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Evaluating the impact of Elon Musk's tweets on Tesla's stock price: an empirical study

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Introduction

The issue regarding the potential impact of Chief Executive Officers' social media activity on the market value of companies has been well-known to the Securities and Exchange Commission (SEC) for over a decade. Nevertheless, few studies have investigated this phenomenon so far.

This matter was first brought to light in 2012, when Netflix CEO Reed Hastings ended up under investigation by the SEC (Securities and Exchange Commission, 2013a) for suspected violation of the Regulation Fair Disclosure (Reg FD) and Section 13(a) of the Securities Exchange Act of 1934 ("Exchange Act") for publishing on his personal Facebook profile on 3 July a post in which he revealed that in June the platform's users had spent a total of more than 1 billion hours. On the same day, the share price of the streaming platform spiked by about 6.2% (Bensinger, 2012).

At the time, the regulatory framework did not foresee corporate or CEOs' accounts on Facebook to be identified as recognised channels of distribution for the disclosure of material, non-public information, unlike press releases or communications through the companies' official websites.

Despite initial controversy, the report of the investigation concluded favourably for Hastings, with the SEC's decision not to pursue any enforcement action against him or Netflix, along with the concomitant choice (SEC, 2013b), to extend the application of the 2008 Commission Guidance on the Use of Company Web Sites (SEC, 2008) to corporate social media outlets. With this clarification by the SEC, it became possible for listed companies to employ these channels to disseminate material, non-public information, provided that investors are notified beforehand (SEC, 2013b).

This event led to an overwhelming growth since 2013 in companies' exploitation of social media channels such as Facebook and Twitter, to convey to all stakeholders.

Since Tesla publicly filed Form 8-K on 5 November 2013 to allow its CEO's Twitter account to be a recognised dissemination channel for material information about the company, Musk has often hit the headlines for his controversial tweets.

Since his famous tweet on 7 August 2018, in which Musk stated: *"Am considering taking Tesla private at $420. Funding secured",* the Tesla tycoon's Twitter activity caught the attention of the SEC, raising the question of whether this was harmful to shareholders. This tweet and the subsequent replies specifying details of the potential ongoing private transaction, such as the price or the creation of a special purpose fund (similar to the Fidelity used for SpaceX), caused a halt to the trading of Tesla's shares by the NASDAQ for more than an hour and then an increase in share price by 6.42% since the first tweet, from $356.67 to $379.57 (SEC v. Musk Civil Action, 2018; SEC v. Tesla Civil Action, 2018).

Over the following months, the transaction to take Tesla private never occurred, prompting the SEC to file two complaints against Elon Musk (SEC v. Musk Civil Action, 2018) for violating Section

10(b) of the Securities Exchange Act of 1934 and Rule 10b-5, and against Tesla (SEC v. Tesla Civil Action, 2018) for failing to comply with Rule 13a-15 of the Exchange Act, on 27 and 29 September 2018, respectively.

The SEC's investigations highlighted that the *"statements by Musk via Twitter were false and misleading and impacted the price of Tesla's stock"* (SEC v. Musk Civil Action, 2018) and that Tesla lacked policies or procedures to oversee Musk's tweets and to ensure that the information contained therein was accurate or complete (SEC v. Tesla Civil Action, 2018).

As a consequence of these allegations by the SEC, both Musk and Tesla were forced by the United States District Court for the Southern District of New York to pay a $20 million penalty each, Musk was compelled to resign as Chairman of Tesla's Board of Directors and the parties reached an agreement whereby a Tesla securities attorney-at-law would have to pre-approve any Musk's tweets or other forms of written communication that *"contain, or reasonably could contain, material information to Tesla or its stockholders"* (SEC v. Musk Final Judgment, 2018).

Nevertheless, already on 19 February 2019, Musk's reply to one of his tweets, in which he declared that *"Tesla made 0 cars in 2011, but will make around 500k in 2019"*, brought the CEO back into trouble with the SEC, who accused him of violating the terms of the previous agreement as the post had been published without pre-approval by a Tesla lawyer (Michaels & Higgins, 2019). The new controversy resulted in a bilateral amendment to subpart (b) of paragraph IV of the Final Judgment, which precisely defined an exhaustive list of topics for which Musk would have to obtain pre-approval before he could post a tweet concerning them, including Tesla's financial results, potential mergers and acquisitions, production volume and sales or delivery numbers (SEC v. Musk Order Amending the Final Judgment, 2019).

Even after this modification, in the following years the SEC lamented Elon Musk's continuous violations of the pre-approval policy of written public statements. Two tweets without pre-authorisation prompted most of the solicitation letters from senior officials of the SEC to Tesla to enforce disclosure controls and procedures (Michaels & Elliott, 2021). In the first one, Tesla's CEO on 29 July 2019 replied to comments under one of his tweets: *"Spooling up production line rapidly. Hoping to manufacture ~1000 solar roofs/week by end of this year",* while in the second one on 1 May 2020, he cryptically affirmed that: *"Tesla's stock price is too high imo",* probably causing the share price to fall by 9% (Higgins, 2020). In both cases, Tesla's lawyers stated that they did not need pre-approval as they did not fall under the list of topics requiring it, but described them respectively as *"wholly aspirational"* and as a *"personal opinion"* (Michaels & Elliott, 2021).

In addition to these disputes with the SEC, there is the class action that Tesla's shareholders (Gharrity v. Musk et al., 2021) have filed against Musk for the 7 August 2018 tweet about Tesla's delisting.

In light of these court disputes, one question arises: *Do Elon Musk's tweets really impact Tesla's share price?* Although the aforementioned legal issues and most of the world's major financial newspapers suggest (Vercoe, 2021) an affirmative answer, no study has empirically proven it to the current state of the knowledge; thus, this paper attempts to answer this question.

The paper is structured as follows. Chapter 1 reviews the relevant literature, defines the research gap and the research question, and finally introduces the hypotheses backed by the theoretical background. Chapter 2 illustrates the collection of data on Tesla's share prices and the tweets published by Elon Musk. Chapter 3 illustrates the two methodologies employed: sentiment analysis and event study methodology. In particular, the tweets selected for analysis are first categorised into three sentiment classes (positive, neutral, negative) using BERTweet (Nguyen et al., 2020), a highly accredited language model, in performing sentiment analysis tasks related to Twitter. Subsequently, an event study based on the market model (Fama et al., 1969) is conducted using daily returns, event windows of [0,1] and [0,2], estimation windows of [-124,-5], and two different market indices to corroborate the results, the NASDAQ-100 and NASDAQ Composite.

Lastly, Chapter 4 presents the results achieved by the study. With regard to the sentiment analysis, it reveals Elon Musk's tendency to express a non-negative sentiment in tweets in which he mentions Tesla. The findings of the event study indicate that Elon Musk's tweets mentioning Tesla, characterised by positive sentiment on average, generate positive and statistically significant cumulative abnormal returns, thus indicating that they can positively influence Tesla's share price. However, concerning the other two sentiment classes, neutral tweets are not found to significantly impact Tesla's share price, while those with negative sentiment constitute an insufficient sample to test the hypothesis of a negative impact on Tesla's stock price.

Finally, the results of the event study also provide interesting insights into some of Elon Musk's most debated tweets. Referring to those mentioned above, it emerges that the 7 August 2018 tweet in which Musk announced: *"Am considering taking Tesla private at $420. Funding secured"*, generated an abnormal return on the day of the tweet above 10% ($p < 0.01$) and a cumulative abnormal return above 8% ($p < 0.01$) in the event window [0,1]. While it appears that the 1 May 2020 tweet *"Tesla's stock price is too high imo"* did not impact Tesla's stock price statistically significantly.

Literature Review

1.1 Investor Sentiment as a Challenge to the Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) during the 1960s garnered tremendous empirical and theoretical support until the occurrence of market crashes such as the Black Monday of 1987 and anomalies such as *underreaction* and *overreaction*, which failed to find an explanation under Fama's theoretical framework (1970). The initial success of the EMH can be succinctly synthesised in the words of Micheal Jensen, one of the leading contributors to the development of the theorem, who asserted that *"there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis"* (Jensen, 1978).

The EMH posits that the market must be able to completely reflect all publicly available information at any time to be considered efficient.

Three are the principal assumptions underlying the theoretical foundations of the EMH: *"First, investors are assumed to be rational and hence to value securities rationally. Second, to the extent that some investors are not rational, trier trades are random and therefore cancel each other out without affecting prices. Third, to the extent that investors are irrational in similar ways, they are met in the market by rational arbitrageurs who eliminate their influence on prices"* (Shleifer, 2000).

Fama breaks down the EMH into three progressively increasing tiers of market efficiency based on three types of *stale information*.

Firstly, the author emphasises past prices and asset returns as relevant information for investors. Upon this stale information, Fama hypothesises the *weak-form* efficiency, which implies that no market participant can predict the price movements of an asset and make profits by exploiting its historical prices as information. Indeed, the author argues that prices follow the so-called random walk (Fama, 1965) when market agents are rational and risk-neutral. This is also supported by the papers of Alexander (1961), Alexander (1964), Samuelson (1965), Mandelbrot (1966) and Fama & Blume (1966).

Secondly, Fama, in the *semi-strong* form of efficiency, broadens the scope of stale information from past prices to any information available to the public. In a semi-strong form efficient market, no investor can gain superior risk-adjusted returns by trading on public information, as it is instantaneously incorporated into prices as soon as it is publicly available. The semi-strong form of market efficiency also finds empirical support in the literature (Fama et al., 1969; Ball & Brown, 1968).

Finally, Fama addresses market efficiency in a situation where few investors benefit from privileged information or so-called insider information. Accordingly, the market is defined as efficient in

a *strong form* following the EMH when even private signals are quickly incorporated into asset prices as a result of the private information being leaked by the few privileged investors to the public.
However, as aforementioned, with the emergence of an array of phenomena against the idea that investors are completely rational and emotionless, a new branch of literature called *behavioural finance* emerged, pointing out a series of subjective factors of investors, such as sentiment.
Although no widely accepted definition exists in the behavioural finance literature, investor sentiment can be described by the definition provided by Baker & Wurgler (2007), which defines it as *"a belief about future cash flows and investment risks that is not justified by the facts at hand"*.
Several models have attempted to go beyond the assumption of complete investor rationality, to investigate and measure the effect of investor sentiment on the price of financial assets, particularly on stock prices. Nevertheless, as the author of the EMH explains *"Following the standard scientific rule, market efficiency can only be replaced by a better model…The alternative has a daunting task. It must specify what it is about investor psychology that causes simultaneous underreaction to some types of events and overreaction to others…. And the alternative must present well-defined hypotheses, themselves potentially rejectable by empirical tests"* (Fama, 1998).
These models can be classified by the approach followed by the authors. While some, such as Barberis et al. (1998) and Daniel et al. (1998), decided to proceed with a bottom-up approach, grounding their theoretical frameworks on different cognitive biases, other researchers, such as Baker & Wurgler (2006, 2007) adopted a top-down or macroeconomic approach.
Both the models of Barberis et al. (1998) and Daniel et al. (1998) deal with the information absorption speed of the market and the phenomena of overreaction and underreaction.
The overreaction hypothesis entails that investors overreact to the latest news, disregarding or paying less attention to past news. This phenomenon implies that when there is good news, investors react in an extremely optimistic manner, and the resulting rise in the share price will cause it to overshoot its intrinsic value, whereas in the case of bad news, the opposite is true.
However, an overreaction phenomenon actually occurs, if, over the medium-long term the share price undergoes a reversion to the mean, not caused by accounting data. Moreover, the greater the magnitude of the first price change, the greater will be the subsequent adjustment in the opposite direction.
Overreaction has been extensively documented (Brown & Harlow, 1988; Cutler et al., 1991; De Bondt and Thaler, 1985, 1987; Chopra et al., 1992; Fama & French, 1992; Lakonishok et al., 1994; La Porta, 1996; Howe, 1986), especially by proving the predictability of future price adjustments based on historical pricing data, in contrast with the weak-form of market efficiency (Fama, 1970).

De Bondt & Thaler (1985) pioneered the study of this phenomenon by analysing the monthly returns data of hundreds of NYSE stocks between 1926 and 1982. The two authors revealed that the portfolios of the 35 extreme loser stocks over the previous five years outperformed the market by an average of 19.6% in the three years following the formation of the portfolios. Conversely, portfolios of stocks that had experienced extraordinary capital gains over the previous five years, had been beaten by the market by an average of 5% in the following three years.

Finally, they conclude that best-performing portfolios are significantly outmatched by worst-performing portfolios by an average of 24.6%.

Underreaction to a piece of news by the market occurs when the response of the participants is insufficient and causes a sluggish absorption of the news into the price.

Similar to overreaction, underreaction is also a phenomenon that has been thoroughly investigated (Cutler et al., 1991; Bernard & Thomas, 1989; Jegadeesh & Titman, 1993; Chan et al., 1996; Rouwenhorst, 1998; Antoniou et al., 2012), examining the possibility of making profits through a momentum strategy. The latter rely on the investment idea that companies that have previously experienced positive (negative) price changes will yield positive (negative) stock returns in the future, thereby indicating a trend.

One of the first articles to reveal this phenomenon is that of Jegadeesh & Titman (1993), in which they observed significant positive stock return serial correlations between 1965 and 1989 on a sample of companies on the NYSE and AMEX. The authors illustrate that in the analysed period momentum strategies based on portfolios defined as *"J-Months/K Months"*[1], would have guaranteed significant abnormal stock returns with J and K ranging from a minimum of three to a maximum of twelve months. In particular, when both the formation period and the holding period have a duration of six months (J=K=6), a strategy that would buy the stocks with the highest positive stock returns and sell those with the worst performance in the formation period would ensure about 1% return per month.

With plenty of empirical evidence of both the overreaction and underreaction phenomena, the need arose to construct a theoretical model capable of explaining their co-existence.

Barberis et al. (1998) provide one of the first frameworks to deeply comprehend the way investors form their beliefs on future earnings, which can account for both the overreaction and underreaction phenomena.

They focus their model in particular on two psychological aspects, *conservatism* and *representativeness heuristic*. The first indicates the reluctance with which individuals change their expectations upon the emergence of new information or evidence and hence the authors pick this

[1] Where J represents the number of months of the formation period and K expresses the number of months of the holding period.

aspect as indicative of the underreaction phenomena. The second, which evokes the overreaction consists of those judgemental shortcuts that lead individuals to identify patterns when actually facing random sequences, and thus to evaluate *"the probability of an uncertain event, or a sample, by the degree to which it is (i) similar in its essential properties to the parent population, (ii) reflects the salient features of the process by which it is generated"* (Kahneman & Tversky, 1974).

This model is composed of a single risk-neutral subject which, who not only reflects the investor consensus forecasts on future earnings, but is also the only one able to affect the share price with its sentiment.

Secondly, in this model there exists only one share available on the market with a pay-out ratio of 100%, so that for reasons of simplicity the equilibrium price of this share will be equal to the net present value of future earnings, based on the beliefs of the sole representative investor.

Thirdly, the discount rate is taken as constant, and future earnings follow an utterly random path.

The authors state that the representative investor is unaware of the randomness of earning streams but believes that the world is governed by two *regimes*, with two different models for determining future earnings, neither including random-walk. *Model 1*, which defines earnings in *regime 1*, implies that they are mean-reverting, whereas in *Model 2* they follow a trend whereby a positive (negative) change in earnings will be followed by another positive (negative) change in future. The authors build up these two models for determining earnings to include the two psychological aspects that lead to overreaction and underreaction phenomena, namely conservatism for Model 1 and representativeness heuristic for Model 2.

In line with the Griffin & Tversky (1992) framework, which attempts to bring conservatism and representativeness heuristic together, the investor sentiment model of Barberis et al. (1998) posits that individuals in formulating predictions about future earnings are more concerned with the strength[2] or extremeness of one piece of evidence than with its statistical weight or credibility.

Thus, investors, in forming beliefs about future earnings (consistent with the psychological phenomenon of conservatism), give little attention and underreact to the information in an isolated quarterly earnings announcement, given a low strength. Conservatism leads individuals not to change previous beliefs or only partially adjust them, suggesting that they underestimate the statistical weight of this news. Nevertheless, because of the representativeness heuristic, investors may be inclined to be overly attentive and overreact to past growth patterns in earnings, given the high strength of such data, even with low statistical weight.

[2] Griffin & Tversky (1992) define the strength and weight of evidence through some examples. One of them is the case where we want to study whether a coin is more likely to come up heads than tails when tossed. In this case the strength is indicated by the authors as the percentage of times the heads event occurs, while the weight is indicated by the sample size.

Daniel et al. (1998), in attempting to bring together the evidence of both overreaction and underreaction, proposed a new integrated theory rooted in two cognitive biases: *investor overconfidence* and *biased self-attribution*. The former relates to the extent to which an investor overweight the accuracy of their private signals, while the second psychological factor is actually included in the model as an explanatory element for the asymmetrical variations in investor overconfidence levels over time. Self-attribution bias increases an investor's overconfidence in their private signals when these are confirmed by publicly available information. However, it does not lead to a commensurate decrease in overconfidence when their private information is inconsistent with public information.

Thus, when public information corroborates a private signal, the investor's overconfidence increases, inducing further overreaction. Therefore, this means that the effect of self-attribution leads to short-run momentum, showing that the phenomenon of overreaction can be associated with short-run positive return autocorrelations, which in literature are usually linked to underreaction phenomenon. However, in the long term, this phenomenon usually turns out to be followed by reversals that drive prices closer to their intrinsic value.

Given these cognitive biases, the researchers draw the conclusion that investors have excessive reactions to their private information. In contrast, they have less intense reactions than what would be rationally appropriate to public information.

Conversely, the first tentative to investigate the effects of investor sentiment on share prices that follows a top-down approach is the one by Baker & Wurgler (2007), who developed three indexes to assess investor sentiment.

The first, called the *Sentiment Changes Index*, is built by aggregating six of the most common proxies used in the literature to gauge investor sentiment: the equity issues over total new issues, the IPO volume, the IPO first-day returns, the share turnover or trading volume, the closed-end fund discount and the dividend premium. While the first four turn out to be positively associated with sentiment levels, the last two are negatively associated with it.

The other two indexes rely instead on mutual fund flows since these can be deployed as an indicator of the decisions undertaken by a large number of unsophisticated investors.

The first index of the two, based on mutual fund flows, is based on the monthly time series of the general demand, which shows inflows and outflows of investors into and out of mutual funds.

The second one is constructed on monthly time series of speculative demand, depicting investors migrating from safer mutual funds to more speculative ones. Measuring the correlation of these two indices with the sentiment changes index, it emerges that the generic demand index is slightly correlated, while the speculative demand index presents a highly significant coefficient of correlation of 0.36.

Baker & Wurgler (2007) found that the stock returns of speculative and *harder-to-arbitrage* stocks are positively associated with investor sentiment and more sensitive to investor sentiment changes, as the effects of general demand, speculative demand, and sentiment betas increase when stocks become more speculative and harder-to-arbitrage. Conversely, *bond-like* stocks show a negative effect of speculative demand, reduced impact of general demand of mutual fund flows and negative sentiment betas and are therefore negatively correlated with changes in sentiment.

Speculative stocks refer to those which are difficult to assess, incorporating high levels of subjectivity into their valuation process due to the lack of earnings and dividend payment history. Additional characteristics that distinguish them are their youth, small size, high volatility and vast opportunities for growth in the future.

Baker & Wurgler (2007) also explore the predictability of future stock returns, conjecturing that speculative stocks that are overvalued due to high investor sentiment will experience lower stock returns in the future as a consequence of a decline in sentiment or revelation of fundamentals.

The researchers illustrate that the average future returns of speculative shares are higher than safe and *easy-to-arbitrage* stocks when sentiment is low and vice versa when sentiment is high. This finding, which is consistent with the previous results of their previous paper (Baker & Wurgler, 2006), is at odds with the traditional asset pricing theory, which states that there exists an inverse relationship between risk and return, as the evidence showed by Baker & Wurgler (2006, 2007) shows that when sentiment is low, the returns of less risky stocks are higher than that of riskier stocks.

In the behavioural finance literature, there are also *psychology-free* approaches (Barberis, 2018) that deal with the interaction of two different actors within the market, such as those of De Long et al. (1990) and Hong & Stein (1999).

De Long et al. (1990) outline a novel framework in which they assume that only two types of market participants operate: *noise traders* and *arbitrageurs*.

The former are defined, in line with earlier papers by Kyle (1985) and Black (1986), as irrational investors who, unable to access insider information, make decisions solely on the basis of *noise*, treating it as relevant information on the future price of an asset. This leads them to form totally erroneous stochastic beliefs and act on them, driving asset prices away from their intrinsic values.

Arbitrageurs are thought to be rational sophisticated investors who are completely capable of detecting the behaviour of noise traders and implementing contrarian strategies aimed at earning from mispricing, and with these actions, drive prices back towards their fundamental values.

As aforementioned, one of the assumptions of the EMH lies in the fact that if there were irrational investors in the market, there would be other rational market participants who were able to eliminate the effect of the former (Friedman, 1953; Fama, 1965). Yet, in contrast to this assumption, prior to the model of De Long et al. (1990), some evidence had been provided of one constraint on arbitrage by rational investors, that is the one to bear the *fundamental risk* (Figlewski, 1979; Shiller, 1984; Campbell & Kyle, 1993).

Through this theoretical model, De Long et al. (1990) highlight what they call *noise trader risk* as an additional limit for rational investors to exploit and correct mispricing created by the erroneous beliefs of noise traders. The additional risk that arbitrageurs ought to bear lies in the possibility that in the short term, noise traders' beliefs might not change, but rather become more extreme. This means that if noise traders are incredibly optimistic about a particular asset and thus drive its price upwards, a rational arbitrageur who implements a contrarian strategy by shorting the asset will have to take into account that the sentiment of noise traders could not revert but become even more bullish. This poses a risk to arbitrageurs because if they have to liquidate their short position before the sentiment of the noise traders changes and reverts to the mean, they will incur a loss.

A further theoretical framework that analyses the interplay of two different types of investors is that of Hong & Stein (1999), who divide market players into *news-watchers* and *momentum traders*. In this model, one of the assumptions mentioned above of the EMH is transcended, as both categories do not enjoy full rationality but are only boundedly rational, as they are unable to process all available information.

In particular, news-watchers make their predictions by relying on private information but without taking past and recent prices into account. Momentum traders, meanwhile, focus on past stock returns and ground their predictions exclusively on them.

Thirdly, the last assumption of the model is that news-watcher investors' private signals propagate gradationally among them.

Hong & Stein (1999) point out that given the last assumption and that news-watchers do not observe prices, only underreaction occurs in a model consisting solely of news-watchers.

Once momentum traders are introduced into the framework, they begin arbitrating this underreaction situation through momentum strategies. These strategies are most profitable for momentum traders in the first phase of what the authors call the *momentum cycle*, immediately after the news comes on to the news-watchers.

However, since the forecasts guiding momentum traders' decisions are merely a function of price data, those who invest in the latter part of the cycle will incur losses. This is because momentum traders entering the early part of the cycle will compensate for the initial underreaction triggered by news-watchers by exploiting the difference between price and long-run equilibrium value. In contrast, late momentum buyers will invest when the price has already fully incorporated the information and has reached equilibrium, resulting in overreaction. In conclusion, they combine the evidence of overreaction and underreaction, stating that an underreaction to the news by news-watchers creates the conditions for making a profit in the early part of the momentum cycle for momentum traders, which, however, culminates in an overreaction in the late part of the cycle by momentum traders.

Unlike previous models that seek to understand how investor sentiment impacts stock price, Lawrence et al. (2007) sought to develop a stock pricing model to encompass investor sentiment in the EMH-based model.

Investor sentiment in this latter paper is interpreted as the future expectations that a given investor has subjectively about a specific company, depending on several variables such as age, risk aversion, individual wealth or educational background.

Lawrence et al. 2007 hypothesise that investor sentiment can affect both the expected discount rate and the expected growth rate. Concerning the former, they include investor sentiment in the beta of the Capital Asset Pricing Model (Sharpe, 1964), whereby if an investor has positive expectations about the future performance of the company, he will perceive it to be less risky and thus both the beta and the expected discount rate will be lower than in the standard classical model and conversely if he has negative expectations.

Regarding the expected growth rate in the Dividend Discount Model (Gordon & Shapiro, 1956), in the case of high investor sentiment, the rate will be higher than the standard rate and vice versa in the case of low sentiment.

By incorporating investor sentiment into the expected discount rate and the expected growth rate, the perceived value of a specific stock by an investor with high sentiment will be higher than by the classical model, while it will be lower for an investor with a low sentiment. Thus, when a given stock's price is higher than the value that low-sentiment investors perceive, they will be driven to sell that stock (and vice versa).

Finally, when at a given share price, the number of low-sentiment investors is larger than the number of high-sentiment investors, this means the investors who are willing to sell the share on the market (the supply) will be larger than those who are willing to buy it (the demand) causing a decrease in the price of that particular share.

In conclusion, the magnitude of the impact of investor sentiment has been well documented in the literature, and several theoretical models have attempted to explain its dynamics. However, they have yet to prove to prevail over the others.

1.2 Twitter Sentiment Analysis as a Tool to Measure Investor Sentiment

Twitter is an online microblogging service born in March 2006 from the brainchild of the engineer Jack Dorsey to save the company Odeo after the launch of iTunes by Apple (Wolan, 2011). From Jack Dorsey's early vision to create a short message service to share short thoughts with friends, it quickly emerged as one of the most important social media of the 21st century worldwide, especially for spreading news and political messages. This success led to the listing of Twitter Inc. on the New York Stock Exchange (NYSE) in November 2013, with a market value of $31 billion (Goel, 2013). However, after Elon Musk's $44 billion takeover at the end of 2022, Twitter Inc. was delisted from the NYSE (Conger & Hirsch, 2022).

The social initially allowed for sharing messages of 140 characters, which was extended to 280 in 2017 (Rosen & Ihara, 2017) and is likely to be extended to 4,000 in the near future for users who purchased the blue checkmark subscription (Reimann, 2023). Among social media's main functionalities, there are the possibilities of following another user's account, liking their tweets, and replying to or retweeting them.

Currently, 368.4 million active users worldwide in 2022 accessed their Twitter accounts at least once a month. However, this number is expected to decrease in 2023 by 3% and by 5.1 % in 2024, bringing the global monthly user base to 335.7 million users (Lebow, 2022).

In addition to the conventional purposes for which social media platforms are generally used, they have recently started to play a crucial role in financial decision-making.

In a survey conducted by the investment firm TIAA, 33% of respondents say they trust social media content to guide their financial decisions, and 32% rely on advice shared by social media influencers and celebrities (KRC Research, 2021).

In another survey conducted by Morning Consult, this time among 2,200 US adults, respondents seeking information about investing in social media increased by four percentage points from 14% in August 2020 to 18% in 2021 (Principato, 2021).

This crescent trend appears to be more relevant for particular targets than for others. According to the CNBC survey, 12% of investors aged between 18 and 34 have learned to invest from social media, and 37% of respondents in the same age group indicate social media as the most used source for new investment ideas. By contrast, for the 35-64 age group, only 3% reported having learned how to invest through social media, and 17% said they use social media for investment ideas. While in terms of income brackets, 28 % of respondents earning less than $50,000 tend to rely more on social for investment advice (Fox, 2021b).

Especially for the young adult segment of the population, Twitter is one of the most used social networks in the financial field. Although 33% of Gen Z and millennials cite Facebook as a source of information that has significantly impacted their financial decisions, Twitter account for and 27%. Furthermore, Twitter is the social platform with the largest number of investor users, with 51% of respondents using Twitter actively investing in financial markets (Principato, 2021).

In this novel setting, where especially unsophisticated investors tend to pay attention to social media in taking their investment decisions, it is relevant to investigate whether the sentiment arising from such social media can impact the share price of the companies mentioned in the posts.

The most influential paper in this area is certainly that of Bollen et al. (2011b). Analysing millions of tweets posted between 28 February and 19 December 2008, the authors show that the public sentiment that arises from Twitter is capable of predicting the price changes of the Dow Jones Industrial Average (DJIA) with an average accuracy of 86.7%. In order to extract the public mood from the tweets of 2.7 million users, Bollen et al. (2011b) employ OpinionFinder[3] and Google Profile of Mood States (GPOMS)[4], while Granger causality analysis and a Self-Organising Fuzzy Neural Network are used to investigate the predictive power of public mood with respect to the stock market. Nevertheless, it appears the mood dimensions of OpinionFinder's assessment have no predictive effect, while in the case of the GPOMS assessment, not all six mood dimensions Granger-cause movements of the DJIA. Among the six mood dimensions used in the second assessment, *Calm* is the one that alone exhibits the most significant Granger causative relationship, improving both predictive accuracy and mean average percentage error.

Other articles, rather than focusing on a specific market index, have devoted their attention to examining the impact on the shares of specific companies. In this field, Smailović et al. (2014) reviewed over 150,000 tweets posted from March 2011 to December of the same year that targeted eight specific listed companies, including Apple, Amazon, Baidu, Cisco, Google, Microsoft, Netflix, and RIM. The authors investigate the sentiment of these tweets through a Support Vector Machine (SVM) classifier that distinguishes not only positive or negative but also considers sentiment-neutral tweets. They use the Granger causality test, Smailović et al. (2014), to demonstrate that public sentiment extracted from Twitter can predict the price movements of the stocks mentioned above a few days in advance.

Broadstock & Zhang (2019), with a sample of six US companies, namely Disney, Ford Motor Company, Walmart, General Electric, Exxon Mobil and Chesapeake Energy, reveal that besides Twitter sentiment relative to the given company, also Twitter sentiment about the market index

[3] OpinionFinder is a software that allows one to analyse the emotional polarity of a sentence by determining whether it expresses a positive or negative mood state.

[4] Google Profile of Mood States is a sentiment analysis tool developed by Bollen et. (2011) based on the psychometric tool called Profile of Mood States (Norcross et al., 1984). GPOMS enables to classify a statement according to the following six dimensions *Calm, Alert, Sure, Vital, Kind* and *Happy*.

S&P500 significantly impacts the intra-day returns of the companies' share prices, albeit with different effects on each of the six companies.

Little attention has been paid to the effect of Twitter sentiment on a specific company's share price. Pagolu et al. (2016) explore how Microsoft's share price may have been influenced by the positive, negative, and neutral sentiment expressed not only about Microsoft's financial issues but also about products and services by Twitter users over one year. The authors find a strong correlation between a company's share price and all three categories of Twitter sentiment.

Some studies have instead focused on investigating possible differences between negative and positive Twitter sentiment. Mendoza-Urdiales et al. (2022), examining a sample of the 24 companies with the largest capitalisation traded on different stock exchanges in different countries, demonstrate that the impact of negative Twitter sentiment on stock performance was more significant than positive Twitter sentiment. This evidence is in line with the findings of Oh & Sheng (2011), who analysing other microblogging platforms such as Yahoo Finance and Stocktwits.com, illustrate that the predictive power of sentiment increases when investors collectively express negative and bearish expectations, while it decreases when these are positive or bullish.

Most of the existing literature has focused more on exploring the extent to which overall Twitter sentiment concerning a given company impacts its share price without distinguishing between the type of information shared on the social platform. Sprenger et al. (2014) shed light on how when one analyses tweets, in addition, to distinguish by sentiment, classifying them into different categories of news event types can provide essential insights about stock returns.

The authors categorise the tweets about each company into six different business-related event categories: *Restructuring Issues, Legal Issues, Financial Issues, Operations, Corporate Governance and Technical Trading*.

One of the most striking findings is that looking solely at the volume of tweets regarding each of the six issues, they find no abnormal share price return on the event day and little cumulative abnormal returns (CARs) in the days before or after. However, the effect of tweets related to these event categories on the companies' share price becomes evident when the bullish or bearish sentiment stemming from the tweets is included in the analysis. Therefore, after examining all six categories and distinguishing by news event sentiment, it emerges that 11 out of 12 events cause abnormal returns during the event day that are statistically significant or at the 5% or 1% level.

More precisely, the results indicate that tweets with bullish sentiment regarding *Restructuring Issues* and *Financial Issues* have a more positive and statistically significant impact on the share price than *Corporate Governance* and *Operations Issues*. On the other hand, *Legal Issues* are found to have a significant negative influence on the stock price only when these issues are expressed in tweets with a negative sentiment.

Furthermore, Sprenger et al. (2014), after having proven that almost all categories of events have a significant impact on share price, turn to a more detailed level of investigation by examining the impact of tweets regarding sixteen specific events such as *M&A, Analyst Rating, Product Development, Earnings*, etc.

The findings reveal that only a few events are associated with statistically significant abnormal returns for both positive and negative Twitter sentiment, most notably *M&A* activity and *Earnings*.

Certain events appear relevant only when accompanied by negative sentiment, such as *Analyst Rating*, *Product Development* and *Marketing*. Specifically, concerning the first event of these three, the result is consistent with the existing literature claiming that since, in most cases, the ratings assigned by analysts are optimistic, investors do not hold them into consideration, and therefore, no noticeable stock price changes occur in relation to them (McNichols & O'Brien, 1997). Nevertheless, *Analyst Rating* events with negative sentiment generate average abnormal returns (AARs) of -2.66%, statistically significant at the 5% level.

Ranco et al. (2015) assert that only at selected points in time, referred to by the authors as *events* and identified as peaks of Twitter volume, is there a strong relationship between Twitter sentiment and the stock market. To support their argument, the researchers examine the sentiment arising from Twitter and the volume of tweets concerning the firms included within the DJIA index over 15 months and discover a low correlation between daily sentiment polarity and stock returns. Even after performing a Granger causality test, they highlight that for only 3 out of the 30 companies in the DJIA, there is a Granger causal relationship between Twitter sentiment polarity and the companies' stock returns, while for 33% of the companies, there exists such a relationship between Twitter volume and stock returns.

Nevertheless, narrowing the analysis to shorter periods in which Twitter volume peaks occur, Ranco et al. (2015) show that Twitter sentiment polarity leads to statistically significant cumulative abnormal returns in the range of 1-2%, where the direction (positive or negative) is determined by sentiment polarity (negative or positive). The presence of CARs applies to events that investors expect, such as earning announcements and volume peaks caused by unexpected news. Abnormal returns are significant at the 1% level for ten days after the event if earning announcements are included in the sample of events analysed, while the window of time for which they persist shrinks to four days by removing earning announcements.

There is also a branch of literature investigating how Twitter sentiment could influence stock returns during the period following a crucial corporate event, the Initial Public Offering (IPO). A relevant article in this field is the one by Liew & Wang (2016), who, analysing a sample of 325 IPOs that took place on the NYSE or NASDAQ between January 2013 and December 2014, shed light on the correlation that exists between the average Twitter sentiment related to a specific company's IPO in the pre-transaction days and first-day performance in terms of share prices. They also provide evidence of a contemporaneous relationship between Twitter sentiment and stock returns during the first day of the IPO.

To the best of my knowledge, in the existing literature, studies exploring how the Twitter activity of a specific influential individual can have an impact on the stock prices of publicly traded companies have primarily focused on the figure of former US president Donald Trump. Ge et al. (2019) present evidence that Donald Trump's tweets had an average impact on the stock price of the cited companies of 0.80% ($p < 0{,}01\%$) from the day of his election to 31 December 2017, which, however, does not persist over time as these companies experienced a reversal in the subsequent days of the initial price impact. Furtherly, they underline how the tweets of the ex-president of the United States had a greater impact between his election and his inauguration on 20 January 2017, equal to 1.21% ($p < 0.01\%$).

Finally, the findings of Ge et al. (2019) suggest that Trump's tweets with positive sentiment generate higher abnormal returns on average (0.93, $p < 0.01$) than those with negative sentiment (-0.37%, $p < 0.01$).

Brans & Scholtens (2020) conduct an event study about 100 tweets concerning listed companies posted by Donald Trump during the first two years after his election. The preliminary results, where the authors do not consider the sentiment of the tweets, show that the abnormal returns in the event window [0,1] are negligible and statistically insignificant according to both parametric and non-parametric tests. However, incorporating sentiment into the event study, they find out that Donald Trump's tweets expressing strongly negative sentiment generate negative average abnormal returns (AARs) that are significant both on the day of the event and the following day.

In contrast to the findings of Ge et al. (2019) and Brans & Scholtens (2020), Juma'h & Alnsour (2018) examining 414 tweets posted by Donald Trump, of which 58 mentioned 23 listed companies, from January 2016 to August 2017, conclude that the sentiment does not cause any statistically significant impact on the share price of the related companies on an event window [-2, 2].

Gauging investor sentiment through textual sentiment analysis of socials such as Twitter is a relatively recent phenomenon. Previous sentiment measures exist, including indices built on market variables such as the Sentiment Changes Index (Baker & Wurgler, 2006, 2007) or Equity Market Sentiment Index (Bandopadhyaya & Jones, 2006) or on surveys such as the Michigan Consumer Sentiment Index or Investors' Intelligence.

Some authors, therefore, inquired to what extent the textual analysis of Twitter sentiment was able to replicate the results of the other methodologies and whether it could even lead to more accurate results.

Bollen et al. (2011a) compare the performance in terms of financial predictive power in both daily and weekly scales of different investor sentiment measures based on diverse data sources. In particular, they include traditional sentiment indicators based on survey data such as Investor Intelligence and Daily Sentiment Index, those based on news data using Negative News Sentiment, those derived from search engine data relying on Google Insights for Search, and finally, tools to extract sentiment from Twitter, using Twitter Investor Sentiment and Tweet Volumes of Financial Search Terms. According to this study, Twitter's two sentiment indicators are the best-performing measures of investor sentiment in predicting price changes in the DJIA market index, trading volumes, market volatility, and gold prices on a daily scale.

While the findings indicate that the traditional surveys have lagging financial predictive power and even no predictive ability when controlling for the other sentiment indicators, Negative News Sentiment turns out to be a statistically significant predictor; however, not as much as Twitter Investor Sentiment and Tweet Volumes of Financial Search Terms.

Finally, Google Insight for Search turns out to have a statistically significant predictive power of the financial markets on a daily scale but especially on a weekly scale. However, since the Tweet volumes of financial terms started to increase earlier than the Google volumes of financial terms, in predicting a substantial fall of the DJIA in July August 2011, it is inferred a greater efficiency of Twitter's two sentiment indicators compared to the Google Insight for Search indicator.

The reliability of Twitter's textual analysis as a sentiment-tracking tool is also proven outside the financial field. O'Connor et al. (2010) demonstrate the accuracy in extracting public sentiment through textual analysis of Twitter posts by comparing the results obtained from the social and daily polls on Barack Obama's presidential job approval rating. The results stemming from the textual analysis of tweets and those from the pools are correlated at most times 80%, showing that the former is able to capture the large-scale trends that would emerge from traditional methodologies.

Furthermore, O'Connor et al. (2010) give evidence of the ability to predict even future changes in pools through textual analysis, which can be considered a valid alternative or essential supplement to the extremely time-consuming traditional pooling methodologies.

In conclusion, the strong performance of Twitter-based indices in tracking investor sentiment has been amply confirmed, even outperforming previously well-established investor sentiment measures in some instances.

1.3 CEOs' Communications Influencing Investor Sentiment

Investor sentiment is a matter to which CEOs devote their attention and try to manage in favour of the companies they run. Bergman & Roychowdhury (2008) contribute to the literature by illustrating that CEOs seek to influence investor sentiment by setting voluntary disclosure policies. The authors reveal that when sentiment is low, managers are more willing to increase voluntary disclosure on long-term earnings forecasts to positively influence analysts' and investors' expectations. Conversely, during periods of high sentiment, managers are arid to voluntarily share information about the company's future earnings to take advantage of the positive valuation associated with positive investor expectations.

To positively affect investor sentiment, a valuable tool for CEOs can be to communicate their strategy as early as possible from their appointment. Whittington et al. (2015) investigate how CEOs' public strategy presentations influence the share price of major US companies. Analysing more than 900 CEOs' communication on the strategies they were planning to implement, such as internationalisation or diversification, they find that, on average, the share price rises on the day of the presentation by 2% to 5% in the following days. Notably, 34% of the sample, who received a significant positive reaction, found their share price increased by an average of 4.5% on the event day, rising to more than 10% the following days. On the other hand, 23% of all strategy communications, which received an adverse market reaction, observed a share price drop on the day of the presentation of -4.9%.

Finally, Whittington et al. (2015) indicate that these effects are amplified when such public communications are made by recently appointed CEOs during their first 100 days in office, especially when they come from industries other than the one in which the company operates. On average, when a new CEO from a different industry presents the future strategy in the first 100 days after their appointment, the company's share price experiences an increase of 12%.

In the field of studies concerning the impact of the sentiment expressed by the CEOs in the letters to shareholders on the company stock price. Boudt & Thewissen (2018), reviewing CEOs' letters to shareholders of companies that were included in the DJIA from 2000 to 2011, illustrate how specific intra-textual dynamics are associated with the sentiment that emerges from such communications. They reveal that sentiment is expressed chiefly at the beginning and end of the CEOs' letters, whereas the middle part seems neutral in terms of sentiment. The peak of the positive words usually lies at the end of the letter after following a U-shape pattern. In contrast, the largest number of negative words usually occurs at the beginning of the letters, and their use follows a left-sided half U-shape pattern, steadily declining from the initial spike towards the middle of the text. These results, coupled with the finding that the average number of positive words in the letters is greater than the average number of negative words, signal a positive net sentiment.

Moreover, Boudt & Thewissen (2018), conducted an event study, which includes three statistics indicating the shape of the intra-textual positioning of sentiment (level, slope and curvature), shed light on the extent to which textual positioning in CEOs' letters to shareholders influences the share price changes of their companies. When the slope and curvature of net sentiment are positive, there is a link between the sentiment expressed in CEOs' letters and the stock price response. However, this phenomenon appears to be short-lasting, as, after 60 days, this effect is no longer statistically significant.

Concerning non-written forms of communication, Bannier et al. (2017) studied the impact of sentiment expressed in speeches by the CEOs of 58 DAX and MDAX firms held during Annual General Meetings (AGMs) between 2008 and 2016. Although such communications by CEOs often contain only marginal information, compared to the disclosure that occurs during AGMs, the authors find that sentiment expressed by CEOs is significantly associated with cumulative abnormal returns. Bannier et al. (2017) employ three event windows [-1,30], [-1,1] and [2,30] to determine whether investor reaction occurs in the short term or is lagged. They find that even though sentiment reaction to CEOs' speeches in the event window [-1,1] is poor and not very significant, it turns out to be larger and statistically significant in the event window [2,30].

Pan et al. (2017) explore the extent to which a specific language attribute, the level of concreteness, may influence the stock price instead of investigating the impact of content or sentiment in managers' communications like previous articles.

After reviewing the transcripts of quarterly conference calls from 2007 to 2013 of 388 companies in the S&P 1,500, the results reveal a substantial benefit in terms of market reaction for CEOs who communicate with a high level of this language attribute, with a 1.36% difference in stock returns between high-level of concreteness and low-level of concreteness.

In the field of top-manager communications on social media and in particular, on Twitter, Malhotra & Malhotra (2015) studying the tweets of 25 CEOs of listed companies, categorise CEOs according to how they use their Twitter accounts to disseminate information: *Generalists*, *Expressionists*, *Information Mavens and Business Mavens*.

Firstly, *Generalists* represent the most numerous category resulting from the cluster analysis. They are characterised by sharing tweets on various topics, including personal opinions, their own interests but also news about the companies they manage. This is the group that tweets the most but enjoys the lowest number of likes and retweets.

Secondly, the *Expressions* category includes all CEOs who use Twitter mainly for non-business related content and therefore focus their social media activity more on relevant news, opinions and personal interests. They turn out to obtain more likes and be retweeted more than *Generalists* and *Information Mavens*, but in terms of these metrics, they remain far behind *Business Mavens*.

Information Mavens tend to spread general news and related links through their accounts. Their posts focus little on company-specific news and, on average, have fewer followers than *Expressionists* and *Business Mavens* and are rarely retweeted and liked.

Finally, the fourth category is constituted of *Business Mavens*, which are CEOs who tweet information mainly related to their company, such as new business lines, strategies or announcements of new product launches. This group has the highest number of followers and is liked and retweeted the most in this categorisation.

Malhotra & Malhotra (2015), through an event study with a 7-day event window, demonstrate that the CEOs' non-business related tweets do not seem to affect the share price performance of their firms. In contrast, the business-related tweets present positive and significant cumulative abnormal returns. Particularly among the latter, those with the strongest impact relate to the company's future outlook on management initiatives, strategies, corporate changes and new product announcements.

With regard to the CEOs' use of Twitter, it has also been proven that it is feasible to predict the performance of the four major US indices, S&P 500, Dow 30, NASDAQ, and Russell 20, by analysing the aggregated sentiment emerging from the tweets of a sample of 4,714 CEOs on Twitter (Lee & Song, 2022).

The relevance of sentiment expressed by CEOs is further emphasised by Gao (2018), who examines the tweets of more than 200 CEOs and proves that a high share of positive words within the tweets results in positive excessive stock returns, especially before their companies' earnings are disclosed.

Finally, some articles compare the Twitter activity of the CEOs and that of the company via its official account, exploring whether these produce different reactions from investors.

In this area, Elliott et al. (2018) find that CEOs' use of their Twitter account to share news following a negative earnings announcement surprise elicits a greater willingness to invest in the company than if the news were disseminated from the company's Twitter account or its website. Similarly, Crowley et al. (2021), analysing the tweets of 556 CEOs and CFOs from the S&P 1500, show that tweets about corporate events from individuals in executive roles trigger stronger reactions from the financial markets than tweets from company accounts. Furthermore, by developing a new measure of *content similarity* between executives' tweets and those of the corporate account, they point out that there is a greater reaction when CEOs' and CFOs' tweets are similar to the company's previous tweets due to the *trust mechanism*. However, they show that investors also react to executives' tweets even when there have been no previous tweets from the corporate account on the same event, supporting that the market reaction may also be driven by the new *information mechanism*.

Although CEOs' Twitter activity has recently gained the attention of many scholars, currently, there are no specific studies investigating how the sentiment expressed by a given CEO in his tweets affects the share price of the company they manage.
Therefore, this paper, with the aim of contributing to filling this gap in literature, intends to analyse the specific case of the most discussed CEO for his Twitter activity, Elon Musk, CEO of Tesla Inc. For this purpose, the objective of this paper is to answer the following research question:

RQ: *Does the sentiment expressed by Elon Musk in his tweets influence Tesla's share price?*

In investigating whether Elon Musk's tweets can have an impact on Tesla's share price, the study will place the focus on sentiment as several of the above-cited articles highlight that merely considering the number of tweets or their increase does not produce statistically significant results.
In particular, Sprenger et al. (2014) argue that: *"…news volume as a measure of information arrival is insufficient and excludes many nuances that have significant effects on the results. Thus, our methodology suggests that event studies need to control for sentiment…"*.
Apparently, Elon Musk himself seems to provide an answer to the research question during an interview for CBS News (Stahl, 2018) regarding the settlement with the Security Exchange Commission that should have forced Tesla's CEO to pre-emptively submit some of his tweets to a Tesla securities attorney (SEC, 2018). As a matter of fact, when asked about this issue by the interviewer Lesley Stahl, Elon Musk stated, *"The only tweets that would have to be said reviewed would be if a tweet had a probability of causing a movement in the stock"*.
However, from an empirical perspective, few studies have affirmed the existence of a correlation between Elon Musk's tweets and Tesla's share price (Kang Kim et al., 2021; Šević et al., 2023) and only Strauss & Smith (2019) conducted an event study. The authors specifically investigate whether two tweets, one from Tesla's official account and the other from Elon Musk, influenced the company's share price when announcing on 23 August 2016 the introduction of a new type of electric battery for the Model X and Model S cars.
Strauss & Smith (2019) conduct event studies characterised by stock price data per minute with event windows of [-10,10] minutes, both on a tweet by Elon Musk at 11.23 a.m. announcing via his account that a new product will be announced at midday and on the following one at 3.30 p.m. by Tesla's official account that actually presents the new product by revealing that it will be new electric batteries.
The conclusion is that both tweets generated statistically significant abnormal returns. Notably, for Elon Musk's tweet, no abnormal returns were observed in the 10 minutes before the tweet, while after

it, abnormal returns were detected for the following 9 minutes. As the majority of the investors bought Tesla's shares after Elon Musk's ambiguous and vague tweet and sold after Tesla's tweet revealing the new product, Strauss & Smith (2019) conclude that market participants did not act rationally as according to the EMH trying to understand the value of the news, but only moved by the belief that Elon Musk's tweet could have resulted in a possible increase in the Tesla's share price.

While little is known about the effect of Elon Musk's tweets on Tesla's share price, some studies have investigated the impact of the Tesla CEO's Twitter activity on another financial instrument often mentioned in his posts, cryptocurrencies.

This phenomenon, called the *"Musk Effect"*, has been highlighted by Ante (2023), who conducted an event study on 47 tweets regarding various cryptocurrencies between April 2019 and July 2021 by the Tesla CEO. The author initially, not making a distinction either by cryptocurrency or by the sentiment expressed by Musk in the 47 tweets in the sample, detects significant average abnormal returns of 1.46% in the minute of the event, which persist until 2 minutes later dropping to an average abnormal return of 0.62%. This is also confirmed by the cumulative abnormal returns, which turn out to be positive and statistically significant at a 1% level in all the windows analysed by Ante (2023).

Focusing on Ante's (2023) findings about the two cryptocurrencies most frequently mentioned by Musk, Dogecoin and Bitcoin, Elon Musk's Twitter activity regarding the first crypto causes statistically significant positive abnormal returns 3 minutes after the event and significant CARs for all windows, while this is not observed for tweets regarding Bitcoin. Nevertheless, after distinguishing for the sentiment expressed by Musk in tweets concerning Bitcoin (non-negative and negative), it becomes evident that non-negative Bitcoin-related Twitter events have a positive and significant impact on Bitcoin's price. On the other hand, even though the sample of negative Bitcoin-related Twitter events does not seem to influence Bitcoin's returns overall, some tweets individually present significant negative CARs. For instance, the tweet where Musk announces that Tesla will no longer accept Bitcoin as currency for the purchase of its products presents CARs that amount to -11.865% after two hours of the event.

Secondly, Huynh (2022), focusing on the impact of Bitcoin, shows that the sentiment expressed in Elon Musk's tweets posted between December 2017 and May 2021 Granger-caused changes in the cryptocurrency's prices.

Finally, Shahzad et al. (2022) point out that Elon Musk's tweets regarding the crypto market in general increase the probability of Bitcoin's *price explosivity*, while Bitcoin's specific tweets had negligible impacts. In the case of Dogecoin, however, Elon Musk's Dogecoin-related tweets played a greater role in the probability of price explosivity of the specific cryptocurrency itself.

Although conducted on a financial asset other than shares, these studies demonstrate Elon Musk's capability to influence the price of a financial instrument by leaking his sentiment through his tweets. In conclusion, based on such empirical evidence and the previously mentioned theoretical framework of De Long et al. (1990), according to which *"noise traders"* acting upon their beliefs can move the share price heavily, it is reasonable to formulate the following hypotheses:

H1. *The sentiment expressed by Elon Musk in his tweets influences Tesla's share price.*

H1a. *The positive sentiment expressed by Elon Musk in his tweets is associated with positive abnormal returns and thus positively influences Tesla's share price.*

H1b. *The negative sentiment expressed by Elon Musk in his tweets is associated with negative abnormal returns and thus negatively influences Tesla's share price.*

Data Collection

2.1 Elon Musk's Tweets Data

The data source from which Tesla's CEO's Twitter posts were collected is the Twitter API (Application Programming Interface). Through a search query, it has been possible to retrieve all 233 tweets in which Elon Musk used the words *"Tesla"* or *"TSLA"* at least once, from 1 August 2018, to 31 December 2021. In particular, the query disregarded the Tesla CEO's replies to his tweets or those of other users, as these achieve a lower level of visibility than the tweets themselves.
The starting date of the analysis period was chosen because the famous tweet about Tesla's delisting took place in August 2018, which brought to light for the first time whether Musk can influence the share price of the company he manages. The date at the end of the period considered was set to exclude from the analysis the beginning of rumours of Elon Musk's future takeover of Twitter.
Besides tweets, it has also been possible to gather additional data on Twitter posts, such as the date, time, number of likes, number of replies and number of retweets. In particular, by summing the last three, a new variable called *"interactions"* (Formula 2.1) was created, which can be interpreted as a proxy for the visibility reached by a given tweet. Indeed, according to the recommendation algorithm[5] publicly released by Twitter on 31 March 2023, the metrics of likes, retweets and replies boost a tweet's reach.
Only tweets in which Tesla is mentioned with the number of interactions for each year were selected to avoid overlapping and confounding effects in the event study. The underlying assumption is that the top tweets in terms of interactions are those that had the largest information propagation and are, therefore, most likely to impact Tesla's share price.
This choice is reinforced by the correlation that Kang Kim et al. (2021) found out between engagement (which in their study takes into account exactly likes, retweets and replies) and Tesla's share price. Furthermore, a similar reasoning is adopted by Ranco et al. (2015), who decided to identify as events able to affect the share price of the 30 stocks of the DJIA index, only those instances in which there are Twitter activity peaks. Finally, composing the sample of the analysis according to this criterion, all the tweets that caused the above-mentioned legal controversies turn out to be included.
The final sample contains 52 tweets (Table 1) and is composed as follows: the leading 15 tweets by number of interactions for the year 2021, the leading 15 tweets by number of interactions for the year 2020, the leading 15 tweets by number of interactions for the year 2019 and the leading 7 tweets by

[5]Available at https://github.com/twitter/the-algorithm

number of interactions in 2018. For the latter, less than half of the Twitter posts were considered, as the analysis period only includes the last five months of 2018.

It is worth noting that this sample does not include the 52 tweets with the highest number of interactions over the entire period analysed. This choice to include in the sample the top tweets for each year and not the top tweets by the number of interactions over the entire period analysed was made to consider the tremendous growth that Musk's followers and visibility have experienced and consequently also his tweets' interactions.

$$Interactions = Likes + Replies + Retweets \tag{2. 1}$$

Furthermore, in order to have the correct correspondence between tweets and share prices, the dates and times of the former were converted to the Eastern Daylight Time (EDT) timezone, which is the one adopted by the National Association of Securities Dealers Automated Quotation (NASDAQ), where Tesla is listed.

The final sample of 52 tweets can be deemed appropriate for examining the hypotheses of this study as it is perfectly consistent with Ante's paper (2023), which studies the impact of Elon Musk's tweets on the price of selected cryptocurrencies with a sample of 47 tweets.

Number	Date	Time	Tweets	Likes	Retweets	Replies	Interactions
1	2018-08-01	4:45:50 PM	If you're into video game development, consider applying to Tesla. We want to make super fun games that integrate the center touch screen, phone & car irl.	65,859	10,030	3,851	79,740
2	2018-08-07	12:48:13 PM	Am considering taking Tesla private at $420. Funding secured.	82,274	14,224	5,940	102,438
3	2018-08-10	11:30:33 PM	Short shorts coming soon to Tesla merch	89,414	12,859	2,297	104,570
4	2018-10-12	2:03:45 PM	Tesla exists to help reduce risk of catastrophic climate change, which affects all species on Earth. Even if your faith in humanity is faltering, this is worth caring about. Support makes a difference. Thank you.	150,375	22,923	3,307	176,605
5	2018-10-25	3:35:32 AM	Massive thanks to Tesla owners & supporters. We wouldn't be here without you.	77,965	3,304	1,881	83,150
6	2018-10-29	4:43:53 PM	Deleted my Tesla titles last week to see what would happen. I'm now the Nothing of Tesla. Seems fine so far.	112,373	7,659	3,228	123,260
7	2018-11-10	12:10:32 AM	If Tesla can help people in California wildfire, please let us know. Model S & X have hospital grade HEPA filters. Maybe helpful for transporting people.	116,916	12,831	2,301	132,048
8	2019-01-01	2:17:51 AM	Congratulations @Tesla team!! https://t.co/PBr9VVBv1S	68,963	2,752	964	72,679
9	2019-01-27	3:29:20 PM	Tap Tesla logo at top of your car's touchscreen & wait 10 secs to open special features box	56,059	2,605	1,465	60,129
10	2019-02-19	7:02:34 PM	4000 Tesla cars loading in SF for Europe https://t.co/BODbSzo3Fr	192,302	15,600	4,443	212,345
11	2019-03-30	5:37:17 PM	Tesla Semi delivering Tesla cars https://t.co/ttEpcW5d8G	179,656	14,488	2,671	196,815
12	2019-04-23	7:26:50 PM	Tesla is going to develop a quiet, electric leafblower	273,025	20,874	9,087	302,986
13	2019-05-02	9:32:22 PM	Changing Tesla horn sound to 🐐	159,456	13,654	3,490	176,600
14	2019-05-18	9:39:07 PM	Tesla does not advertise or pay for endorsements. Instead, we use that money to make the product great.	56,126	5,309	1,361	62,796
15	2019-05-31	5:51:07 PM	New Tesla Summon will 🧨 ur 🧠	97,765	5,239	1,687	104,691
16	2019-07-27	2:15:32 PM	Ability to stream YouTube & Netflix when car is stopped coming to your Tesla soon! Has an amazingly immersive, cinematic feel due to the comfy seats & surround sound audio.	106,196	7,852	1,960	116,008
17	2019-10-23	5:09:18 PM	Tesla Q3 results: - Shanghai Giga ahead of schedule - Model Y ahead of schedule	65,841	5,797	1,916	73,554
18	2019-10-28	2:09:19 PM	If you're directly affected by wildfire power outages, Tesla is reducing Solar+Powerwall prices by $1000 as of today	61,717	4,036	734	66,487
19	2019-10-31	10:34:49 PM	Tesla Solarglass vs 🎃 Happy Halloween!! https://t.co/p5tXeJYqne	77,069	4,314	1,094	82,477
20	2019-11-21	4:26:45 PM	Tesla Cybertruck (pressurized edition) will be official truck of Mars	109,613	8,994	2,090	120,697
21	2019-12-19	3:05:09 AM	Tesla Moth Mode (better late than never) https://t.co/Rcu87A8NkO	164,069	17,296	1,102	182,467
22	2019-12-19	10:28:05 PM	Tesla holiday software update has FSD sneak preview, Stardew Valley, Lost Backgammon & a few other things	57,631	2,685	1,605	61,921
23	2020-01-01	1:50:06 AM	Congratulations Tesla & SpaceX on great 2019! You rock!! Looking forward to epic 2020 ♥🚀🛰 🚘 ☀	145,313	6,711	1,857	153,881
24	2020-01-07	4:47:04 AM	At Tesla Giga Shanghai NSFW!! https://t.co/1yrPyzJQGZ	265,299	29,960	6,153	301,412
25	2020-01-11	10:20:41 PM	Teslas will soon talk to people if you want. This is real. https://t.co/8AJdERX5qa	138,529	12,201	2,893	153,623

Table 1. Sample of Elon Musk's selected tweets. Tweets are displayed in their format before pre-processing, and an identification number has been assigned to each. The table continues on the next page.

Number	Date	Time	Tweets	Likes	Retweets	Replies	Interactions
25	2020-01-11	10:20:41 PM	Teslas will soon talk to people if you want. This is real. https://t.co/8AJdERX5qa	138,529	12,201	2,893	153,623
26	2020-01-29	2:08:09 PM	A friend just sent me this excerpt from a Tesla blog I wrote 14 years ago https://t.co/Hr8w52ithY	322,322	31,603	3,758	357,683
27	2020-03-09	10:32:21 PM	Congratulations Tesla team on making our 1,000,000th car!! https://t.co/5M99a9LLQi	232,108	17,818	3,580	253,506
28	2020-03-31	11:27:02 AM	We have extra FDA-approved ventilators. Will ship to hospitals worldwide within Tesla delivery regions. Device & shipping cost are free. Only requirement is that the vents are needed immediately for patients, not stored in a warehouse. Please me or @Tesla know.	279,072	61,880	11,395	352,347
29	2020-04-16	1:54:18 PM	Partial list of hospitals to which Tesla sent ventilators https://t.co/sfI6yuUbrM	168,279	14,513	3,861	186,653
30	2020-05-01	11:11:26 AM	Tesla stock price is too high imo	176,558	19,476	11,612	207,646
31	2020-05-11	4:36:52 PM	Tesla is restarting production today against Alameda County rules. I will be on the line with everyone else. If anyone is arrested, I ask that it only be me.	429,229	56,860	28,230	514,319
32	2020-06-19	1:06:03 PM	Juneteenth is henceforth considered a US holiday at Tesla & SpaceX	374,614	28,577	5,462	408,653
33	2020-06-26	1:57:58 AM	Only a matter of time before someone steals a Tesla while playing GTA on a Tesla	329,018	28,183	3,261	360,462
34	2020-07-02	2:40:47 PM	Tesla will make fabulous short shorts in radiant red satin with gold trim	152,154	9,392	4,555	166,101
35	2020-08-20	3:11:02 PM	More fun games coming soon to ur Tesla	231,642	26,391	3,947	261,980
36	2020-12-21	8:04:16 AM	Thanks to everyone who worked so hard to make Tesla successful. My heart goes out to you.	315,983	9,838	7,544	333,365
37	2020-12-25	3:54:29 PM	Change your horn sound to 🐐, 🐍🎷, 💨 or holiday jingles with latest Tesla software update!	171,226	6,138	4,838	182,202
38	2021-02-06	5:12:57 PM	Time to tell the story of Tesla & SpaceX	378,022	21,195	10,932	410,149
39	2021-03-14	10:00:29 AM	Play your favorite song in a Tesla & turn the volume to 11 You will see. You will feel.	155,846	7,107	7,402	170,355
40	2021-03-24	3:02:40 AM	You can now buy a Tesla with Bitcoin	828,762	102,739	33,598	965,099
41	2021-04-08	5:41:16 AM	Thanks Tesla suppliers for providing us with critical parts!	173,292	5,371	4,798	183,461
42	2021-04-17	6:32:03 PM	Tesla with Autopilot engaged now approaching 10 times lower chance of accident than average vehicle	148,646	16,421	10,507	175,574
43	2021-04-22	1:49:17 AM	Tesla Solar + Powerwall battery enables consumers to be their own utility	161,242	10,427	9,622	181,291
44	2021-05-11	4:13:35 AM	Do you want Tesla to accept Doge?	376,305	89,637	93,266	559,208
45	2021-05-19	10:42:44 AM	Tesla has 💎 🙌	433,938	52,399	66,615	552,952
46	2021-05-20	3:54:54 AM	Tesla Model S Plaid delivery event June 3 at our California factory Fastest production car ever	186,127	13,233	17,122	216,482
47	2021-06-23	9:10:10 PM	Shout out to the awesome Tesla global team. Thanks for working so hard to make Tesla successful!	143,079	6,859	8,585	158,523
48	2021-07-02	9:09:28 AM	Congrats Tesla Team on over 200,000 car built & delivered in Q2, despite many challenges!!	163,665	9,073	7,484	180,222
49	2021-07-28	11:59:25 PM	Tesla AI Day August 19th	172,634	11,473	14,407	198,514
50	2021-08-04	10:12:10 PM	If you're curious about Tesla, SpaceX & my general goings on, @WalterIsaacson is writing a biography	137,692	7,591	8,046	153,329
51	2021-11-06	3:17:49 PM	Much is made lately of unrealized gains being a means of tax avoidance, so I propose selling 10% of my Tesla stock. Do you support this?	142,753	23,019	53,933	219,705
52	2021-12-14	5:34:23 AM	Tesla will make some merch buyable with Doge & see how it goes	347,671	51,881	53,279	452,831

2.2 Tesla's Stock Price Data

With respect to the financial market data, daily prices of Tesla's stock (TSLA) and the two market benchmarks used for the event study, NASDAQ-100 (^NDX) and NASDAQ Composite (^IXIC), were retrieved from Bloomberg via Bloomberg Terminal. Price data was collected on 2 February 2018, that is, 124 trading days prior to the date of the first tweet until the date of the last tweet, 14 December 2021.

In order to closely adhere to the original event study methodology (MacKinlay, 1997), in the paper, raw returns instead of log returns were used as daily returns for both Tesla and the two indices, calculated according to the following formula:

$$R_{TSLA,d} = \left(\frac{p_{TSLA,d} - p_{TSLA,(d-1)}}{p_{TSLA,(d-1)}}\right) \tag{2. 2}$$

where $R_{TSLA,d}$ represents the daily return, p_d the closing price on day *d*, p_{d-1} the closing price on day *d-1*.

Methods

3.1 Twitter Sentiment Analysis

One of the most exhaustive definitions describing sentiment analysis is that provided by Liu, B. (2012) in his book Sentiment Analysis and Opinion Mining, who defines it as *"the field of study that analyses people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organisations, individuals, issues, events, topics, and their attributes"*.

Although, in recent years, this has been one of the most attractive research areas for academics, thanks to technological advances and the development of new techniques that have facilitated its implementation on a large scale, it should not be viewed as a purely recent branch. Mäntylä et al. (2017), in their review on the evolution of sentiment analysis, illustrate that the topic probably finds its roots in 1940 with the paper *"The Cross-Out Technique as a Method in Public Opinion Analysis"* (Stagner, 1940). However, due to technical difficulties and differences in the terminology used to refer to this branch, including opinion mining, sentiment classification, opinion classification, opinion analysis, and semantic orientation, the outbreak of modern sentiment analysis is usually dated in 2002 with the paper *"Thumbs up? Sentiment classification using machine learning techniques"* by Pang et al. (2002) and *"Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews"* by Turney (2002).

In the last two decades, with the proliferation of user-generated content, such as tweets, sentiment analysis has been adopted in a wide range of real-world applications, beyond those mentioned in the second section of the literature review, such as reputation management (Olaleye et al., 2018), brand perception (Smith et al., 2012; Ghiassi et al., 2016), advertising (Fan & Chang, 2009; Qiu et al., 2010; Kulkarni et al., 2020), psychology (Wang et al., 2013; Kaur & Kautish, 2019), political elections (Wang et al., 2012; Ceron et al., 2013), policy making (Zavattaro et al., 2015; Georgiadou et al., 2020), healthcare (Gohil & Darzi, 2018), and many others.

Amongst the various methodologies that have been developed over time to conduct sentiment analysis tasks illustrated in the Figure 1, most of the papers with similar purposes to this one reported in section two of the literature review have predominantly relied on three methods, the Dictionary Based Approach (Ge et al., 2019), Support Vector Machine classifier (Smailović et al., 2014; Ranco et al., 2015) or Naïve Bayesian text classification (Sprenger et al., 2014). However, recent works (Sudhir & Suresh, 2021; Hartmann et al., 2022) carried out to identify the best methodology in terms of accuracy for sentiment detection have shown that the transfer learning model (Transformers Networks in Fig. 1), most of which are based on the BERT architecture (Delvin et al., 2019), clearly outperform other classification techniques. Notably, Hartmann et al. (2022) demonstrate that transfer learning models exceed lexicon-based approaches and traditional machine learning methods such as Support Vector Machine and Naïve Bayes in terms of sentiment analysis accuracy on average by between 10 and 20 percentage points. In light of these findings, to analyse the sentiment of Elon Musk's tweets in this paper, it was decided to use BERTweet[6] (Nguyen et al., 2020), a language model (LM) developed to perform Twitter-specific downstream tasks and pre-trained from the outset on a massive corpus of around 850 million tweets. This draws on the architecture built by the Google AI team called Bidirectional Encoder Representations from Transformers or BERT (Delvin et al., 2019). Nevertheless, it implements several pre-training procedures used from another language model, the Robustly optimised BERT approach or RoBERTa (Liu et al., 2019), which was also developed by the Meta AI team. These modifications involve removing the Next Sentence Prediction loss, using dynamic masking instead of static, and employing larger mini-batches.

BERTweet does not represent the only attempt to develop an ad-hoc language model for Twitter; for instance, RoBERTabase (Barbieri et al., 2020) and XLM-T (Barbieri et al., 2021) are two valid alternatives in this field. However, BERTweet appears to be the best-performing model, according to the TweetEval benchmark (Barbieri et al., 2020).

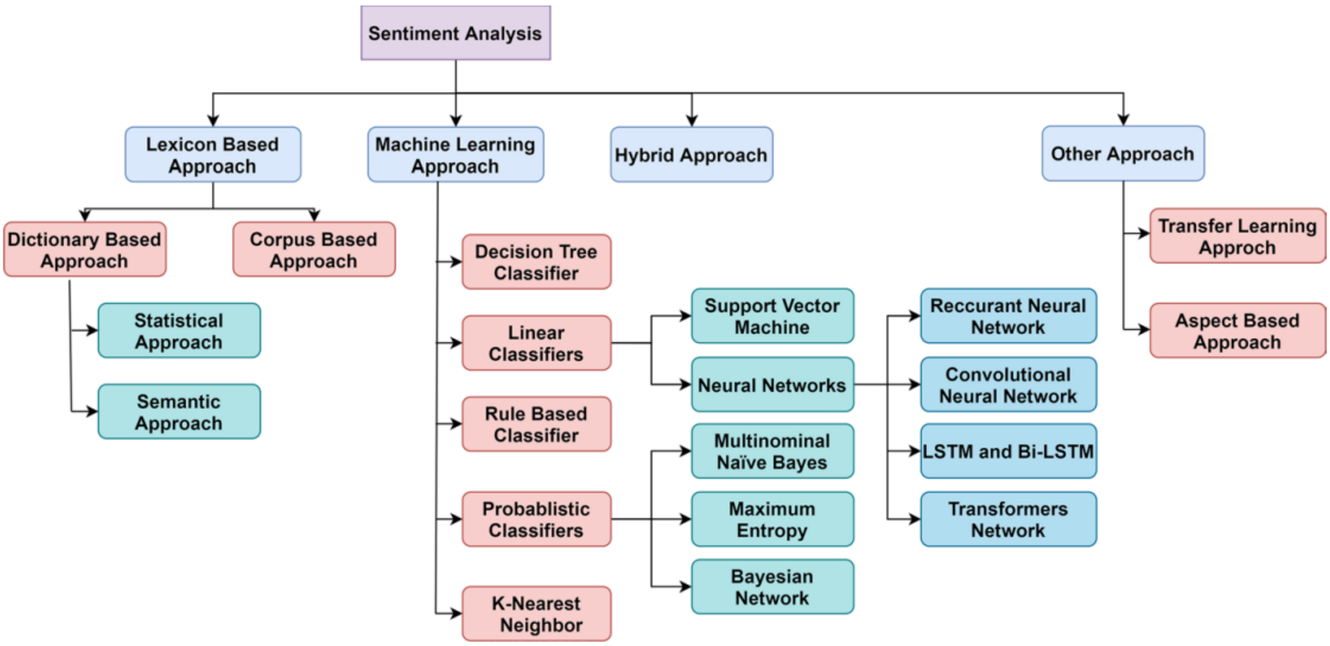

Fig. 1. The different approaches for conducting sentiment analysis (Wankhade et al., 2022). This figure illustrates the state of the art of the different approaches implemented in sentiment analysis tasks so far.

[6] Available at https://github.com/VinAIResearch/BERTweet . In particular, a finetuned version of BERTweet was used for sentiment analysis available at https://huggingface.co/finiteautomata/bertweet-base-sentiment-analysis (Pérez et al., 2021).

The latter is a novel unified framework consisting of seven classification tasks to investigate the state of the art of LMs in the Twitter context, including Emotion Recognition (Mohammad et al., 2018), Emoji Prediction (Barbieri et al., 2018), Irony Detection (Van Hee et al., 2018), Hate Speech Detection (Basile et al., 2019), the Offensive Language Identification (Zampieri et al., 2019), Sentiment Analysis (Rosenthal et al., 2019) and Stance Detection (Mohammad et al., 2016). Loureiro et al. (2022), to evaluate the performance of an updated version of the RoBERTabase, compare it according to TweetEval benchmark criteria to other LMs, including BERTweet, and the results show that the latter has the highest average score on the seven Twitter tasks and in particular the best score on the Irony Detection task, which in the specific case of Elon Musk's tweets could be a relevant factor.

The coding language used to perform the sentiment analysis on the 52 tweets in the sample is Python. Prior to proceeding to opinion mining, the script initially pre-processes the tweets according to ad-hoc procedures for Twitter (Agarwal et al., 2011), including the replacement of all the usernames tagged in Musk's tweets (every word beginning with @) with a predefined token *"@user"*, and the replacement of all the links (every word beginning with http or https) with the predefined token *"http"*.

The sentiment analysis provides as a final output the classification of each tweet as positive, negative or neutral and also provides a score for each of these categories, between 0 and 1, with the sum of the three always having to be equal to 1. Therefore, a tweet is classified as belonging to one of the three sentiment labels according to which of them has the highest score.

Finally, to better visualise the sentiment analysis results, the positive, negative and neutral scores are combined for each tweet to obtain a single score, called the relative score, which lies in a range from -1 to 1. Thus, tweets with a relative score close to -1 will be highly negative, while tweets close to 1 will be highly positive, and tweets close to 0 will count as neutral. The following formula explains how the relative score is computed:

$$Relative\ Score = (Positive\ Score - Negative\ Score) \times (1 - Neutral\ Score) \tag{3. 1}$$

For example, taking tweet number 30 in the sample where Elon Musk on 1 May 2020 at 11:11:26 AM (EDT) declared *"Tesla stock price is too high imo"* the sentiment analysis gives as output a negative score of 0.940685987, a neutral score of 0.056060817 and positive score of 0.003253098, while a relative score of -0.884879636, thus classifying the post with extremely negative sentiment.

3.2 Event Study Methodology

Event studies represent a time-tested methodology designed to assess the market's response to a firm-specific event containing new informational content by observing the price behaviour of the security affected by the event over the time it took place (Brown & Warner, 1980).

It is widely accepted that this methodology has been pioneered by the two papers by Ball & Brown (1968) and Fama et al. (1969), though some argue that the first article to adopt it may actually be that of Dolley (1933). The event study methodology has been highly successful since its early days, to the extent that Fama (1991) acknowledged it to have substantially contributed to the flourishing period of research in the field of corporate finance from the 1970s to the 1990s, and the author himself claimed that the most relevant evidence on market efficiency came from this methodology. Event studies have been adopted to investigate the speed at which market prices absorb new information for a variety of different events, such as stock splits (Fama et al., 1969), earning announcements (Ball & Brown, 1968), dividend changes (Charest, 1978), new issues of common stocks (Asquith & Mullins, 1986), capital structure changes (Masulis, 1980), repurchase tender offers (Lakonishok & Vermaelen, 1990) and corporate-control transactions (Mandelker, 1974), which generated an estimated 500 papers between 1974 and 2000 (Kothari & Warner, 2007).

Since the 1990s, the applicability of this methodology has further broadened to include new types of events, such as corporate brand name changes (Kalaignanam & Bahadir, 2012), executive appointments (Boyd et al., 2010), product announcements (Warren & Sorescu, 2017), distribution channels expansion (Homburg et al., 2014), new large player market entry (Gielens et al., 2008) which consequently expanded the use of event studies to other branches of economic studies beyond finance.

Several different approaches are available for conducting an event study, all of which have in common the objective of verifying and estimating the presence of abnormal or excess returns around the event date, as the difference between observed returns and expected returns, computed through the chosen return generating model (Peterson, 1989). The most frequently employed models include the mean-adjusted returns model or average return model (Masulis, 1980), the market-adjusted return model or index model (Lakonishok & Vermaelen, 1990), the market model (Fama et al., 1969), Fama-French (1993) three-factor model.

The market model, besides being the one most commonly adopted, also seems to be the one that provides the most reliable estimates of abnormal returns, to the extent that Armitage (1995), reviewing several papers in which the market model is compared to other approaches concluded that *"across each of the range of circumstances tested, it [the market model] is always at least as powerful as the best alternative"*. Specifically, Brown & Warner, based on the simulation experiment results they obtained in 1980 on monthly returns and 1985 on daily returns, inferred that *"beyond a simple,* *one-factor market model, there is no evidence that more complicated methodologies convey any benefit".*

In light of this evidence, this paper will follow the market model approach in analysing the impact of the sentiment of Elon Musk's tweets on Tesla's share price. Specifically, in the case of this research, the market model entails that the expected abnormal returns are computed by estimating the relationship between the returns of Tesla's shares and returns of the NASDAQ-100 market index (and NASDAQ Composite) over the period of time called estimation window, through the following one factor ordinary least squares (OLS) regression equation:

$$E\left[R_{TSLA,d}\right] = \alpha_{TSLA} + \beta_{TSLA} R_{NDX,d} \tag{3. 2}$$

where, α_{TSLA} and β_{TSLA} represent the coefficients of the regression and, in detail, the former the intercept and the latter the correlation with NASDAQ-100, while $R_{NDX,d}$ is the actual daily return of the NASDAQ-100 on a given day *d*. Therefore, after having determined the expected return $E\left[R_{TSLA,d}\right]$, the abnormal return at day *d* of the event window is calculated as:

$$AR_{TSLA,d} = R_{TSLA,d} - E\left[R_{TSLA,d}\right]$$
$$AR_{TSLA,d} = R_{TSLA,d} - \left(\alpha_{TSLA} + \beta_{TSLA} R_{NDX,d}\right) \tag{3. 3}$$

where, $R_{TSLA,d}$ stands for the actual daily return of Tesla that occurred on day *d*.

Once the abnormal returns for each day within the event window have been obtained, by summing them up it is possible to calculate the cumulative abnormal return, $CAR_{TSLA}(\tau_1, \tau_2)$, which took place in the established event window (τ_1, τ_2).

$$CAR_{TSLA}(\tau_1, \tau_2) = \sum_{d=\tau_1}^{\tau_2} AR_{TSLA,d} \tag{3. 4}$$

Furthermore, for each of the three sentiment categories the average abnormal returns, $\widehat{AAR}_{s,t}$, for each day included in the event windows, and cumulative average abnormal returns, $\widehat{CAAR}_s$, for the two event windows considered, have also been calculated. The $\widehat{AAR}_{s,t}$ are estimated by averaging the $AR_{TSLA,t}$ occurring on a day *d*, corresponding to all (N) the events *e* classified by the sentiment analysis as belonging to a specific sentiment class *s*.

$$\widehat{AAR}_{s,d} = \frac{1}{N}\sum_{e=1}^{N} AR_{TSLA,d}$$

(3. 5)

Similarly, the $\widehat{CAAR}_s$ are computed by averaging the CAR_{TSLA} occurring in a given event window (τ_1, τ_2), corresponding to all the events e classified by the sentiment analysis as belonging to the same sentiment category s.

$$\widehat{CAAR}_s(\tau_1, \tau_2) = \frac{1}{N}\sum_{e=1}^{N} CAR_{TSLA}\,(\tau_1, \tau_2)$$

(3. 6)

Four parametric tests were used to verify that the study's results were statistically significant. Regarding abnormal returns, according to the procedure of standardisation of abnormal returns (Peterson, 1989; Mitchell & Netter, 1994, Benninga, 2014), the following formulas were used:

$$TS = \frac{AR_{TSLA,d}}{se(AR_{TSLA,d})}$$

(3. 7)

$$se\left(AR_{TSLA,d}\right) = \sqrt{\sigma^2\left(1 + \frac{1}{T} + \frac{\left(R_{NDX,d} - \hat{R}_{NDX}\right)^2}{\sum_{t=1}^{T}\left(R_{NDX,t} - \hat{R}_{NDX}\right)^2}\right)}$$

(3. 8)

where $se\left(AR_{TSLA,d}\right)$ denotes the standard error of the forecast for Tesla's share price on day d within one of the two event windows and T the number of observations (days) included in the estimation window.

Secondly, for cumulative abnormal returns, the t-statistic was computed as follows (Kothari & Warner, 2007; Ranco et al., 2015):

$$TS = \frac{CAR_{TSLA}(\tau_1, \tau_2)}{\sqrt{\sigma^2(\tau_1, \tau_2)}}$$

(3. 9)

$$\sigma^2(\tau_1, \tau_2) = L^2\sigma^2\left(AR_{TSLA,d}\right)$$

(3. 10)

where, L represents the number of days in the event window for which cumulative abnormal returns were calculated.

Finally, the following cross-sectional tests were implemented for average abnormal returns and cumulative average abnormal returns (Brown & Warner, 1980; Saens, R., & Sandoval; 2005, Boehmer, 1991):

$$TS = \frac{\widehat{AAR}_{s,d}}{se(\widehat{AAR}_{s,d})} \tag{3. 11}$$

$$se(\widehat{AAR}_{s,d}) = \sqrt{\frac{1}{N(N-1)} \sum_{e=1}^{N} \left(AR_d - \widehat{AAR}_{s,d}\right)^2} \tag{3. 12}$$

$$TS = \frac{\widehat{CAAR}_s(\tau_1, \tau_2)}{se(\widehat{CAAR}_s(\tau_1, \tau_2))} \tag{3. 13}$$

$$se\left(\widehat{CAAR}_s(\tau_1, \tau_2)\right) = \sqrt{\frac{1}{N(N-1)} \sum_{e=1}^{N} \left(CAR_e(\tau_1, \tau_2) - \widehat{CAAR}_s(\tau_1, \tau_2)\right)^2} \tag{3. 14}$$

Two preliminary steps were performed before conducting the event study so that the sample of tweets would be suitable for this type of analysis.

The first one was to solve the issue of the tweets that were published by Musk outside the NASDAQ trading days and trading hours and therefore do not have a daily price directly associated. Indeed, the stock market on which Tesla is listed is open every week from Monday to Friday from 9:30 AM to 4:00 PM (EDT) but closed every Saturday, Sunday and on 9 American holidays (Nasdaq, 2023), while Elon Musk can decide to tweet at any time. Table 1 shows that only 21% of the tweets included in the sample took place during trading days and trading hours, while the remaining 79% were outside of them. Consequently, to measure the market response to these tweets, they were assigned the price of the closest trading days following the tweet, consistent with Brans & Scholtens (2020) and Ge et al.'s (2019) studies on the impact of former US President Trump's tweets on the share price of the companies he mentioned. The second procedure, instead, has been necessary to limit the overlaps between the event windows of some tweets that occurred within a few days and to avoid the potential confounding effects that these overlaps could create. Therefore, to overcome this issue, tweets 17-18, 21-22, and 45-46 have been grouped in pairs and assigned the date and time of the first of the two tweets comprising them. As a result, although the number of tweets included in the sample is 52, the number of events became 49 after the grouping step. Furthermore, following this procedure, the newly grouped tweets were analysed again through the same previous sentiment analysis procedure. Ge et al. (2019) and Brans & Scholtens (2020) opted for a similar procedure when former US President Donald Trump published tweets on the same company within a few days.

Regarding the details of the event study, Krivin et al. (2003) define the five subjective decisions that the event study methodology leaves analysts, which can significantly impact research results. They involve determining: the estimation window, the index used as the market benchmark, the event window, the frequency with which the data are studied and the type of price measurement.

The term estimation window refers to the time over which the correlation between the share price of the target company of the event study and the market index is studied. Therefore, an appropriate estimation window length is crucial for the calculation of β_i and α_i. Any analyst should bear in mind the following trade-off in making such a decision; the longer the estimation window length, the greater the accuracy in estimating βi and α_i parameters, but the higher the probability of including time intervals when the target company and market parameters were significantly different (Peterson, 1989; Armitage, 1995; Krivin et al., 2003). Hence, in this study, an estimation period with a length of 120 trading days is applied (Dyckman et al., 1984; Peterson, 1989; MacKinlay, 1997; Sprenger et al., 2014; Ranco et al., 2015), which in the financial literature proves to be the most widely applied to event studies that follow the market model approach and use daily price data. In particular, the estimation window spans over an interval [-124,-5], with the start date 130 trading days before the event. The end date instead occurs five trading days before the event date, as one common practice in event studies is to create a *"buffer"* of time between the estimation window and the event window to prevent overlapping and the potential abnormal returns of the event influencing the normal returns predicted by the market model (MacKinlay, 1997).

Secondly, with regard to the market index, it was not feasible to adopt the S&P500 since Tesla did not join the index until 21 December 2020 (Goodwin, 2020) and, thus, approximately two and a half years after the start of the period under analysis. Hence, the NASDAQ-100 (^NDX) has been selected as the first benchmark, a market index reproducing the performance of the 100 largest capitalised non-financial companies listed on the NASDAQ, including Tesla, since 2013. In addition, the NASDAQ Composite (^IXIC), which reproduces the overall performance of NASDAQ-listed companies, is employed to corroborate the results.

The third step in conducting an event study concerns the length of the event window, which can be defined as the time interval along which an event's effect is actually measured (McWilliams & Siegel, 1997). Although, as emphasised by Krivin et al. (2003), the choice of the length of the event window is probably the factor most likely to distort the final results, currently, there is no common consensus in the financial literature on which length is the most appropriate, ranging from long-term event windows of even more than 100 days to short-term windows of only 2, 3 or 5 days. This is because there are several phenomena characterised by different patterns of information releases (Ryngaert & Netter, 1990), and therefore *"the nature of the event being studied should determine the length of the event window used"* (McWilliams & Siegel, 1997).

However, scholars seem to express more scepticism when long-term event windows are used, firstly because this implies the underlying assumption that β_i and α_i remain constant over a long period. Secondly, in long-term event studies, it is more arduous to control for confounding effects (McWilliams & Siegel, 1997).

On the other hand, several studies support the validity of studies with short-term event windows. Brown & Warner's (1985) and Dyckman et al.'s (1984) research results show that investigating abnormal returns over short event windows leads to considerably superior hypothesis tests. Furthermore, Thompson (1995) and Armitage (1995) state that when it is possible to identify the event date accurately, two-days event windows should be sufficient to capture the event's effect on the stock price, even for stocks characterised by low trading volume.

In this paper, the event windows over which the potential occurrence of ARs and CARs is analysed are two, the first one [0,1] spanning two trading days and the second one [0,2] covering three trading days. Event windows extending over one or two days prior to the event date are not considered, given the particular characteristics of the type of event analysed (McWilliams & Siegel, 1997). Unlike, for instance, earning announcements, it seems complicated to believe that there could be a leakage of information concerning the Tesla CEO's tweets or that someone other than Elon Musk himself would know what he would or would not publish on Twitter and thus decide to sell or buy the company's shares before the tweet was published. This decision is supported by Brans & Scholtens (2020), who, when investigating the impact on the share price of the shares mentioned by Trump in investigating tweets, analysed abnormal returns on a single event window of type [0,1], which does not include days before the tweet date. In addition, although Ante (2023) conducts an intra-day event study and, therefore, with price data per minute, it likewise uses event windows that do not comprise the minutes preceding the Tesla tycoon's tweets.

Finally, concerning the last two aspects mentioned by Krivin et al. (2003), the frequency and type of price measurement, this study was conducted using daily closing prices since, as mentioned earlier, most of the tweets in the sample have been published by Musk outside of the NASDAQ trading hours, which made it impossible to study the effects at the intra-day level as done by Ante (2023) for the cryptocurrencies price.

Results

4.1 Twitter Sentiment Analysis Results

The sentiment analysis results (Fig. 2) indicate a clear tendency for Elon Musk to express non-negative sentiment in tweets in which he mentions Tesla. The tweets for which Musk was found to have expressed positive sentiment are 44% (23 out of 52), neutral sentiment 52% (27 out of 52), and only in 4% of the tweets he expressed negative sentiment (2 out of 52). This trend, which is evident from the sentiment analysis conducted on the 52 tweets with the highest number of interactions, is highly informative of Musk's general behaviour when he cites Tesla in his tweets.

Performing the same sentiment analysis procedure previously described, on all tweets in which Musk mentioned Tesla during the analysed period without selecting only those with a higher number of interactions (Fig. 3), emerges a distribution of Twitter posts for the three sentiment classes highly similar that confirms the Tesla CEO's propensity to express a positive or neutral sentiment. Indeed, of the 233 tweets about Tesla posted between August 2018 and December 2021, 48% (111 out of 233) present positive sentiment, 48% (113 out of 233) neutral sentiment and 4% (9 out of 233) negative sentiment. This insight is clearly visible when comparing Figure 2, which shows the results of the sentiment analysis of the 52 tweets with the most interactions for each year, and Figure 3, which displays the sentiment analysis of all 233 tweets in which Musk mentioned Tesla.

Surprisingly, Ante (2023) reaches similar results and finds a small percentage of tweets with negative sentiment by classifying the sentiment of Elon Musk's tweets in which he mentions Bitcoin not using sentiment analysis techniques but based on the ratings assigned by three financial experts.

As mentioned in the section on event study methodology in Chapter 3, to make the sample of tweets suitable for this type of analysis, six tweets were grouped into three pairs to limit overlapping problems and confounding effects, resulting in a sample of 49 events. Once the sentiment analysis was performed again on the three new tweets originated by the grouping, the distribution of sentiment classes remained more or less unchanged, with 23 events showing positive sentiment (47%), 24 exhibiting neutral sentiment (49%), and 2 having negative sentiment (4%).

Unfortunately, a sample of only two negative tweets does not allow to investigate the hypothesis H1b and, thus, the effect of Elon Musk's tweets with negative sentiment on Tesla's share price.

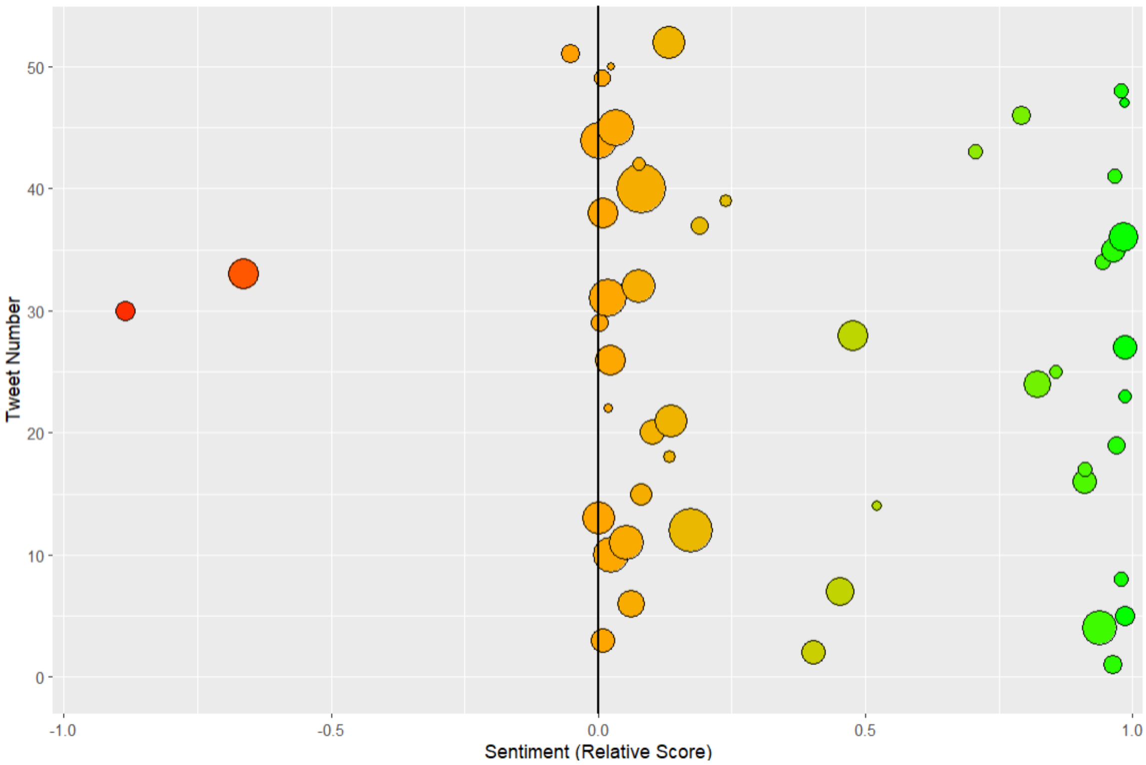

Fig. 2. Sentiment Analysis results of Elon Musk's tweets included in the sample (52). The figure shows a scatter plot with the results of the sentiment analysis of the tweets with the higher number of interactions per year. The x-axis expresses the relative score of each tweet, the y-axis indicates the tweet's identification number and the size of the dots represent the number of interactions proportionally.

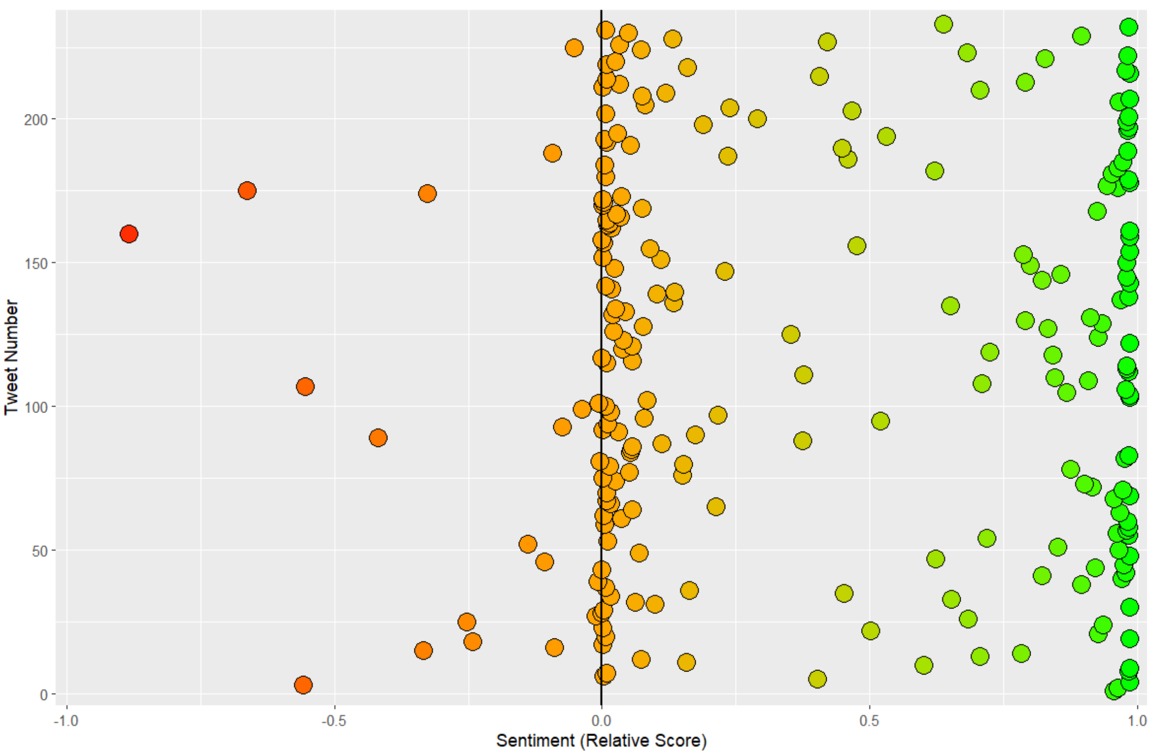

Fig. 3. Sentiment Analysis results of all Elon Musk's tweets mentioning Tesla (233). The figure shows a scatter plot with the results of the sentiment analysis of all the 233 Elon Musk's tweets mentioning Tesla over the analysed period. The x-axis expresses the relative score of each tweet and the y-axis indicates the tweet's identification number.

4.2 Event Study Results

The subsequent findings of the event study are presented separately for the three different sentiment categories.

Regarding positive tweets, adopting the NASDAQ-100 as the market benchmark, positive abnormal returns are observed on the first two days and negative on the third, yet only the AAR occurring on day one turns out to be statistically significant at a 90% confidence interval. Specifically the AARs are, respectively, 2.089%, 1.463% ($p < 0.1$) and -0.523%. Nevertheless, using the NASDAQ composite as the market index, the average abnormal returns are slightly higher and the AAR on the day 0 is also found to be statistically significant. These amount to 2.162% ($p < 0.1$), 1.466% ($p < 0.1$) and -0.523%.

Moreover, the cumulative abnormal returns that, on average, occur in the case of positive tweets are positive and statistically significant in both event windows. Event window [0,1] presents a CAAR of 3.552% ($p < 0.05$) using the NASDAQ-100 as a benchmark, while it is slightly higher using the NASDAQ Composite (3.628%, $p < 0.05$). In the [0.2] event window, the cumulative abnormal return averaged 3.267% ($p < 0.1$) and 3.295% ($p < 0.1$), using the NASDAQ-100 and NASDAQ Composite as an index, respectively.

The positive event with the greatest impact in terms of both ARs and CARs is the one grouping tweets number 17 and 18, according to the procedure outlined in the second section of Chapter 3. In the first tweet, Musk emphasised the most positive aspects of Tesla's Q3 2019 financial results, while in the second, he announced that: *"If you're directly affected by wildfire power outages, Tesla is reducing Solar+Powerwall prices by $1000 as of today".*

In relation to that tweet, abnormal returns occurred between 16.317% ($p < 0.01$) and 16.463% ($p < 0.01$) on the event date and between 8.409% ($p < 0.01$) and 8.458% ($p < 0.01$) on the following day. The cumulative abnormal returns that emerge from the two event windows analysed are even more surprising. Along the [0,1] window using the NASDAQ-100 as a benchmark, a CAR of 24.726% ($p < 0.01$) and in the [0,2] window of 23.192% ($p < 0.01$) was observed, while 24.921% ($p < 0.01$) and 23.319% ($p < 0.01$), respectively, when adopting the NASDAQ Composite.

Two factors probably influence these outstanding results. The first is that this event is the result of the grouping of two tweets, and therefore both tweets could have generated abnormal returns which, as a result of the grouping, merged. The second is the earnings announcement that took place approximately 1.30 hours (Tesla Investor Relations, 2019) after the Tesla CEO's tweet. Interestingly, this result is consistent with the findings of Gao (2018), who showed that a high share of positive words within tweets predicts positive abnormal stock returns, especially before companies' earnings are released.

Positive Tweets	NASDAQ-100					NASDAQ Composite				
	Abnormal Returns			Cumulative Abnormal Returns		Abnormal Returns			Cumulative Abnormal Returns	
	AR [0]	AR[1]	AR[2]	CAR [0,1]	CAR[0,2]	AR [0]	AR[1]	AR[2]	CAR [0,1]	CAR[0,2]
If you're into video game development, consider applying to Tesla. We want to make super fun games that integrate the center touch screen, phone & car irl.	14.643%***	-0.621%	-2.331%	14.022%***	11.691%***	14.601%***	-0.400%	-2.455%	14.200%***	11.746%***
Am considering taking Tesla private at $420. Funding secured.	10.726%***	-2.346%	-4.583%*	8.380%***	3.797%	10.692%***	-2.311%	-4.696%*	8.381%***	3.685%
Tesla exists to help reduce risk of catastrophic climate change, which affects all species on Earth. Even if your faith in humanity is faltering, this is worth caring about. Support makes a difference. Thank you.	-1.722%	2.422%	1.988%	0.700%	2.688%	-1.239%	1.951%	1.711%	0.712%	2.424%
Massive thanks to Tesla owners & supporters. We wouldn't be here without you.	4.252%	8.706%**	4.314%	12.958%***	17.272%***	4.541%	8.480%**	3.870%	13.021%***	16.890%***
If Tesla can help people in California wildfire, please let us know. Model S & X have hospital grade HEPA filters. Maybe helpful for transporting people.	-2.274%	1.962%	2.351%	-0.311%	2.040%	-2.363%	1.981%	2.392%	-0.382%	2.010%
Congratulations @Tesla team!! https://t.co/PBr9VVBv1S	-7.470%*	-0.189%	1.463%	-7.6590%**	-6.196%	-7.485%*	-0.397%	1.488%	-7.882%**	-6.394%
Tesla does not advertise or pay for endorsements. Instead, we use that money to make the product great.	-0.666%	-0.776%	-5.232%*	-1.442%	-6.674%*	-0.818%	-0.918%	-5.171%*	-1.736%	-6.907%*
Ability to stream YouTube & Netflix when car is stopped coming to your Tesla soon! Has an amazingly immersive, cinematic feel due to the comfy seats & surround sound audio.	4.130%	3.582%	1.652%	7.711%***	9.364%***	4.274%*	3.316%	1.595%	7.5905%***	9.185%***
Tesla Q3 results: - Shanghai Giga ahead of schedule - Model Y ahead of schedule - Solar installs +48% from Q2 - GAAP profitable - Positive free cash flow If you're directly affected by wildfire power outages, Tesla is reducing Solar+Powerwall prices by $1000 as of today	16.317%***	8.409%***	-1.534%	24.726%***	23.192%***	16.463%***	8.458%***	-1.602%	24.921%***	23.319%***
Tesla Solarglass vs 😜 Happy Halloween!! https://t.co/p5tXeJYqne	-2.026%	0.227%	-0.266%	-1.798%	-2.064%	-2.342%	0.251%	-0.316%	-2.091%	-2.407%
Congratulations Tesla & SpaceX on great 2019! You rock!! Looking forward to epic 2020 ♥🚀🛰🚘 ⭘	0.362%	3.658%	0.703%	4.020%*	4.723%	0.671%	3.529%	0.761%	4.201%*	4.962%
At Tesla Giga Shanghai NSFW!! https://t.co/1yrPyzJQGZ	3.518%	3.570%	-3.705%	7.088%***	3.383%	3.519%	3.649%	-3.657%	7.168%***	3.511%
Teslas will soon talk to people if you want. This is real. https://t.co/8AJdERX5qa	7.895%***	2.585%	-4.042%	10.480%***	6.438%*	8.018%***	2.371%	-4.123%	10.389%***	6.266%*
Congratulations Tesla team on making our 1,000,000th car!! https://t.co/5M99a9LLQi	-4.769%	5.578%	4.875%	0.809%	5.684%	-4.249%	6.317%	5.466%	2.068%	7.534%
We have extra FDA-approved ventilators. Will ship to hospitals worldwide within Tesla delivery regions. Device & shipping cost are free. Only requirement is that the vents are needed immediately for patients, not stored in a warehouse. Please me or @Tesla know.	4.794%	-3.547%	-8.884%*	1.247%	-7.637%	4.778%	-3.128%	-8.663%*	1.650%	-7.012%
Tesla will make fabulous short shorts in radiant red satin with gold trim	6.554%	9.772%*	1.560%	16.326%***	17.886%**	6.610%	10.045%*	1.688%	16.655%***	18.343%**
More fun games coming soon to ur Tesla	4.350%	1.091%	-2.980%	5.441%	2.461%	4.711%	1.385%	-3.006%	6.096%	3.089%
Thanks to everyone who worked so hard to make Tesla successful. My heart goes out to you.	-6.480%	-2.641%	1.160%	-9.120%**	-7.960%	-6.977%*	-3.282%	0.801%	-10.259%***	-9.458%*
Thanks Tesla suppliers for providing us with critical parts!	-0.134%	-2.328%	3.747%	-2.463%	1.284%	-0.225%	-2.159%	4.163%	-2.385%	1.778%
Tesla Solar + Powerwall battery enables consumers to be their own utility	-1.350%	-1.222%	-0.131%	-2.572%	-2.703%	-1.664%	-1.647%	-0.689%	-3.311%	-3.999%
Tesla has 💎 🙌 Tesla Model S Plaid delivery event June 3 at our California factory Fastest production car ever 0 to 60mph in under 2 secs	-2.981%	-0.089%	0.109%	-3.069%	-2.960%	-2.570%	0.049%	-0.082%	-2.521%	-2.603%
Shout out to the awesome Tesla global team. Thanks for working so hard to make Tesla successful!	2.400%	-0.697%	0.113%	1.704%	1.816%	2.201%	-0.854%	0.528%	1.347%	1.875%
Congrats Tesla Team on over 200,000 car built & delivered in Q2, despite many challenges!!	-2.031%	-3.452%	-2.380%	-5.483%*	-2.380%	-1.417%	-2.975%	-2.044%	-4.392%	-2.044%
Average Abnormal Return Positive Tweets	**2.089%**	**1.463%***	**-0.523%**			**2.162%***	**1.466%***	**-0.523%**		
Cumulative Average Abnormal Return Positive Tweets				**3.552%****	**3.267%***				**3.628%****	**3.295%***

Table 2. Event study results for Elon Musk's positive events. The table presents the abnormal returns (ARs) and the cumulative abnormal returns (CARs) for each event detected as positive. Furthermore, the average abnormal returns (AARs) and cumulative average abnormal returns (CAARs) are at the bottom of the table. The left-hand side of the table shows the outcomes obtained using the NASDAQ-100 as a market benchmark, while the right-hand side displays the results using the NASDAQ Composite as market index. Finally, *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Another insight that can be gleaned from Table 2 concerns the well-known tweet on 7 August 2018, which triggered the beginning of the litigation between Musk and the SEC and between Musk and the Tesla shareholders in which the CEO announced: *"Am considering taking Tesla private at $420. Funding secured"*. Under the assumptions and circumstances of this study, it turns out that positive abnormal returns of between 10.726% and 10.692% actually occurred on the day of the event (depending on whether one adopts the NASDAQ-100 or the NASDAQ Composite as the market index), statistically significant at a 99% confidence interval. This positive impact, however, dissipated quickly in the following days, both of which present negative abnormal returns, of which only that of the second day is significant ($p < 0.1$). Indeed, on event window [0,1], a CAR of 8.380% ($p < 0.01$) occurred using the NASDAQ-100 as the index and of 8.381% ($p < 0.01$), adopting the NASDAQ Composite instead. In contrast, the second event window shows no statistically significant positive cumulative abnormal returns for any benchmark.

In contrast to the positive tweets, those characterised by neutral sentiment do not significantly impact the share price. In this case, the average abnormal returns are slightly negative on each day in the two event windows, but none is statistically significant. Specifically, employing the NASDAQ-100 as the market index, the ARRs for days 0, 1 and 2 are -0.584%, -0.748% and -0.072%, respectively, while in the case of the NASDAQ Composite, these turn out to be -0.583%, -0.670% and -0.093%. Similarly, the cumulative average abnormal returns are also negative but not statistically significant for both indices used, where in the case of the NASDAQ-100, they are -1.332% in the first event window and -1.404% in the second, while in the case of the NASDAQ Composite, they are -1.252% during event window [0,1] and -1.345% in event window [0,2].

The neutral tweet that has most affected Tesla's share price, both in terms of abnormal returns and cumulative abnormal returns, is the one on 6 November 2021, in which Musk polled his 62.5 million (at the time) Twitter followers: *"Much is made lately of unrealised gains being a means of tax avoidance, so I propose selling 10% of my Tesla stock. Do you support this?"*. In addition to this tweet, Musk later replied to it that he would abide by whatever the outcome was, specifying that since he did not earn a cash salary or other bonuses, his only way to pay taxes would be to sell a share of his Tesla stock.

Musk published this tweet in a scenario where two crucial events closely related to the post's topic were occurring. Firstly, Democrats were tabling new taxes for long-term capital gains on tradable assets, even if unrealised (Shibu & Jin, 2021), which constituted the major part of Musk's estimated 271 billion in assets at the time (Peterson-Withorn, 2021).

Neutral Tweets	NASDAQ-100					NASDAQ Composite				
	Abnormal Returns			Cumulative Abnormal Returns		Abnormal Returns			Cumulative Abnormal Returns	
	AR [0]	AR[1]	AR[2]	CAR [0,1]	CAR[0,2]	AR [0]	AR[1]	AR[2]	CAR [0,1]	CAR[0,2]
Short shorts coming soon to Tesla merch	0.448%	-3.261%	-0.772%	-2.812%	-3.585%	0.707%	-3.422%	-0.573%	-2.715%	-3.288%
Deleted my Tesla titles last week to see what would happen. I'm now the Nothing of Tesla. Seems fine so far.	-3.584%	-1.099%	-0.107%	-4.683%	-4.790%	-3.923%	-0.832%	-0.665%	-4.755%	-5.420%
Tap Tesla logo at top of your car's touchscreen & wait 10 secs to open special features box	0.966%	1.152%	0.978%	2.118%	3.096%	0.773%	1.024%	1.328%	1.797%	3.125%
4000 Tesla cars loading in SF for Europe https://t.co/BODbSzo3Fr	-1.092%	-3.482%	0.342%	-4.574%	-4.233%	-1.184%	-3.464%	0.185%	-4.648%	-4.463%
Tesla Semi delivering Tesla cars https://t.co/ttEpcW5d8G	2.003%	-1.480%	1.412%	0.523%	1.935%	1.996%	-1.473%	1.383%	0.523%	1.906%
Tesla is going to develop a quiet, electric leafblower	-1.740%	-4.629%	-5.172%	-6.369%**	-11.541%***	-1.816%	-4.457%	-5.372%*	-6.273%**	-11.645%***
Changing Tesla horn sound to 🐐	3.375%	1.077%	-1.051%	4.452%*	3.401%	3.276%	0.956%	-0.950%	4.233%*	3.282%
New Tesla Summon will 💉 ur 🧠	-0.659%	5.908%**	1.257%	5.248%**	6.505%*	-1.074%	5.799%**	1.329%	4.725%*	6.055%
Tesla Cybertruck (pressurized edition) will be official truck of Mars	-6.675%**	-1.039%	-2.808%	-7.714%***	-10.521%***	-6.810%**	-1.259%	-2.850%	-8.069%***	-10.919%***
Tesla Moth Mode (better late than never) https://t.co/Rcu87A8NkO Tesla holiday software update has FSD sneak preview, Stardew Valley, Lost Backgammon & a few other things	1.563%	-0.507%	2.772%	1.057%	3.829%	1.587%	-0.512%	2.725%	1.075%	3.800%
A friend just sent me this excerpt from a Tesla blog I wrote 14 years ago https://t.co/Hr8w52ithY	1.747%	9.238%***	2.888%	10.985%***	13.873%***	1.798%	9.370%***	2.868%	11.168%***	14.036%***
Partial list of hospitals to which Tesla sent ventilators https://t.co/sfI6yuUbrM	-0.800%	-0.514%	-0.369%	-1.315%	-1.683%	-0.610%	-1.213%	-0.545%	-1.823%	-2.368%
Tesla is restarting production today against Alameda County rules. I will be on the line with everyone else. If anyone is arrested, I ask that it only be me.	1.434%	-1.530%	-0.412%	-0.096%	-0.508%	1.562%	-1.120%	-0.324%	0.442%	0.118%
Juneteenth is henceforth considered a US holiday at Tesla & SpaceX	-0.993%	-2.846%	-0.918%	-3.840%	-4.758%	-1.104%	-2.793%	-0.930%	-3.897%	-4.827%
Change your horn sound to 🐐, 🐌🎷, 💨 or holiday jingles with latest Tesla software update!	-2.427%	-0.432%	3.583%	-2.858%	0.725%	-1.964%	0.509%	3.327%	-1.455%	1.872%
Time to tell the story of Tesla & SpaceX	-0.646%	-2.246%	-5.563%	-2.893%	-8.455%	-1.247%	-2.580%	-5.432%	-3.826%	-9.258%*
Play your favorite song in a Tesla & turn the volume to 11 You will see. You will feel.	0.101%	-5.413%*	2.894%	-5.312%*	-2.418%	0.136%	-4.657%	2.883%	-4.521%	-1.638%
You can now buy a Tesla with Bitcoin	-2.170%	1.566%	-6.384%*	-0.604%	-6.988%	-1.189%	1.176%	-5.939%*	-0.013%	-5.952%
Tesla with Autopilot engaged now approaching 10 times lower chance of accident than average vehicle	-1.975%	1.601%	1.679%	-0.374%	1.305%	-1.727%	2.174%	1.052%	0.447%	1.499%
Do you want Tesla to accept Doge?	-1.999%	0.648%	-4.997%	-1.351%	-6.348%	-1.873%	1.166%	-4.825%	-0.706%	-5.531%
Tesla AI Day August 19th	4.642%*	3.061%	3.590%	7.703%***	11.293%***	4.791%*	3.359%	3.476%	8.150%***	11.626%***
If you're curious about Tesla, SpaceX & my general goings on, @WalterIsaacson is writing a biography	-0.507%	-0.873%	2.090%	-1.380%	0.711%	-0.904%	-1.048%	2.000%	-1.952%	0.048%
Much is made lately of unrealized gains being a means of tax avoidance, so I propose selling 10% of my Tesla stock. Do you support this?	-5.094%**	-11.571%***	5.631%**	-16.665%***	-11.033%***	-5.355%**	-11.640%***	6.070%***	-16.996%***	-10.926%***
Tesla will make some merch buyable with Doge & see how it goes	0.065%	-1.287%	-2.297%	-1.222%	-3.519%	0.168%	-1.134%	-2.441%	-0.967%	-3.408%
Average Abnormal Return Neutral Tweets	**-0.584%**	**-0.748%**	**-0.072%**			**-0.583%**	**-0.670%**	**-0.093%**		
Cumulative Average Abnormal Return Neutral Tweets				**-1.332%**	**-1.404%**				**-1.252%**	**-1.345%**

Table 3. Event study results for Elon Musk's neutral events. The table presents the abnormal returns (ARs) and the cumulative abnormal returns (CARs) for each event detected as neutral. Furthermore, the average abnormal returns (AARs) and cumulative average abnormal returns (CAARs) are at the bottom of the table. The left-hand side of the table shows the outcomes obtained using the NASDAQ-100 as a market benchmark, while the right-hand side displays the results using the NASDAQ Composite as market index. Finally, *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Secondly, Musk would have called by August 2022 (Peterson-Withorn, 2021) to exercise a large portion of his non-qualified options amounting to \$23 billion, which would have triggered the immediate burden of paying a large amount of taxes at a higher tax rate than that charged on the sale of the shares.

Given this background, Musk offered his followers the opportunity via a Twitter pool to express their opinion on whether or not to sell stocks valued at \$21 billion at the time (Reuters, 2021), in which 58% of voters responded *"Yes"* (Peterson-Withorn, 2021). This Twitter post shows how including the sentiment-neutral category in the analysis is relevant, as in this case, investor sentiment is probably not influenced solely by Musk but by what the majority of his followers vote for.

The results of the event study reveal that in relation to this tweet, ARs between -5.094% ($p < 0.05$) and -5.355% ($p < 0.05$) occurred on the event date, between -11.571% ($p < 0.01$) and -11. 640% ($p < 0.01$) on the next day, and between 5.631% ($p < 0.05$) and 6.070% ($p < 0.01$) two days after the date of the tweet, depending on whether NASDAQ-100 or NASDAQ Composite is adopted as the index. Looking at the CARs, using the NASDAQ-100 as a benchmark, they amounted to -16.665% ($p < 0.01$) in the first event window and -11.033% ($p < 0.01$) in the second event window, while with the NASDAQ Composite, they accounted for -16.996% ($p < 0.01$) in event window [0,1] and -10.926% ($p < 0.01$) in event window [0,2]. These findings, which clearly reveal a drop in Tesla's share price around the event, are by no means influenced by the actual sale of \$6.9 billion worth of shares (Jin & Patnai, 2021) by Elon Musk, as this only took place on 12 November 2021 (6 days after the tweet).

Therefore, as these ARs and CARs are realised prior to the offloading of shares, they probably reflect the expectations of the public of investors, shaped by the outcome of the poll, that Tesla's CEO would sell a huge quantity of shares and cause a future decrease in Tesla's shares.

A further deterioration of the relations between the SEC and Musk arose due to Musk's reply stating that Tesla would produce 500,000 cars in 2019, to his tweet on 19 February 2019 in which he stated that *"4000 Tesla cars loading in SF for Europe"*. In that instance, the SEC accused him of violating the terms of the agreement under which Musk's tweets regarding specific topics, such as production numbers, had to be pre-approved by a Tesla attorney prior to publication (Michaels & Higgins, 2019).

As explained in the first section of the chapter on the methodology implemented for this study, Musk's replies to his own or other users' tweets are excluded from the scope of the analysis. The findings related to the tweet under which Musk posted the incriminated reply (on the same day) show that even though abnormal returns and slightly negative cumulative abnormal returns occurred, these were not statistically significant using either the NASDAQ-100 or the NASDAQ Composite. These results indicate that neither the tweet nor the reply has any daily effects on the share price.

Regarding the tweets with negative sentiment, as explained above due to the very small sample size it is not possible to verify whether these have a statistically significant influence on Tesla's stock price. Indeed, the only result that emerges from the overall analysis of the abnormal returns of the two tweets with negative sentiment is an AAR on day 1, that is, the day after the event between 4.684% ($p < 0.01$) and 4.624% ($p < 0.01$), which as derived from a sample of only two events cannot be considered informative of the market reaction to Musk's negative tweets. In addition, this finding concerning the average abnormal return on day 1, is not reflected in any statistically significant cumulative abnormal returns in either event windows.

However, it is worth noting that the popular tweet *"Tesla's stock price is too high imo"*, generated, based on the index used, abnormal returns between -7.439% and -7.274% on the day of the event, between 6.269% and 6.296% on the following day and -1.106% and -1.234% two days after the event, but none of them statistically significant, as the CARs in the two event windows considered. Thus, based on these findings, Tesla's share price was not affected by the tweet on at least a daily level.

Finally, the event study results show that the only sentiment category able to return one average, statistically significant abnormal returns and cumulative abnormal returns is the positive one. This finding leads to the conclusion that the hypothesis H1a is validated and that on the sample of tweets used for the analysis, those with positive sentiment positively influenced Tesla's share price statically significantly. On the other hand, the tweets included in the neutral sentiment class were not able to impact the share price, while those included in the negative sentiment class constituted too small a sample to explore hypothesis H1b.

Negative Tweets	NASDAQ-100					NASDAQ Composite				
	Abnormal Returns			Cumulative Abnormal Returns		Abnormal Returns			Cumulative Abnormal Returns	
	AR [0]	AR[1]	AR[2]	CAR [0,1]	CAR[0,2]	AR [0]	AR[1]	AR[2]	CAR [0,1]	CAR[0,2]
Tesla stock price is too high imo	-7.439%	6.269%	-1.106%	-1.170%	-2.276%	-7.274%	6.296%	-1.234%	-0.978%	-2.212%
Only a matter of time before someone steals a Tesla while playing GTA on a Tesla	-0.402%	3.100%	3.922%	2.698%	6.619%	-0.222%	2.951%	3.937%	2.729%	6.666%
Average Abnormal Return Negative Tweets	**-3.920%**	**4.684%*****	**1.408%**			**-3.748%**	**4.624%*****	**1.351%**		
Cumulative Average Abnormal Return Negative Tweets				**0.764%**	**2.171%**				**0.876%**	**2.227%**

Table 4. Event study results for Elon Musk's negative events. The table presents the abnormal returns (ARs) and the cumulative abnormal returns (CARs) for each event detected as negative. Furthermore, the average abnormal returns (AARs) and cumulative average abnormal returns (CAARs) are at the bottom of the table. The left-hand side of the table shows the outcomes obtained using the NASDAQ-100 as a market benchmark, while the right-hand side displays the results using the NASDAQ Composite as market index. Finally, *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Conclusion

Elon Musk’s controversial tweets have caught the eye of the media and regulatory authorities, such as the SEC, for at least half a decade since the famous tweet in which the Tesla CEO announced that he would take the firm private. Nevertheless, to the current knowledge, little is known about the relationship between these Twitter posts and Tesla’s share.

Some scholars demonstrated a medium-high correlation between Musk’s tweets and Tesla’s share price (Kang Kim et al., 2021; Šević et al., 2023). Strauss & Smith (2019) showed for the very first time that a Musk Tweet could affect the share price of the company he managed. They conducted an intraday event study, comparing the effects on the share price of two tweets on 23 August 2016, one posted by Elon Musk at 11.23 a.m. in which he stated that a new product would be announced at noon and the tweet from Tesla’s official account at 3.30 p.m. in which the new product was actually announced. Strauss & Smith (2019) conclude that in this instance, investors acted merely on the belief that Musk’s tweet would cause a rise in the share price, as they report statistically significant positive abnormal returns after Musk’s tweet but conversely statistically significant negative abnormal returns after the tweet in which Tesla unveiled the new product.

Finally, Ante (2023) proved for the first time that the Tesla CEO’s Twitter activity could impact the price of a financial asset, calling this phenomenon the *“Musk Effect”*. The author, who conducted an intra-day event study, concluded that Musk’s tweets affected the price of various cryptocurrencies and that tweets about Bitcoin in which non-negative sentiment is expressed are associated, on average, with positive and statistically significant abnormal returns and cumulative abnormal returns.

Thus, this paper continues the previous studies and aims to empirically investigate the impact of Elon Musk’s tweets on Tesla’s share price over the period from 1 August 2018, to 31 December 2021.

This dissertation particularly emphasises the sentiment expressed by Elon Musk in the analysed tweets as, in the majority of the papers present in the literature, exploring the impact on a financial asset by the Twitter activity of a specific subject or multiple users without distinguishing for sentiment often did not produce significant results.

The tweets sampled (Table 1) in the study have been selected from those in which Musk mentioned Tesla during the period under analysis using a variable, called *“interactions”* that sums up the number of likes, retweets and replies (Formula 2.1). Therefore, the sample is composed as follows: the 7 tweets with the highest number of interactions in 2018 and the 15 tweets with the highest number of interactions for 2019, 2020 and 2021.

The 52 tweets are subsequently classified according to sentiment into three categories (positive, neutral and negative) using the BERTweet (Nguyen et al., 2020) language model.

Moreover, an event study on daily returns has been conducted, adopting the market model (Fama et al., 1969) approach. Specifically, for the event study, an estimation window of 120 trading days, two event windows [0,1] and [0,2] have been defined, and two benchmarks have been selected, the first, the NASDAQ-100, and the second, the NASDAQ composite, to corroborate the results.
The major findings of this dissertation can be summarised in the following points:

- The sentiment analysis reveals a clear tendency of Elon Musk to avoid expressing a negative sentiment when he mentions Tesla in his tweets. Indeed, in all 233 tweets in which he cites Tesla in the period under analysis, as well as in the 52 tweets with the highest number of interactions, those with negative sentiment account for between 3-4%.

- The event study demonstrates that the positive sentiment category is the only one able to influence Tesla's share price statistically significantly. On average, the positive events show cumulative abnormal returns on the first event window [0,1] between 3.552% ($p < 0.05$) and 3.628% ($p < 0.05$), while on the event window [0,2] a CAAR between 3.267% ($p < 0.1$) and 3.295% ($p < 0.1$) was found. This finding validates the hypothesis H1a of this dissertation and is consistent with the conclusions of Gao (2018), who, analysing over 120,000 tweets of 200 CEOs, concludes that a high percentage of positive words predicts positive abnormal returns and with the results of Ante (2023), who, in studying the impact of Elon Musk's tweets on the price of Bitcoin, shows that only those classified as having non-negative sentiment (in this paper only two categories of sentiment are considered, negative and non-negative) can generate abnormal returns.

- The event study indicates that both average abnormal returns on each day considered and cumulative average abnormal returns on both event windows for tweets classified as neutral are slightly negative, but none is statistically significant. Nevertheless, some neutral tweets individually generate statistically significant abnormal returns and cumulative abnormal returns, as in the case of the tweet in which Musk polled his followers, asking whether he should sell 10 % of his Tesla shares. Moreover, the tweets classified as negative constitute a too small sample to examine the hypothesis H1b that they negatively impact Tesla's share price.

Furthermore, the event study also provides insights into some of the most debated tweets that led to the above-mentioned SEC legal litigations. For instance, in the case of the tweet on 7 August 2018, in which Musk expressed his plans to take Tesla private, an abnormal return between 10.726% ($p < 0.01$) and 10.692% ($p < 0.01$) is observed, and a cumulative abnormal return on the event window [0,1] between 8.380% and 8.381% ($p < 0.01$), indicating that this tweet positively influenced Tesla's share price. In contrast, when Musk tweeted on 1 May 2020, that Tesla's share price was too high in his opinion, negative ARs and CARs are detected, but surprisingly, they are not statistically significant.

The theoretical implications of this dissertation contribute to extending the existing literature on how CEO communications in written or verbal form influence investor sentiment and the share price of the companies they manage. However, it is worth noting that this paper discusses the short-term effects of the sentiment expressed in Musk's tweets on Tesla's share price without investigating the mechanisms behind this phenomenon. Therefore, new theoretical models akin to that of De Long et al. (1990), but more contemporary and able to accommodate the underlying dynamics behind social media platforms, are needed.

Arguably, this study's most critical limitation lies in its limited generalisability, as it is based on a specific CEO (Elon Musk) and a specific company (Tesla).

Firstly, the results cannot be interpreted as applicable to all CEOs of listed companies who use Twitter daily, as only Elon Musk and Tesla are considered in the analysis. This dissertation, to my knowledge, appears to be the only one that attempts to isolate the effects of the sentiment expressed in the tweets of a specific CEO on the share price of the company they manage, so future research similar to this one could be conducted on other specific case studies.

Secondly, the findings of this work are not generalizable to companies mentioned by Elon Musk in his tweets other than Tesla. The CEO of Tesla is used to mentioning even companies he has no business relationship with or no stake in, including Amazon, Facebook & WhatsApp, Etsy, GameStop and Shopify. However, the most striking case is surely the one in which Musk in January 2021 tweeted "*Use Signal*", which is an encrypted instant messaging app. After this tweet, the app was downloaded by 1.3 million users (Nicas et al., 2021), compared to the average of 50,000 downloads per day, but ambiguous was what happened in the financial markets, where investors probably confused the company with another listed company. Indeed, Signal is not a listed company, but Signal Advance (SIGL) is an over-the-counter (OTC) traded company. Even though the latter is a medical devices manufacturer (Signal Advance) having no connection with the messaging app (Signal), in the days following Elon Musk's tweet, it experienced a share price increase by 11.708% (Fox, 2021) to the extent that Signal had to specify that investors were buying the shares of another unrelated company.

This dissertation does not explain how the sentiment expressed by Musk in his tweets influences the share price of each company he mentions, so other articles could also include other firms and investigate possible differences in terms of impact.

Furthermore, a limitation that emerges from the methodology to compose the sample of tweets lies in the decision to pick only those tweets in which Tesla is mentioned; however, other tweets in which the company remains unmentioned might also be able to influence its share price. Therefore, different methodologies could be developed in this regard.

An additional limitation resides in the impossibility of investigating the sentiment displayed in the images (especially memes) that Tesla's CEO usually attaches to his tweets to express his opinion. Indeed, the sentiment resulting from these could significantly impact the classification of the tweets, especially for those classified as neutral in this study. Presumably, with the tremendous development of large language models we are witnessing, it will also be possible to account for the sentiment of the images in the immediate future.

Finally, a limitation of the study is the assumption that the textual sentiment that emerges from Elon Musk's tweets coincides with the sentiment perceived by followers when a gap may actually exist between these two. A possible avenue for future research in this sense, both concerning Musk precisely or other CEOs of listed companies using Twitter, could be to include in the analysis not only the sentiment expressed by the author in a tweet but also the overall sentiment expressed in the replies to that tweet by his followers. The latter could indicate whether followers perceived a given tweet as positive, neutral or negative and suggest possible differences between the sentiment expressed by the user posting the tweet and the sentiment perceived by other users reacting to this tweet. This would enable one to assess whether there is a significant effect on the share price when the sentiment expressed by the CEO and that expressed by his followers in replies coincide (positive-positive, negative-negative, neutral-neutral) or when they differ (positive-negative, positive-neutral, negative-positive, negative-neutral, neutral-positive and neutral-negative).

This kind of analysis could provide further insights, particularly for tweets in which a CEO expressed a neutral sentiment, such as the one in which Musk asked his followers whether or not to sell 10% of his Tesla shares, indicating whether the tweet was perceived as neutral or actually had a polarity.

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SUMMARY

Introduction

The issue regarding the potential impact of Chief Executive Officers' social media activity on the market value of companies has been well-known to the Securities and Exchange Commission (SEC) for over a decade. Nevertheless, few studies have investigated this phenomenon so far.
This matter was first brought to light in 2012, when Netflix CEO Reed Hastings ended up under investigation by the SEC (SEC, 2013a) for suspected violation of the Regulation Fair Disclosure (Reg FD) and Section 13(a) of the Securities Exchange Act of 1934 ("Exchange Act") for publishing on his personal Facebook profile on 3 July a post in which he revealed that in June the platform's users had spent a total of more than 1 billion hours. In this case, the SEC chose not to pursue any enforcement action against Hastings or Netflix, along with the concomitant decision (SEC, 2013b), to extend the application of the 2008 Commission Guidance on the Use of Company Web Sites (SEC, 2008) to corporate social media outlets. This event led to an overwhelming growth since 2013 in companies' exploitation of social media channels such as Facebook and Twitter, to convey to all stakeholders.
Since Tesla publicly filed Form 8-K on 5 November 2013 to allow its CEO's Twitter account to be a recognised dissemination channel for material information about the company, Musk has often hit the headlines for his controversial tweets. The tweet on 7 August 2018, in which Musk stated: *"Am considering taking Tesla private at $420. Funding secured"*, represents the first time Tesla tycoon's Twitter activity caught the attention of the SEC, raising the question of whether this was harmful to shareholders. Following this event, Musk and Tesla reached an agreement with the SEC (SEC v. Musk Final Judgment, 2018), which was later amended (SEC v. Musk Order Amending the Final Judgment, 2019) due to other tweets violating the rules of the former one, according to which a Tesla securities attorney-at-law would have to pre-approve any Musk's tweets or other forms of written communication. However, even after the second agreement, the SEC continued to complain about infringements of the provisions included in the agreement without finding a definitive solution either in court or through a further agreement with Tesla and Musk.
In addition to these disputes with the SEC, there is the class action that Tesla's shareholders (Gharrity v. Musk et al., 2021) have filed against Musk for the 7 August 2018 tweet about Tesla's delisting.
In light of these court disputes, one question arises: *Do Elon Musk's tweets really impact Tesla's share price?* Although the aforementioned legal issues and most of the world's major financial newspapers suggest (Vercoe, 2021) an affirmative answer, no study has empirically proven it to the current state of the knowledge; thus, this paper attempts to answer this question.

Literature Review

1.1 Investor Sentiment as a Challenge to the Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) during the 1960s garnered tremendous empirical and theoretical support until the occurrence of market crashes such as the Black Monday of 1987 and anomalies such as *underreaction* and *overreaction*, which failed to find an explanation under Fama's theoretical framework (1970). With the emergence of an array of phenomena against the idea that investors are completely rational and emotionless, a new branch of literature called *behavioural finance* emerged, pointing out a series of subjective factors of investors, such as sentiment.

Although no widely accepted definition exists in the behavioural finance literature, investor sentiment can be described by the definition provided by Baker & Wurgler (2007), which defines it as *"a belief about future cash flows and investment risks that is not justified by the facts at hand"*.

Several models have attempted to go beyond the assumption of complete investor rationality, however as the author of the EMH explains *"The alternative has a daunting task. It must specify what it is about investor psychology that causes simultaneous underreaction to some types of events and overreaction to others"* (Fama, 1998). These models can be classified by the approach adopted by the authors. While some scholars, such as Barberis et al. (1998) and Daniel et al. (1998), decided to proceed with a bottom-up approach, grounding their theoretical frameworks on different cognitive biases, other researchers, such as Baker & Wurgler (2006, 2007) adopted a top-down or macroeconomic approach.

Both the models of Barberis et al. (1998) and Daniel et al. (1998) deal with the information absorption speed of the market and the phenomena of overreaction and underreaction. The overreaction hypothesis entails that investors overreact to the latest news, disregarding or paying less attention to past news. Conversely, the underreaction to a piece of news by the market occurs when the response of the participants is insufficient and causes a sluggish absorption of the news into the price.

Barberis et al. (1998) provide one of the first frameworks to deeply comprehend the way investors form their beliefs on future earnings. They focus their model in particular, on two psychological aspects, *conservatism* and *representativeness heuristic*. In line with the Griffin & Tversky (1992) framework, the investor sentiment model of Barberis et al. (1998) posits that individuals in formulating predictions about future earnings are more concerned with the strength or extremeness of one piece of evidence than with its statistical weight or credibility.

Daniel et al. (1998) proposed a new integrated theory rooted in two cognitive biases: *investor overconfidence* and *biased self-attribution*. Given these cognitive biases, the researchers draw the

conclusion that investors have excessive reactions to their private information. In contrast, they have less intense reactions than what would be rationally appropriate to public information.
Conversely, the first tentative to investigate the effects of investor sentiment on share prices that follows a top-down approach is the one by Baker & Wurgler (2007), who developed three indexes to assess investor sentiment: *Sentiment Changes Index*, general demand mutual fund index and speculative demand mutual fund index. The authors found that the stock returns of speculative and *harder-to-arbitrage* stocks are positively associated with investor sentiment and more sensitive to investor sentiment changes, as the effects of general demand, speculative demand, and sentiment betas increase when stocks become more speculative and harder-to-arbitrage. Conversely, *bond-like* stocks show a negative effect of speculative demand, reduced impact of general demand of mutual fund flows and negative sentiment betas and are therefore negatively correlated with changes in sentiment. Baker & Wurgler (2007) also explore the predictability of future stock returns, conjecturing that speculative stocks that are overvalued due to high investor sentiment will experience lower stock returns in the future as a consequence of a decline in sentiment or revelation of fundamentals. The researchers illustrate that the average future returns of speculative shares are higher than safe and *easy-to-arbitrage* stocks when sentiment is low and vice versa when sentiment is high.
In the behavioural finance literature, there are also *psychology-free* approaches (Barberis, 2018) that deal with the interaction of two different actors within the market, such as those of De Long et al. (1990) and Hong & Stein (1999). De Long et al. (1990) outline a novel framework in which they assume that only two types of market participants operate: *noise traders* and *arbitrageurs*. The former are defined, in line with earlier papers by Kyle (1985) and Black (1986), as irrational investors who, unable to access insider information, make decisions solely on the basis of *noise*, treating it as relevant information on the future price of an asset. This leads them to form totally erroneous stochastic beliefs and act on them, driving asset prices away from their intrinsic values. Arbitrageurs are thought to be rational, sophisticated investors who are completely capable of detecting the behaviour of noise traders and implementing contrarian strategies aimed at earning from mispricing, and with these actions, drive prices back towards their fundamental values.
Through this theoretical model, De Long et al. (1990) highlight what they call *noise trader risk* as an additional limit to the *fundamental risk* (Figlewski, 1979; Shiller, 1984; Campbell & Kyle, 1993), for rational investors to exploit and correct mispricing created by the erroneous beliefs of noise traders. The additional risk that arbitrageurs ought to bear lies in the possibility that, in the short term, noise traders' beliefs might not change but rather become more extreme. This represents a risk for

arbitrageurs because if they have to liquidate their position before the sentiment of noise traders changes, they will suffer a loss.
A further theoretical framework that analyses the interplay of two different types of investors is that of Hong & Stein (1999), who divide market players into *news-watchers* and *momentum traders*, where the former make their predictions by relying on private information but without taking past and recent prices into account, while the latter focus on past stock returns and ground their predictions exclusively on them. Thirdly, the last assumption of the model is that news-watcher investors' private signals propagate gradationally among them. Hong & Stein (1999) infer that an underreaction to the news by news-watchers creates the conditions for making a profit in the early part of the momentum cycle for momentum traders, which, however, culminates in an overreaction in the late part of the cycle by momentum traders, as they focus exclusively on past stock returns.
In conclusion, the magnitude of the impact of investor sentiment has been well documented in the literature, and several theoretical models have attempted to explain its dynamics. However, they have yet to prove to prevail over the others.

1.2 Twitter Sentiment Analysis as a Tool to Measure Investor Sentiment

In addition to the conventional purposes for which social media platforms are generally used, they have recently started to play a crucial role in financial decision-making. In a survey conducted by the investment firm TIAA, 33% of respondents say they trust social media content to guide their financial decisions, and 32% rely on advice shared by social media influencers and celebrities (KRC Research, 2021). This crescent trend appears more relevant for particular targets than others. According to the CNBC survey, 12% of investors aged between 18 and 34 have learned to invest from social media, and 37% of respondents in the same age group indicate social media as the most used source for new investment ideas. While in terms of income brackets, 28 % of respondents earning less than $50,000 tend to rely more on social for investment advice (Fox, 2021b). Within this context, Twitter is the social platform with the largest number of investor users, with 51% of respondents using Twitter actively investing in financial markets (Principato, 2021).
In this novel setting, where especially unsophisticated investors tend to pay attention to social media in taking their investment decisions, it is relevant to investigate whether the sentiment arising from such social media can impact the share price of the companies mentioned in the posts.
The most influential paper in this area is certainly that of Bollen et al. (2011b). Analysing millions of tweets posted between 28 February and 19 December 2008, the authors show that the public sentiment that arises from Twitter can predict the price changes of the Dow Jones Industrial Average (DJIA) with an average accuracy of 86.7%. Among the six mood dimensions of the GPOMS assessment used

to extract the public sentiment, *Calm* is the one that alone exhibits the most significant Granger causative relationship, improving both predictive accuracy and mean average percentage error.
Other articles, rather than focusing on a specific market index, devoted their attention to examining the impact on the shares of specific companies. In this field, Smailović et al. (2014) reviewed over 150,000 tweets that targeted eight specific listed companies and demonstrated that public sentiment extracted from Twitter could predict the price movements of these stocks a few days in advance.
Sprenger et al. (2014) shed light on how when one analyses tweets, in addition, to distinguish by sentiment, classifying them into different categories of news event types can provide essential insights about stock returns. The authors categorise the tweets about each company into six different business-related event categories: *Restructuring Issues, Legal Issues, Financial Issues, Operations, Corporate Governance and Technical Trading*. One of the most striking findings is that looking solely at the volume of tweets regarding each of the six issues, they find no abnormal share price return on the event day and little cumulative abnormal returns (CARs) in the days before or after. However, the effect of tweets related to these event categories on the companies' share price becomes evident and statistically significant when the bullish or bearish sentiment stemming from the tweets is included in the analysis.
Ranco et al. (2015) assert that only at selected points in time, referred to by the authors as *events* and identified as peaks of Twitter volume, is there a strong relationship between Twitter sentiment and the stock market. They show that when Twitter volume peaks occur, Twitter sentiment polarity leads to statistically significant cumulative abnormal returns in the 1-2% range, where sentiment polarity (positive or negative) determines the direction (negative or positive). The presence of CARs applies to events that investors expect, such as earning announcements and volume peaks caused by unexpected news.
To the best of my knowledge, in the existing literature, studies exploring how the Twitter activity of a specific influential individual can have an impact on the stock prices of publicly traded companies have primarily focused on the figure of former US president Donald Trump. The findings of Ge et al. (2019) suggest that Trump's tweets with positive sentiment generate higher abnormal returns on average (0.93%) than those with negative sentiment (-0.37%). Brans & Scholtens (2020) find out that his tweets expressing strongly negative sentiment generate negative average abnormal returns (AARs) that are significant both on the day of the event and the following day. In contrast to these findings, Juma'h & Alnsour (2018) conclude that the sentiment expressed by Trump does not have any statistically significant impact on the share price of the related companies.
Since Twitter sentiment analysis is not the only existing method of tracking general sentiment, some authors inquired to what extent the textual analysis of Twitter sentiment could replicate the results of

the other methodologies and whether it could even lead to more accurate results. Bollen et al. (2011a) compare the performance in terms of financial predictive power in both daily and weekly scales of different investor sentiment measures based on diverse data sources. According to this study, Twitter's two sentiment indicators are the best-performing measures of investor sentiment in predicting price changes in the DJIA market index, trading volumes, market volatility, and gold prices on a daily scale. In conclusion, the strong performance of Twitter-based indices in tracking investor sentiment has been amply confirmed, even outperforming previously well-established investor sentiment measures in some instances.

1.3 CEOs' Communications Influencing Investor Sentiment

Investor sentiment is a matter to which CEOs devote their attention and try to manage in favour of the companies they run. Bergman & Roychowdhury (2008) contribute to the literature by illustrating that CEOs seek to influence investor sentiment by increasing voluntary disclosure policies when investors' expectations are averse and being reluctant to share information when those are positive.

To positively affect investor sentiment, a valuable tool for CEOs can be to communicate their strategy as early as possible from their appointment. Whittington et al. (2015), analysing more than 900 CEOs' public strategy presentations, on average, the share price rises on the day of the presentation by 2% to 5% in the following days.

Written and oral communications have been explored in the field of research on the impact of CEO communications on investor sentiment and share prices. Boudt & Thewissen (2018), reviewing CEOs' letters to shareholders of DJIA companies from 2000 to 2011, illustrate how specific intra-textual dynamics are associated with sentiment and stock price changes. Bannier et al. (2017), studying the impact of sentiment expressed in speeches by the CEOs of 58 DAX and MDAX firms held during Annual General Meetings (AGMs) between 2008 and 2016, is significantly associated with CARs, especially in the event window in the event window [2,30], even if these speeches often contain only marginal information.

With the proliferation of social media platforms, such as Twitter, a growing number of CEOs embraced them, so these types of communications were also studied. Malhotra & Malhotra (2015), through an event study with a 7-day event window about the tweets of 25 CEO of listed companies, demonstrated that only business-related tweets present positive and significant cumulative abnormal returns, and those with the strongest impact relate to the company's future outlook on management initiatives, strategies, corporate changes and new product announcements. The relevance of sentiment expressed by CEOs in their social communication is emphasised by Gao (2018), who examines the tweets of more than 200 CEOs and proves that a high share of positive words within the tweets results in positive excessive stock returns, especially before their companies' earnings are disclosed.

Furthermore, articles such as that of Crowley et al. (2021) compare the Twitter activity of top managers and that of the company via its official account, finding that those of individuals in executive roles trigger stronger reactions from financial markets than tweets from corporate accounts. Although CEOs' Twitter activity has recently gained the attention of many scholars, currently, there are no specific studies investigating how the sentiment expressed by a given CEO in his tweets affects the share price of the company they manage. Therefore, this paper, with the aim of contributing to filling this gap in the literature, intends to analyse the specific case of the most discussed CEO for his Twitter activity, Elon Musk, CEO of Tesla Inc.

For this purpose, the objective of this paper is to answer the following research question:

RQ: *Does the sentiment expressed by Elon Musk in his tweets influence Tesla's share price?*

In investigating whether Elon Musk's tweets can have an impact on Tesla's share price, the study will place the focus on sentiment as several articles (Sprenger et al., 2014; Brans & Scholtens, 2020; Ante, 2023) highlight that merely considering the volume of tweets or their increase does not produce statistically significant results.

To the current knowledge, little is known about the relationship between these Twitter posts and Tesla's share. Some academics demonstrated a medium-high correlation between Musk's tweets and Tesla's share price (Kang Kim et al., 2021; Šević et al., 2023). Strauss & Smith (2019) showed for the very first time that a Musk tweet could affect the share price of the company he managed. They conducted an intraday event study, comparing the effects on the share price of two tweets on 23 August 2016, one posted by Elon Musk at 11.23 a.m. in which he stated that a new product would be announced at noon and the tweet from Tesla's official account at 3.30 p.m. in which the new product was actually announced. Strauss & Smith (2019) conclude that in this instance, investors acted merely on the belief that Musk's tweet would cause a rise in the share price, as they report statistically significant positive abnormal returns after Musk's tweet but conversely statistically significant negative abnormal returns after the tweet in which Tesla unveiled the new product.

Finally, Ante (2023) proved for the first time that the Tesla CEO's Twitter activity could impact the price of a financial asset, calling this phenomenon the *"Musk Effect"*. The author, who conducted an intra-day event study, concluded that Musk's tweets affected the price of various cryptocurrencies and that tweets about Bitcoin in which non-negative sentiment is expressed are associated, on average, with positive and statistically significant abnormal returns and cumulative abnormal returns.

Although conducted on a financial asset other than shares, these studies demonstrate Elon Musk's capability to influence the price of a financial instrument by leaking his sentiment through his tweets.
In conclusion, based on such empirical evidence and the previously mentioned theoretical framework of De Long et al. (1990), according to which *"noise traders"* acting upon their beliefs can move over the short term, the share price heavily, it is reasonable to formulate the following hypotheses:

H1. *The sentiment expressed by Elon Musk in his tweets influences Tesla's share price.*

H1a. *The positive sentiment expressed by Elon Musk in his tweets is associated with positive abnormal returns and thus positively influences Tesla's share price.*

H1b. *The negative sentiment expressed by Elon Musk in his tweets is associated with negative abnormal returns and thus negatively influences Tesla's share price.*

Data Collection

2.1 Elon Musk's Tweets Data

The data source where Tesla's CEO's Twitter posts were collected is the Twitter API (Application Programming Interface). Through a search query, it has been possible to retrieve all 233 tweets in which Elon Musk used the words *"Tesla"* or *"TSLA"* at least once, from 1 August 2018, to 31 December 2021.
Only tweets in which Tesla is mentioned with the number of interactions (the sum of the number of likes, retweets and replies per tweet) for each year were selected to avoid overlapping and confounding effects in the event study. The underlying assumption is that the top tweets in terms of interactions are those that had the largest information propagation and are, therefore, most likely to impact Tesla's share price. This choice is reinforced by the correlation that Kang Kim et al. (2021) find between engagement (which in their study takes into account exactly likes, retweets and replies) and Tesla's share price. Furthermore, a similar reasoning is adopted by Ranco et al. (2015), who decided to identify as events able to affect the share price of the 30 stocks of the DJIA index, only those instances in which there are Twitter activity peaks.
The final sample contains 52 tweets and is composed as follows: the leading 15 tweets by number of interactions for the year 2021, the leading 15 tweets by number of interactions for the year 2020, the leading 15 tweets by number of interactions for the year 2019 and the leading 7 tweets by number of interactions in 2018. For the latter, less than half of the Twitter posts were considered, as the analysis period only includes the last five months of 2018.

2.2 Tesla's Stock Price Data

With respect to the financial market data, daily prices of Tesla's stock (TSLA) and the two market benchmarks used for the event study, NASDAQ-100 (^NDX) and NASDAQ Composite (^IXIC), were retrieved from Bloomberg via Bloomberg Terminal. In order to closely adhere to the original event study methodology (MacKinlay, 1997), in the paper, raw returns instead of log returns were used as daily returns for both Tesla and the two indices.

Methods

3.1 Twitter Sentiment Analysis

One of the most exhaustive definitions describing sentiment analysis is that provided by Liu, B. (2012) in his book Sentiment Analysis and Opinion Mining, who defines it as *"the field of study that analyses people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organisations, individuals, issues, events, topics, and their attributes"*.

Amongst the various methodologies that have been developed over time to conduct sentiment analysis tasks illustrated, most of the papers with similar purposes to this one have predominantly relied on three methods, the Dictionary Based Approach (Ge et al., 2019), Support Vector Machine classifier (Smailović et al., 2014; Ranco et al., 2015) or Naïve Bayesian text classification (Sprenger et al., 2014). However, recent works like the one of Hartmann et al. (2022) demonstrate that transfer learning models (most of which are based on the BERT architecture) exceed lexicon-based approaches and traditional machine learning methods such as Support Vector Machine and Naïve Bayes in terms of sentiment analysis accuracy on average by between 10 and 20 percentage points.

In light of these findings, to analyse the sentiment of Elon Musk's tweets in this paper, it was decided to use BERTweet[7] (Nguyen et al., 2020), a language model (LM) developed to perform Twitter-specific downstream tasks and pre-trained from the outset on a massive corpus of around 850 million tweets. This draws on the architecture built by the Google AI team called Bidirectional Encoder Representations from Transformers or BERT (Delvin et al., 2019). Nevertheless, it implements several pre-training procedures used from another language model, the Robustly optimised BERT approach or RoBERTa (Liu et al., 2019), which was also developed by the Meta AI team.

[7] Available at https://github.com/VinAIResearch/BERTweet . In particular, a finetuned version of BERTweet was used for sentiment analysis available at https://huggingface.co/finiteautomata/bertweet-base-sentiment-analysis (Pérez et al., 2021).

BERTweet appears to be the best-performing model (Loureiro et al., 2022), according to the TweetEval benchmark (Barbieri et al., 2020), which is a unified framework consisting of seven classification tasks to investigate the state of the art of LMs in the Twitter context.
The coding language used to perform the sentiment analysis on the 52 tweets in the sample is Python. Prior to proceeding to opinion mining, the script pre-processes the tweets according to ad-hoc procedures for Twitter (Agarwal et al., 2011).
The sentiment analysis provides as a final output the classification of each tweet as positive, negative or neutral and also provides a score for each of these categories, between 0 and 1, with the sum of the three always having to be equal to 1. Therefore, a tweet is classified as belonging to one of the three sentiment labels according to which of them has the highest score.

3.2 Event Study Methodology

Event studies represent a time-tested methodology designed to assess the market's response to a firm-specific event containing new informational content by observing the price behaviour of the security affected by the event over the time it took place (Brown & Warner, 1980).
The market model is the approach most commonly adopted for conducting an event study and seems to be the one that provides the most reliable estimates of abnormal returns, to the extent that Armitage (1995), reviewing several papers in which the market model is compared to other approaches concluded that *"across each of the range of circumstances tested, it [the market model] is always at least as powerful as the best alternative"*. In light of this evidence, this paper will follow the market model approach in analysing the impact of the sentiment of Elon Musk's tweets on Tesla's share price. Specifically, in the case of this research, the market model entails that the expected abnormal returns are computed by estimating the relationship between the returns of Tesla's shares and returns of the NASDAQ-100 market index (and NASDAQ Composite) over the period of time called estimation window, through the following one factor ordinary least squares (OLS) regression equation:

$$E\left[R_{TSLA,d}\right] = \alpha_{TSLA} + \beta_{TSLA} R_{NDX,d}$$

where, α_{TSLA} and β_{TSLA} represent the coefficients of the regression and, in detail, the former the intercept and the latter the correlation with NASDAQ-100, while $R_{NDX,d}$ is the actual daily return of the NASDAQ-100 on a given day *d*. Therefore, after having determined the expected return $E\left[R_{TSLA,d}\right]$, the abnormal return at day *d* of the event window is calculated as:

$$AR_{TSLA,d} = R_{TSLA,d} - E\left[R_{TSLA,d}\right]$$

$$AR_{TSLA,d} = R_{TSLA,d} - \left(\alpha_{TSLA} + \beta_{TSLA} R_{NDX,d}\right)$$

where, $R_{TSLA,d}$ stands for the actual daily return of Tesla that occurred on day d.

Once the abnormal returns for each day within the event window have been obtained, by summing them up, it is possible to calculate the cumulative abnormal return, $CAR_{TSLA}(\tau_1, \tau_2)$, which took place in the established event window (τ_1, τ_2).

$$CAR_{TSLA}(\tau_1, \tau_2) = \sum_{d=\tau_1}^{\tau_2} AR_{TSLA,d}$$

Furthermore, for each of the three sentiment categories the average abnormal returns, $\widehat{AAR}_{s,t}$, for each day included in the event windows, and cumulative average abnormal returns, $\widehat{CAAR}_s$, for the two event windows considered, have also been calculated. The $\widehat{AAR}_{s,t}$ are estimated by averaging the $AR_{TSLA,t}$ occurring on a day d, corresponding to all the events e classified by the sentiment analysis as belonging to a specific sentiment class s.

$$\widehat{AAR}_{s,d} = \frac{1}{N} \sum_{e=1}^{N} AR_{TSLA,d}$$

Similarly, the $\widehat{CAAR}_s$ are computed by averaging the CAR_{TSLA} occurring in a given event window (τ_1, τ_2), corresponding to all the events e classified by the sentiment analysis as belonging to the same sentiment category s.

$$\widehat{CAAR}_s(\tau_1, \tau_2) = \frac{1}{N} \sum_{e=1}^{N} CAR_{TSLA}\,(\tau_1, \tau_2)$$

Furthermore, four parametric tests were used to verify whether the results are statistically significant. Two preliminary steps were performed before conducting the event study so that the sample of tweets would be suitable for this type of analysis. The first one was to solve the issue of the tweets that were published by Musk outside the NASDAQ trading days and trading hours and therefore do not have a daily price directly associated. Consequently, to measure the market response to these tweets, they were assigned the price of the closest trading days following the tweet, consistent with Brans & Scholtens (2020) and Ge et al.'s (2019) studies on the impact of former US President Trump's tweets on the share price of the companies he mentioned. The second procedure, instead, has been necessary to limit the overlaps between the event windows of some tweets that occurred within a few days and to avoid the potential confounding effects that these overlaps could create. Therefore, to overcome this issue, 6 tweets have been grouped in pairs and assigned the date and time of the first of the two tweets comprising them. As a result, although the number of tweets included in the sample is 52, the number of events became 49 after the grouping step. Furthermore, following this procedure, the newly grouped tweets were analysed again through the same previous sentiment analysis procedure. Ge et al. (2019) and Brans & Scholtens (2020) opted for a similar procedure when former US President Donald Trump published tweets on the same company within a few days.

Regarding the details of the event study, Krivin et al. (2003) define the five subjective decisions of the event study methodology. They involve determining: the estimation window, the index used as the market benchmark, the event window, the frequency with which the data are studied and the type of price measurement. The term estimation window refers to the time over which the correlation between the share price of the target company of the event study and the market index is studied. Hence, in this study, an estimation period with a length of 120 trading days is applied (MacKinlay, 1997; Sprenger et al., 2014; Ranco et al., 2015), which in the financial literature proves to be the most widely applied to event studies that follow the market model approach and use daily price data. In particular, the estimation window spans over an interval [-124,-5], with the start date 130 trading days before the event.

Secondly, with regard to the market index, the NASDAQ-100 (^NDX) has been selected as the first benchmark, a market index reproducing the performance of the 100 largest capitalised non-financial companies listed on the NASDAQ, including Tesla, since 2013. In addition, the NASDAQ Composite (^IXIC), which reproduces the overall performance of NASDAQ-listed companies, is employed to corroborate the results.

The third step in conducting an event study concerns the length of the event window, which can be defined as the time interval along which an event's effect is actually measured (McWilliams & Siegel, 1997). There is no consensus in the financial literature on which length is the most appropriate. Scholars seem to express more scepticism when long-term event windows are used; on the other hand, several studies support the validity of studies with short-term event windows (Brown & Warner, 1985; Dyckman et al., 1984). Following the hint of Thompson (1995) and Armitage (1995) in this paper, the event windows over which the potential occurrence of ARs and CARs is analysed are two, the first one [0,1] spanning two trading days and the second one [0,2] covering three trading days. Event windows extending over one or two days prior to the event date are not considered, given the particular characteristics of the type of event analysed (McWilliams & Siegel, 1997). Unlike, for instance, earning announcements, it seems complicated to believe that there could be a leakage of information concerning the Tesla CEO's tweets or that someone other than Elon Musk himself would know what he would or would not publish on Twitter and thus decide to sell or buy the company's shares before the tweet was published.

Finally, concerning the last two aspects mentioned by Krivin et al. (2003), the frequency and type of price measurement, this study was conducted using daily closing prices.

Results

4.1 Twitter Sentiment Analysis Results

The sentiment analysis results indicate a clear tendency for Elon Musk to express non-negative sentiment in tweets in which he mentions Tesla. The tweets for which Musk was found to have expressed positive sentiment are 44%, neutral sentiment 52%, and only in 4% of the tweets he expressed negative sentiment. Even after grouping the six tweets mentioned above and re-conducting the sentiment analysis, the sentiment distribution remains about the same.

This trend, which is evident from the sentiment analysis conducted on the 52 tweets with the highest number of interactions, is highly informative of Musk's general behaviour when he cites Tesla in his tweets. Performing the same sentiment analysis procedure previously described, on all 233 tweets in which Musk mentioned Tesla during the analysed period emerges that 48% present positive sentiment, 48% neutral sentiment and 4% negative sentiment.

4.2 Event Study Results

The subsequent findings of the event study are presented separately for the three different sentiment categories.

Regarding positive tweets, adopting the NASDAQ-100 as the market benchmark, positive abnormal returns are observed on the first two days and negative on the third, yet only the AAR occurring on day one turns out to be statistically significant at a 90% confidence interval. Specifically the AARs are, respectively, 2.089%, 1.463% ($p < 0.1$) and -0.523%. Nevertheless, using the NASDAQ composite as the market index, the average abnormal returns are slightly higher and the AAR on the day 0 is also found to be statistically significant. These amount to 2.162% ($p < 0.1$), 1.466% ($p < 0.1$) and -0.523%. Moreover, the cumulative abnormal returns that, on average, occur in the case of positive tweets are positive and statistically significant in both event windows. Event window [0,1] presents a CAAR of 3.552% ($p < 0.05$) using the NASDAQ-100 as a benchmark, while it is slightly higher using the NASDAQ Composite (3.628%, $p < 0.05$). In the [0.2] event window, the cumulative abnormal return averaged 3.267% ($p < 0.1$) and 3.295% ($p < 0.1$), using the NASDAQ-100 and NASDAQ Composite as an index, respectively.

Furthermore, the tweets categorised with positive sentiment include the one on 7 August 2018 in which Musk announced that he wanted to make Tesla a private company. Under the assumptions and circumstances of this study, it turns out that positive abnormal returns of between 10.726% and 10.692% actually occurred on the day of the event, statistically significant at a 99% confidence interval. This positive impact, however, dissipated quickly in the following days, both of which present negative abnormal returns, of which only that of the second day is significant ($p < 0.1$). Indeed, on event window [0,1], a CAR of 8.380% ($p < 0.01$) occurred using the NASDAQ-100 as the index and of 8.381% ($p < 0.01$), adopting the NASDAQ Composite instead. In contrast, the second event window shows no statistically significant positive cumulative abnormal returns for any benchmark.

In contrast to the positive tweets, those characterised by neutral sentiment do not significantly impact the share price. In this case, the average abnormal returns are slightly negative on each day in the two event windows, but none is statistically significant. Specifically, employing the NASDAQ-100 as the market index, the ARRs for days 0, 1 and 2 are -0.584%, -0.748% and -0.072%, respectively, while in the case of the NASDAQ Composite, these turn out to be -0.583%, -0.670% and -0.093%. Similarly, the cumulative average abnormal returns are also negative but not statistically significant for both indices used, where in the case of the NASDAQ-100, they are -1.332% in the first event window and -1.404% in the second, while in the case of the NASDAQ Composite, they are -1.252% during event window [0,1] and -1.345% in event window [0,2].

The neutral tweet that has most affected Tesla's share price, both in terms of abnormal returns and cumulative abnormal returns, is the one on 6 November 2021, in which Musk polled his 62.5 million (at the time) Twitter followers: *"Much is made lately of unrealised gains being a means of tax avoidance, so I propose selling 10% of my Tesla stock. Do you support this?"*. To this poll, 58% of voters answered *"Yes"* in the next two days. The results of the event study reveal that in relation to this tweet, ARs between -5.094% ($p < 0.05$) and -5.355% ($p < 0.05$) occurred on the event date, between -11.571% ($p < 0.01$) to -11. 640% ($p < 0.01$) on the next day, and between 5.631% ($p < 0.05$) and 6.070% ($p < 0.01$) two days after the date of the tweet, depending on whether NASDAQ-100 or NASDAQ Composite is adopted as the index. Looking at the CARs, using the NASDAQ-100 as a benchmark, they amounted to -16.665% ($p < 0.01$) in the first event window and -11.033% ($p < 0.01$) in the second event window, while with the NASDAQ Composite, they accounted for -16.996% ($p < 0.01$) in event window [0,1] and -10.926% ($p < 0.01$) in event window [0,2]. These findings, which clearly reveal a drop in Tesla's share price around the event, are by no means influenced by the actual sale of $6.9 billion worth of shares (Jin & Patnai, 2021) by Elon Musk, as this only took place on 12 November 2021 (6 days after the tweet).

Therefore, as these ARs and CARs are realised prior to the offloading of shares, they probably reflect the expectations of the public of investors, shaped by the outcome of the poll, that Tesla's CEO would sell a huge quantity of shares and cause a future decrease in Tesla's shares.

Finally, regarding the tweets with negative sentiment, due to the very small sample size, it is not possible to verify whether these have a statistically significant influence on Tesla's stock price.

However, it is worth noting that the popular tweet *"Tesla's stock price is too high imo"*, generated, based on the index used, abnormal returns between -7.439% and -7.274% on the day of the event, between 6.269% and 6.296% on the following day and -1.106% and -1.234% two days after the event, but none of them statistically significant, as did the CARs in the two event windows considered. Thus, based on these findings, Tesla's share price was not affected by the tweet at a daily level.

Conclusion

Elon Musk's controversial tweets have caught the eye of the media and regulatory authorities, such as the SEC, for at least half a decade since the famous tweet in which the Tesla CEO announced that he would take the firm private. Nevertheless, to the current knowledge, little is known about the relationship between these Twitter posts and Tesla's share. In investigating this topic, this dissertation reaches the following findings.

Firstly, the sentiment analysis reveals a clear tendency of Elon Musk to avoid expressing a negative sentiment when he mentions Tesla in his tweets. Secondly, the event study results show that the only sentiment category able to return one average, statistically significant cumulative abnormal returns is the positive one. This finding leads to the conclusion that the hypothesis H1a is validated, meaning that on the sample of tweets used for the analysis, those with positive sentiment positively influenced, on average, Tesla's share price statically significantly. On the other hand, the tweets included in the neutral sentiment class were not able to impact the share price, while those included in the negative sentiment class constituted too small a sample to explore hypothesis H1b.

This finding is consistent with the conclusions of Gao (2018), who finds that a high percentage of positive words in CEO's tweets predicts positive abnormal returns and with the results of Ante (2023), who in studying the impact of Elon Musk's tweets on the price of Bitcoin, shows that only those classified as having non-negative sentiment (in this paper only two categories of sentiment are considered, negative and non-negative) can generate abnormal returns. Thirdly, the event study also provides insights into some of the most debated tweets that led to the above-mentioned SEC legal litigations.

Finally, the theoretical implications of this dissertation contribute to extending the existing literature on how CEO communications in written or verbal form influence investor sentiment and the share price of the companies they manage. However, it is worth noting that this paper discusses the short-term effects of the sentiment expressed in Musk's tweets on Tesla's share price without investigating the mechanisms behind this phenomenon, which could constitute a topic for future research.