 2020	30	–0.011	–0.012	–0.0006	–0.0096
Nov 27, 2020	31	0.004	0.008	–0.0098	–0.0028
Jan 19, 2021	32	–0.003	–0.007	0.0079	–0.0018
Nov 22, 2021	33	0.124	0.006	0.0073	–0.0026

Note(s): The first column shows the market trading days defined as events in the day/month/year format. The second column shows the number assigned to each event. Under the estimation models' names, we can find the mean daily abnormal return in the days of the event window for each of the estimations (with or without the five-days pre-event window). Standard errors are available upon request to the corresponding author.
, ** and * represent statistical significance at the level of 10%, 5%, and 1%, respectively.*

Table 2 shows that, using the pre-event window to estimate abnormal returns with the Five-Factor Model, we find only two events with statistically significant abnormal returns (three using the CAPM) in the entire sample of 33 events. Only one tweet resulted in abnormal returns across both window estimations and both models (September 6, 2013), and it was a negative return. Nevertheless, if we exclude the pre-event window, the number of statistically significant abnormal returns after Elon Musk's tweets about Tesla increases to six events, with three exhibiting positive returns both with the Five-Factor Model and the CAPM estimations of expected returns. We can reject the hypothesis that tweets do not influence Tesla's stock prices only on events 1, 7, 13, 16, 26, and 27 (six out of thirty-three events). Both models show the same results, but only the CAPM model achieves significance at the 1% level. We find more statistically significant abnormal returns if we exclude the five trading days before the tweet from the abnormal return estimation. This shows that the market reacts in advance to fundamental information that Elon Musk tweets, neutralizing abnormal returns. Still, the stock prices react abnormally to some random tweets, at least for the next five days after the tweet. This finding raises the question of whether abnormal returns could be generated by trading on Elon Musk's social media activity and investing in Tesla stock on the day of the tweet, while divesting by the end of the trading day. We formally test this possibility in the following section.

ROBUSTNESS TESTS

In the previous section, we used the ten-day and five-day event windows to test whether tweets affect Tesla's stock price, finding that in most event windows, it is not possible to find a statistically significant relationship between the two that could be systematically exploited under a trading strategy. In this section, we want to test if such a strategy could be possible on the day of the tweet (one-day event window), meaning that the investor would have to buy (sell) Tesla's stock immediately after the tweet was published and sell (buy) at the closing price of the tweet's trading day.

Daily abnormal returns

As mentioned, we will only consider the exact day of the event (one-day window) to compute the abnormal return. Table 3 presents the abnormal returns for each day, categorized by event, along with their corresponding t-statistics.

Table 3. *One-day abnormal returns following Elon Musk's tweets*

Events	Five-Factor Model	CAPM
1	0.0754***	0.0709***
2	0.0372*	0.0329
3	–0.0347*	–0.0342*
4	0.0023	–0.0116*
5	0.0016	–0.0072
6	0.0023	0.0111
7	–0.0418**	–0.0307***
8	0.0246	0.0281
9	0.0448**	0.0423*
10	–0.0352**	–0.0487**
11	0.1302***	0.1402***

Table 3. *(continued)*

Events	Five-Factor Model	CAPM
12	0.0031	–0.0179
13	–0.0257***	–0.0184***
14	–0.0015	0.0063
15	–0.0015	0.0172
16	0.0179**	0.0431***
17	–0.0129	–0.0180
18	0.0220*	0.0241**
19	–0.0171	–0.0053
20	–0.0074	–0.0114*
21	–0.0025	–0.0131
22	0.0165	0.0175
23	–0.0169	–0.0345**
24	0.0308**	0.0316**
25	0.0060	–0.0006
26	0.0283***	0.0319***
27	0.0028	0.0052
28	0.0546*	0.0584*
29	–0.0131	0.0022
30	0.0426***	0.0394***
31	–0.0165	0.0061
32	–0.0101	–0.0024
33	0.0306**	0.0174

Note(s): The first column shows the number assigned to each event. Under the names of the estimation models, we can find the daily abnormal return on the day of the event. Standard errors are available upon request to the corresponding author.
, ** and * represent statistical significance at the level of 10%, 5%, and 1%, respectively.*

The Five-Factor Model has fifteen statistically significant events (sixteen for the CAPM), representing less than 50% of the sample days. It shows a strong interaction between the financial market and X sentiment only for a few instances.

Logit regression

To determine whether the statistically significant events considered in our empirical study could be systematically exploited to develop profitable investment strategies, we conducted a second robustness test by measuring the relationship between all daily tweets (621, as described earlier in subsection on *Events*) and all abnormal return days using a logit regression model. A logit regression consists of a generalized linear model whose statistical approach is based on the conditional probability, and the dependent variable is qualitative, typically of the dichotomous or binary type (Greene 2002; Trueck–Rachev 2009). The logit model's dependent variable is binary, assuming the value of one when there are statistically significant abnormal returns ('dummyFF' for the Five-Factor Model and 'dummyCAPM' for CAPM) and zero otherwise. The independent variable is also a dummy variable representing Elon Musk's activity on X, with a value of one on days when there are tweets and zero when there is no interaction.

Thus, it is assumed that logistic regression translates into the following equation (Trueck–Rachev 2009):

$$ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_t \tag{9}$$

Where P represents the probability of abnormal returns occurring on day t, t represents the trading days, and X assumes the value of one if there was a tweet and zero if there was no tweet. The probability of an abnormal return occurrence is given through the following equation:

$$P = \frac{e^{\beta_0+\beta_1 X_t}}{1+e^{\beta_0+\beta_1 X_t}} \tag{10}$$

The specifications used with the Five-Factor Model and the CAPM are translated, respectively, into the following regressions:

$$Logit(P(DummyFF = 1)) = \beta_0 + \beta_1 \; Tweets \tag{11}$$

$$Logit(P(DummyCAPM = 1)) = \beta_0 + \beta_1 \; Tweets \tag{12}$$

The first day considered in this regression is May 22, 2012, with a total sample of 2,420 trading days, of which 621 days have tweets (see subsection on *Events*) and 202 days exhibit abnormal returns according to the Five-Factor Model (207 according to the CAPM). The estimation results are expressed in Table 4 below.

Table 4. *Logistic regression results*

Variables	Five-Factor Model	CAPM
Constant	–1.083*** (0.049)	–1.075*** (0.049)
Tweets	0.222 (0.162)	0.132 (0.162)
R-squared	0.001	0.000
Deviance	2754.463	2.755.648

*Note(s): Standard errors in parentheses. *** represents statistical significance at the 1% level.*

The goodness of fit of both regressions is low and similar. We do not find statistically significant abnormal returns on days when tweets are posted. The constant term, representing the log-odds of abnormal returns on days without tweets, is statistically significant at the 1% level. For both models, this exerts a negative influence, meaning that the probability of abnormal returns on non-tweet days is less than 50%. The following expressions are deduced for the two models, the Five-Factor Model (Equation 11) and CAPM (Equation 12), respectively:

$$P = \frac{e^{\beta_0}}{1 + e^{\beta_0}} = \frac{e^{-1.083}}{1 + e^{-1.083}} = 0.25$$

The probability of a Tesla stock price abnormal return on a trading day without Elon Musk tweeting is 0.25. The result with the CAPM is the same:

$$P = \frac{e^{\beta_0}}{1 + e^{\beta_0}} = \frac{e^{-1.075}}{1 + e^{-1.075}} = 0.25$$

Knowing the baseline probability of abnormal returns on tweet-free days provides a benchmark to assess the incremental predictive power of tweet presence.

The robustness tests confirm the estimated results. Although some days of abnormal returns coincide with Elon Musk's interactions, we did not find evidence that Elon Musk's tweets have an influence on Tesla's stock prices.

DISCUSSION

Our results contradict the findings of Sul et al. (2017), who concluded that a trading strategy based on tweets could deliver abnormal returns, and do not support the Strauss and Smith (2019) and Agrrawal and Agarwal (2023) hypothesis that following corporate managers' posting on X is a valuable market information source for trading with profit. In the specific case of Elon Musk, we find that although there were a few trading days with intraday abnormal returns (in line with the findings of Ranco et al. 2015), after the 2018 ruling (SEC 2018), there was no five days event with abnormal returns on Tesla's stocks, suggesting that the market supervision authorities play an essential role in regulating the dissemination of information about the fundamental value of stocks. The abnormal returns observed in cryptocurrency markets following Elon Musk's tweets about his investments in Bitcoin and Dogecoin (Ante 2023) could serve as a control group to study the effects of communications on financial asset returns. As there is no supervisory authority in the cryptocurrency markets, no regulator could investigate and fine Elon Musk for his tweets if they contained misleading information, thereby facilitating the gain of abnormal returns through communication. We understand that there should be a correlation between Tesla's stock prices and Elon Musk's tweets about Tesla (as shown by Šević et al. 2023, and Kim et al. 2021) because, in many cases, he will be tweeting about new models, profit announcements, investments, etc. However, in a regulated market, this type of fundamental information must be published simultaneously by Tesla's investor relations department (unlike in non-regulated markets such as cryptocurrencies). So, the source of the stock returns will be the fundamental information, not Elon Musk's tweet. Our results suggest that consistently generating abnormal returns through day trading on tweets is unlikely. However, small opportunities may exist that could not be detected due to methodological limitations or data noise. The robustness test using a one-day event window confirms prior findings from Machus et al. (2022) and Tafti et al. (2016), who found temporary spikes in trading activity following tweets but no long-term price impact. Our results similarly suggest that while tweets may briefly influence stock returns, these effects are neither consistent nor strong enough to form the basis of reliable trading strategies.

CONCLUSIONS

Social media communication has become increasingly influential in stock market activity in recent years, making it crucial to investigate its potential impact on corporate communication activities. The empirical study described in our paper contributes to the existing literature on corporate communications in two ways. First, we conducted an extensive study of Elon Musk's tweets by collecting and analyzing 3,158 tweets over ten years, measuring the tweets' effects on Tesla's stock price using several statistical tests. Second, by excluding from the event window the trading days before the tweet (the pre-event window), we measured only the influence of Elon Musk's tweets on stock prices, controlling for fundamental information (such as considering taking Tesla private or announcing a new battery) that the market had already priced into Tesla stock. We found statistically significant abnormal returns when the pre-event window was excluded, indicating that in some cases, Elon Musk's tweets temporarily affect stock prices. This finding suggests that the tweets may generate market noise, as Strauss and Smith (2019) found. However, the market can correct these inefficiencies almost immediately. Using the event study methodology, we conclude that consistently generating abnormal returns through day trading on tweets is unlikely. However, small opportunities may exist that could not be detected due to methodological limitations or data noise.

Our findings have significant implications for the issue of market efficiency and are of interest to investors, regulators, policymakers, and corporate managers. As observed in our empirical study, the rapid correction of market inefficiencies caused by Elon Musk's tweets aligns with what one would expect in an informationally efficient stock market. In an inefficient market, an investor could develop investment strategies that systematically generate abnormal returns, absent transaction costs. However, our results suggest that Elon Musk's tweets cannot be effectively used for this purpose. Therefore, the evidence presented suggests that investors should adopt investment strategies consistent with an informationally efficient market, namely, passive investment strategies. Our results are also of interest to regulators and policymakers as they demonstrate that the upper echelons of the corporate world, such as Elon Musk, do not appear to have the capacity to significantly and durably influence prices through social media. Corporate managers should be aware that communicating through social media may affect their company's stock prices for short periods (such as one day) but will not consistently impact stock returns.

One of the study's limitations is related to the analysis of tweets. There are doubts about whether retweets and comments have no bearing on investor decision-making since, in many situations, Elon Musk shares a tweet and unfolds scenarios from it. In future investigations, retweets and responses could be considered, for example, when there is a larger number of interactions. Another limitation is that we did not consider the effect of stock trading volumes on prices during the event windows. We did not follow that path because it was not the primary purpose of this research project; however, we leave this hypothesis as a suggestion for future research.

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