

PRICING-IN PERSONALITY: USING SUPPORT VECTOR MACHINE TO MODEL
IMPACT OF MUSK'S TWEETING BEHAVIOR ON TESLA VOLATILITY

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PRICING-IN PERSONALITY: USING SUPPORT VECTOR MACHINE TO MODEL
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Abstract

Elon Musk's social media presence is known to have a significant impact on markets. There are studies showing his tweets increase the volatility of Tesla Stock. We constructed a model using the sentiment of his tweets to predict Tesla stock volatility. The machine learning model Support Vector Machine was used to categorize Musk's tweets into positive or negative. Results show his positive tweets have a volatility dampening effect on Tesla stock. This dampening effect gets more significant over the years as Musk's twitter presence grows.

KEYWORDS: Elon Musk, Tesla, Tweets, Volatility, Sentiment Analysis, Support Vector Machine

JEL CODE: G14

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Riasat

Signature

TABLE OF CONTENTS

| | |
|----------------------------------------------------------------------|----|
| ABSTRACT | 2 |
| 1 INTRODUCTION | 5 |
| 2 MUSK AND THE START OF TESLA | 7 |
| 3 LITERATURE REVIEW | 9 |
| 3.1 Elon Musk’s Biography, leadership style, and online persona..... | 9 |
| 3.2 Integration of Media and Markets..... | 10 |
| 3.3 Macroeconomic Factors on Stock Volatility..... | 11 |
| 3.4 Sentiment Analysis Techniques Using Machine Learning..... | 13 |
| 4 DATA AND METHODS | 15 |
| 4.1 Response Variable..... | 15 |
| 4.2 Independent Variables..... | 15 |
| 4.2.1 Sentiment Variables..... | 15 |
| 3.2.2 Control Variables..... | 17 |
| 4.3 Timeline Selection and Robustness Checks..... | 18 |
| 5 RESULTS | 19 |
| 6 DISCUSSION AND CONCLUSION | 24 |
| 7 REFERENCES | 27 |

Introduction

In the digital age, the power of 280 characters cannot be underestimated, especially when those characters are typed by Elon Musk, the outspoken and controversial CEO of Tesla Motors Inc. On May 1, 2020, a single tweet from Musk declaring that Tesla's stock price was “too high” sent shockwaves through the financial markets. Within hours, Tesla's stock plummeted by 9%, wiping out a staggering \$13 billion in market value and nearly \$3 billion from Musk's personal stake in the company (Randewich 2020). But this was not an isolated incident. Over the years, Musk's tweets and media statements have consistently demonstrated an uncanny ability to move markets. In August 2018, Tesla's shares rose by nearly 11% after Musk tweeted about considering taking Tesla private. This led to a fraud case by the U.S. Securities and Exchange Commission, which Musk settled by agreeing to pay \$20 million and having a Tesla lawyer pre-screen significant company-related tweets. However, this did not stop him from being outspoken in his social media use. Through 2020 and 2021 Musk had a string of tweets and statements that caused significant movements in security prices. Elon Musk's tweets significantly impact Tesla's stock volatility, affecting shareholder decisions. Investors must understand the drivers of Tesla stock's volatility to align their investment strategies with their goals. Long-term investors often prefer stable stocks, while traders may seek volatile stocks for quick profits. Recognizing these volatility factors is crucial for fundamental analysis and determining a stock's real value. This understanding helps in effective capital allocation, diversifying portfolios, and avoiding emotional investing. Moreover, options market makers need to be aware of these factors to minimize losses. Research indicates a strong link between social media and market

dynamics, with CEO tweets, especially Elon Musk's, notably affecting Tesla's stock price. Studies (Metta et. al., 2022; Kuokka, 2021) confirm Musk's significant influence on Tesla's stock movements. Although Tesla has evolved from a startup to an investment-grade company, the market may have already adjusted to the volatility Musk's tweets introduce. With Moody's recently assigning Tesla Blue Chip status (Toppe 2023), the stock, initially popular among Musk enthusiasts and unconventional investors like Cathie Woods, is now increasingly featured in risk-averse portfolios, including pensions and 401Ks. So, the research question is: Does the increasing perceived and operational reliability of the Tesla stock contribute to Elon Musk's Tweets having a decreasing effect on its price volatility. So far there is no research proving this theory. To test this hypothesis a model incorporating sentiment of Musk's Tweeting patterns is constructed. A form of machine learning called Support Vector Machine (SVM) is used to generate a binary sentiment of each of his tweets and compute the daily sentiment of his tweets. The model also contains market volatility and macroeconomic volatility control variables. The results indicate that a positive tweeting pattern about Tesla lessens the price volatility of Tesla stock. However, this volatility dampening effect from positive tweets seems to diminish over the years. Variance Inflation Factor is done on all variables to check for multicollinearity issues. Some potential concerns consist of the reliability of the SVM model and not having the option to categorize neutral tweets.

Musk and the Start of Tesla

Elon Musk, one of the world's richest men with diverse ventures like SpaceX, Boring Company, Solar City, and Open A.I., is not just another multinational CEO. Holding a 13% stake in Tesla, a company valued at \$850 billion, Musk's ambitions reach beyond mere wealth accumulation. He is often described as a "Thrillionaire", a term for ultra-rich individuals driven by adventure and vision rather than just profit (Larry 2015). Thrillionaires, like Musk, are known for their tenacity and desire to give back, as demonstrated by Musk's endeavors such as the SpaceX collaboration with NASA and various philanthropic ventures through the Musk Foundation. These visionaries aim to leave a significant impact, with many of their initiatives being not-for-profit, showcasing their commitment to humanity's betterment. After earning two Bachelor of Science degrees from the University of Pennsylvania, he briefly attended Stanford University before leaving to pursue entrepreneurial ambitions. He co-founded Zip2, which was later acquired by Compaq for \$307 million, earning him \$22 million. Musk then co-founded X.com, which, after several changes, became PayPal and was bought by eBay for \$1.5 billion, giving Musk \$165 million as the largest shareholder. These endeavors highlight his expertise in leading innovative tech companies. With a history of successful enterprises, Elon Musk gained favor with Silicon Valley financiers when pursuing sustainable energy through Tesla Motors, originally founded in 2003 by Martin Eberhard and Marc Tarpinning. In 2004, Musk invested \$7.5 million, becoming a pivotal investor and chairman, while assuming significant operational control. Transitioning from software, which offers flexibility and low overhead, to car manufacturing presented challenges. Car production necessitates vast assembly plants costing \$1-\$2 billion and

involves substantial overhead like raw materials, labor, and machinery costs, constituting about 80% of a car's selling price. Additionally, producing a new car model involves a learning phase with defect reductions and assembly time improvements. Distribution also posed a challenge, reliant on organized dealership networks. Recognizing these hurdles, Musk strategically introduced the Tesla Roadster, an elite electric sports car priced at \$109,000 and targeting celebrities. This move sidestepped Tesla's initial disadvantages, with Musk viewing the Roadster as the precursor to accessible, high-quality electric vehicles for all. Elon Musk announced Tesla's first profitable quarter on March 31, 2013 which was a significant turning point for Tesla. By May, Tesla reported a net income surpassing \$10 million, outpacing major competitors in U.S. electric car sales. This achievement began Tesla's ascent in the financial markets, with its stock almost tripling within months. By March 2023, Tesla was recognized as a Blue Chip Stock. Moody's upgraded Tesla's rating from 'Ba1' (speculative) to 'Baa3', marking it as an investment grade stock. A pivotal moment came in December 2020 when Tesla was inducted into the S&P 500, an index showcasing stable and significant U.S. companies. Inclusion isn't just about company size; it's based on profit consistency, liquidity, a minimum market cap of \$8.2 billion, a public float of at least 10%, and a seasoned domestic IPO of a year or more. Being part of the S&P 500 offers various benefits, including obligatory stock purchases by index funds and ETFs, resulting in heightened stock demand. The increased institutional interest can enhance stock liquidity, potentially stabilizing the historically volatile Tesla stock as index funds generally hold shares long-term. While S&P 500 inclusion means increased scrutiny and analysis, it also spotlights any company shortcomings. However, it is evident that Tesla has achieved a reliable investment grade

status as validated by its consistent revenue increases and increasing profit margins. Furthermore, it has been more than 10 years since Tesla's IPO and it could be reasonable to assume that the market has already priced in the volatility surrounding Elon Musk's tweets which provides relevance for the research question.

Literature Review

Elon Musk's Biography, leadership style, and online persona.

The rise of individuals whose influence transcends traditional boundaries to blur lines between celebrity and business magnate is emblematic of our era of financialized capitalism. Notably, Elon Musk stands at the forefront of this trend. Braun (2022) astutely observes how the public image of figures like Musk has become a tradable commodity. Musk's influence extends far beyond the realm of entrepreneurship; he is perceived as a visionary, a disruptor, and at times, a provocateur. The democratization of information dissemination, especially through platforms like Twitter, amplifies Musk's voice, granting him significant power to sway markets, public opinions, and the valuation of entire companies. Such power is double-edged; while it provides opportunities for rapid market growth, it also introduces volatility based on the person's statements and actions.

Reflecting on Musk's early ventures, Mair (2015) identifies a recurrent theme of high-risk, high-reward entrepreneurship. Musk's leadership is characterized by visionary ambitions, an unwavering focus on innovation, and a penchant for personal investment in his endeavors. These attributes, as Mair (2015) posits, can be traced back to Musk's foundational experiences as a budding entrepreneur.

Interestingly, Phillips & Pohl (2022) provide a fresh perspective on Musk's decision-making paradigm. Traditional economic models, grounded in rational decision-making, seem to be at odds with some of Musk's choices. Investing his PayPal earnings into ventures like SpaceX and Tesla, perceived as high-risk by many, challenges conventional economic and decision-making theories.

Integration of Media and Markets

A study by Kuokka (2021) highlighted the tangible effects of specific social media events on stock market movements. The magnitude of stock market reactions was found to be contingent on various factors, such as the nature of the event and the entities involved. Significantly, activities involving influential figures or major corporations resulted in pronounced market reactions. This observation aligns with a separate study by Metta et al. (2022), which examined the impact of Elon Musk's tweets on stock prices. They confirmed that tweets from influential figures, especially those related to their associated companies, can cause immediate and long-lasting stock price fluctuations.

The role of CEOs on social media extends beyond mere market dynamics. Men & Tsai (2016) delved into the motivations behind public engagement with CEOs and the resulting relational outcomes. Their findings underscored the importance of CEO approachability and authenticity in fostering trust, enhancing brand loyalty, and facilitating valuable two-way communication. Similarly, a subsequent study by Men & Tsai (2017) indicated that the personal branding of a CEO on social media could profoundly influence the corporate brand, thus affecting market dynamics.

Sentiment analysis has emerged as a potent tool for predicting stock movements. Nguyen (2015) employed various methods, from lexicon-based to deep learning approaches, to analyze sentiment on social media platforms like Twitter. Their findings reinforced the idea that sentiment, particularly from influential sources, strongly correlates with stock movements, especially when aligned with temporal patterns.

The juxtaposition of social and conventional media's effects on markets was the core of a study by Yu et al. (2013). Both media types serve as crucial informational conduits, shaping public perception and investor decisions. However, while social media's rapid dissemination influences immediate market reactions, conventional media's credibility can have longer-term implications. This duality underscores the multifaceted nature of media's influence on markets.

Macroeconomic Factors on Stock Volatility

Volatility is the fluctuation of stock prices. Its association with macroeconomic factors has been a topic of considerable interest among scholars and practitioners. Various studies have sought to identify and understand the underlying factors that drive stock market volatility and its implications for individual stocks. Binder & Merges (2001) shed light on the cyclic nature of stock market volatility. Their study concluded that stock market volatility intensifies during economic contractions and diminishes during recoveries. This finding underscores the pivotal role that broader economic conditions play in influencing stock market dynamics.

So & Lei (2015) focused on the VIX index, a prominent measure of market expectations for near-term volatility. Their research found that a surge in the VIX index is

indicative of heightened investor fear and uncertainty. Interestingly, they also identified a positive correlation between the VIX index and trading volume variability, suggesting that higher levels of uncertainty lead to more erratic trading volumes. The release of key macroeconomic data can act as potential triggers for stock price volatility. So & Lei (2015) emphasized the significance of GDP, Unemployment, and CPI announcements in determining market dynamics. The days surrounding the release of such data can witness pronounced volatility, reflecting the market's responsiveness to economic health indicators. Another intriguing facet is the influence of financial market conditions. So & Lei (2015) incorporated the Quality Spread, which represents the difference between yields of high-quality and low-quality securities, as a volatility control. This spread provides insights into market perceptions of risk and the broader financial environment.

Diving deeper into firm-specific characteristics, Arisoy (2005) discovered variations in volatility risk based on firm size and type. The study found that during high-volatility periods, smaller firms and value-oriented firms were more exposed to downside risk. On the contrary, big-growth firms, due to their perceived stability, acted as a hedge against volatility.

Expanding the horizon of macroeconomic determinants, Corradi et al. (2013) selected specific indicators like inflation (CPI) and industrial production growth to elucidate equity market volatility. Their choice of variables accentuates the nuanced relationship between macroeconomic health and stock market behavior.

In the context of Tesla, it's pivotal to consider these overarching themes. As a growth company, Tesla's stock price volatility could be influenced by a combination of these macroeconomic factors, its position in the electric vehicle industry, and its broader

corporate trajectory. The literature underscores the intricate web of factors affecting stock volatility, providing a foundational basis for any empirical examination of stocks like Tesla.

Sentiment Analysis Techniques Using Machine Learning

The rapidly growing field of sentiment analysis has been increasingly applied to understand the impact of influential figures' statements on various sectors, particularly the stock market. Several studies have employed machine learning and natural language processing techniques to analyze the sentiment embedded in Elon Musk's tweets since they have significant impact on stock prices and market volatility.

In a study by Erkatal & Yilmaz (2022), the authors delved into the application of Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN) adept at remembering long-term dependencies. The LSTM was trained on labeled datasets to classify the sentiment of tweets as positive, negative, or neutral. Augmenting this approach, the study also integrated the Adaptive Neuro-Fuzzy Inference System (ANFIS) to discern fuzzy relationships between words and sentiments. The Support Vector Machine (SVM) then classified these fuzzy relationships into distinct sentiment categories.

Ševi'c et al. (2022) embarked on an event-based study, focusing on tweets around dates with notable stock price changes. The research combined Musk's tweets from up to five days preceding significant price shifts, accounting for engagement metrics and mentions of Tesla. The authors employed the Rapid Automatic Keyword Extraction (RAKE) algorithm for keyword extraction. For sentiment analysis, the study utilized the

TextBlob Python library, which averages polarity scores for each word, furnishing a composite polarity for more extensive texts. The study measured volatility based on stock price extremes within specific time windows.

Bhadamkar & Bhattacharya's (2022) study offered an intricate methodology, starting with Exploratory Data Analysis (EDA) to identify data patterns. Sentiment analysis categorized tweets into positive, neutral, or negative sentiments, leveraging Python's Scikit-learn package. TextBlob, a versatile NLP toolkit, enabled tokenization, lemmatization, noun phrase extraction, and part-of-speech tagging. The authors highlight that TextBlob's sentiment analysis yields two pivotal values: polarity, ranging between -1 (highly negative) and 1 (highly positive), and subjectivity, which discerns between factual information and subjective content. The study integrated these insights with the Facebook Prophet tool for time series forecasting, considering the intricate non-linear trends, seasonality, and even holiday impacts.

Data and Methods

Response Variable

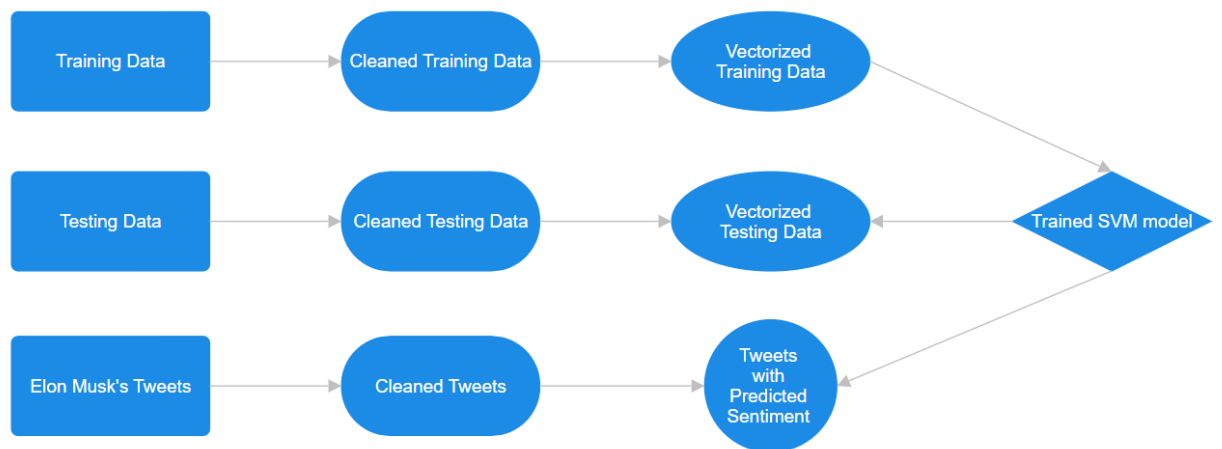
The response variable is daily Tesla stock price volatility: *tslavol*. It is measured by taking the difference between the daily highest and lowest price of the stock. This variable originates from Sevic et al., (2013) which performs event study to measure changes in Tesla volatility. The data is obtained from Yahoo Finance.

Independent Variables

Sentiment Variables

The predictor variables are *positive_sentiment_score* which measures number of Elon Musk's positive tweets per day and *negative_sentiment_score* which measures number of Elon Musk's negative tweets per day. The dataset of Elon Musk's Tweets is divided into two based on if the tweet mentioned Tesla or not. The sentiment labels are generated by a binary classification machine learning process called Support Vector Machine (SVM).

Figure 1: Construction and Implementation of Support Vector Machine Model



A training dataset of 160,000 and a testing dataset 100,000 tweets with symmetrical distribution of positive and negative labels were obtained. Another dataset with all of Elon Musk's tweets from 2010 to 2021 was obtained. The texts in the datasets were cleaned to remove punctuation and transform to lowercase characters. Because of limited computation power to train the model, a sample of 100,000 tweets was obtained from the clean training dataset with equal positive and negative tweets. The training and testing dataset were tokenized using Python's Natural Language Processing toolkit to represent it as a collection of words without respect to its structure and grammar. The tokenized data was then converted into vectorized data using the "Term Frequency - Inverse Document Frequency" (TF-IDF) method. Due to memory limitations and the simple classification nature of the model, the number of features to construct TF-IDF vectors were chosen to be 5000 words. This constructs a 5000 dimensional dataset where the TF-IDF generates a vector for each matrix coordinate by considering its frequency and importance inside the tweet and among the other tweets in the dataset. The Support Vector Machine model is trained on the vectorized training dataset and validated on the vectorized testing dataset. This ensures the consistency of the model across bodies of text. The predictive SVM model had an overall accuracy of approximately 74.95% on the testing dataset. It had a F1 score of 0.72 for negative tweets and 0.78 for positive tweets. F1 score is a metric that explains the model's ability to capture larger proportions of correct predictions without giving up accuracy of predictions. This means that the model was slightly better at predicting positive tweets while balancing total number of predictions and accuracy. At each step the python code was implemented using ChatGPT.

Control variables

The model also incorporated control variables that account for systematic market volatility and volatility generated from macroeconomic conditions. The primary systematic volatility variable *sp500vol* was constructed using the daily volatility of SPY which is an ETF that tracks the S&P 500. It was obtained from Yahoo Finance. The daily VIX (*vix*) index was used as a variable that predicts near term market volatility. The index is published by the Chicago Board of Options Exchange and they use a proprietary algorithm factoring the vega values of its near term SPY option contracts (Volatility index methodology CBOE volatility index.).

The macroeconomic control variables consist of the dummy variables *gdprelease20* and *covid19*. *gdprelease20* is constructed from the GDP release and revision release date data published by BLS and accessed through ALFRED. It includes 1 for the dates that fall within two days including the date of a GDP release or revision and 0 otherwise. The Covid 19 pandemic was known to cause worldwide market volatility exemplified by the almost 30% drawdown in U.S. equities. The *covid19* dummy variable tracks the start of the pandemic by including 1 starting from the date January 1, 2020 and 0 before that. The *qualitychange* variable is constructed by taking the difference between the 10 year treasury yield and the yield on Moody's Baa corporate bond Yield, and the data was obtained from FRED. Initially a dummy variable tracking the inclusion of Tesla in the S&P 500 was used. It was dropped due to collinearity issues with Covid 19 since both dummy variables are constructed using events that happen close to each other.

Timeline Selection and Robustness Checks

Regressions were performed on data between 2012 to 2021 since the first two years of Tesla's IPO were not considered representative of typical stock volatility. To address multicollinearity concerns Variance Inflation Factor was performed on all the independent variables. All the VIF metrics were below 5, the highest being 2.68 for daily S&P 500 volatility and the mean being 1.70. This indicates there are no multicollinearity concerns among the independent variables.

Results

The results only accounting for Musk's tweets about Tesla show that almost a third of Tesla stock's volatility reduction was because of his positive tweets. Even though negative tweets did not prove significant, according to its coefficient it slightly contributed to volatility reduction. The dummy variable for the trading day being within two days of a GDP release date did not prove significant. Daily S&P 500 volatility strongly correlates with Tesla's Daily volatility with high statistical significance. Spikes in the Daily VIX Index, which is the fear gauge for the market, contributes to almost a quarter of Tesla's daily volatility reduction. The change in daily quality spread did not prove statistically significant. The Dummy variable for Covid 19 was statistically significant proving high volatility in Tesla stock introduced by the Covid 19 pandemic starting January of 2020.

Table 1: Regression with Tesla Tweets

| VARIABLES | Daily Tesla volatility |
|-----------------------------|------------------------|
| Positive sentiment score | -0.311*** |
| | (0.07) |
| Negative sentiment score | -0.11 |
| | (0.113) |
| 2 days within GDP release | -0.0207 |
| | (0.168) |
| Daily S&P 500 volatility | 0.820*** |
| | (0.0363) |
| Daily VIX index | -0.217*** |
| | (0.0142) |
| Daily Quality Spread change | -1.506 |
| | (2.23) |
| Covid 19 | 8.359*** |
| | (0.171) |
| Constant | 2.336*** |
| | (0.196) |
| Observations | 2,932 |
| R-squared | 0.66 |

This is an OLS regression predicting Tesla stock's daily volatility. Independent variables are Elon Musk's number of daily positive tweets about Tesla, number of negative tweets about Tesla, dummy variable of the trading day being within 2 days of GDP release or revision, daily VIX index by CBOE, daily change in Quality Spread, and the dummy variable for covid 19. Standard errors are in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results for the regression with Musk's tweets not about Tesla indicated that Elon Musk's positive tweets not about Tesla contributed to around eight percent of Tesla's volatility reduction. His negative tweets were statistically insignificant. All other control variables had similar results to the regression with his tweets about Tesla.

Table 2: Regression with non-Tesla tweets

| VARIABLES | Daily Tesla volatility |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------|
| Positive sentiment score | -0.0874*** |
| | (0.028) |
| Negative sentiment score | -0.0892 |
| | (0.0631) |
| 2 days within GDP release | -0.000715 |
| | (0.168) |
| Daily S&P 500 volatility | 0.818*** |
| | (0.0363) |
| Daily VIX index | -0.219*** |
| | (0.0141) |
| Quality Spread Change | -0.715 |
| | (2.224) |
| Covid 19 | 8.369*** |
| | (0.171) |
| Constant | 2.433*** |
| | (0.195) |
| Observations | 2,932 |
| R-squared | 0.66 |
| This is an OLS regression predicting Tesla stock's daily volatility. Independent variables are Elon Musk's number of daily positive tweets not about Tesla, number of negative tweets not about Tesla, dummy variable of the trading day being within 2 days of GDP release or revision, daily VIX index by CBOE, daily change in Quality Spread, and the dummy variable for covid 19. Standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1 | |

When the number of positive and negative tweets is interacted with year on the dataset accounting Elon Musk's tweets about Tesla, between 2012 to 2021 Musk's positive tweets had an increasing volatility dampening effect as the years increased. The year interaction was not statistically significant for his negative tweets. In this regression the coefficient for the positive tweets has an inflated value due to the interaction with the year variable. All other control variables have similar results as the previous regressions

Table 3: Regression with Tesla Tweets interacted with Year

| VARIABLES | Daily Tesla volatility |
|-----------------------------------|------------------------|
| Positive sentiment score | 176.7** |
| | (83.48) |
| Positive sentiment score and Year | -0.0877** |
| | (0.0413) |
| Negative sentiment score | 81.48 |
| | (124.5) |
| Negative sentiment score and Year | -0.0404 |
| | (0.0617) |
| 2 days within GDP release | -0.013 |
| | (0.168) |
| Daily S&P 500 volatility | 0.807*** |
| | (0.0391) |
| Daily VIX index | -0.210*** |
| | (0.0155) |
| Quality Spread Change | -1.674 |
| | (2.231) |
| Covid 19 | 8.361*** |
| | (0.261) |
| Constant | -25.8 |
| | (69.17) |
| Observations | 2,932 |
| R-squared | 0.66 |

This is an OLS regression predicting Tesla stock's daily volatility. Independent variables are Elon Musk's number of daily positive tweets about Tesla, number of daily positive tweets about Tesla interacted with year, number of negative tweets about Tesla, number of negative tweets about Tesla interacted with year, dummy variable of the trading day being within 2 days of GDP release or revision, daily VIX index by CBOE, daily change in Quality Spread, and the dummy variable for covid 19. Standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1

The results indicate that positive sentiment tweets about Tesla lowers Tesla stock volatility significantly and positive sentiment tweets that were not about Tesla slightly lowers volatility. Negative sentiment tweets always prove statistically insignificant, When positive sentiment tweets are interacted with year it shows that the volatility dampening effect from Musk's positive tweets about Tesla have more power in the later years indicated by the negative coefficient on the interaction term.

Daily S&P 500 volatility seems to be the control variable with the most explanatory power on Tesla's daily volatility.

The VIX index proved to be significant with unexpected results. It indicates that when the markets expect a higher near term volatility the Tesla stock seems to stabilize itself. Near term volatility is defined as volatility within the next month (Volatility index methodology CBOE volatility index).

Furthermore, the control variable for Covid 19 was significant and it indicates that tesla volatility increased significantly during the start of the pandemic. The overall fit of the model does not change between the different regressions.

Discussion and Conclusion

The results show Elon Musk's positive tweets about Tesla has the ability to stabilize Tesla's daily price volatility and this effect increases through the years. One possible explanation for this increasing effect on volatility is Musk's growing online presence and reach towards financial market participants whose actions impact Tesla stock movements. This result relates to Braun (2022)'s commentary because Elon Musk's

celebrity status is increasingly being financialized to influence the stock price of his company.

The model presents one glaring area of concern. Using ChatGPT to implement machine learning code poses a reliability concern for the truthfulness of the SVM model in terms of how much of the model was influenced by the training data. It also poses a concern for the reliability of the output dataset of predicted sentiment labels on Elon Musk's tweets. An in house implementation of the machine learning code could address the reliability concerns. To construct the *GDPrelease20* variable GDP release and revision dates were used instead of just GDP release dates. This is an aspect to be wary of since the inaccurate data could be a reason why the variable proved insignificant.

The SVM model was simplistic and offers room for improvement. There could be an opportunity to use a severity scale like Šević et al. (2022) or a positive, negative, and neutral classification system like Bhadamkar & Bhattacharya's (2022) instead of binary sentiments to classify Musk's tweets.

The negative tweets in the model proved statistically insignificant. Literature suggests that negative tweets undoubtedly have an effect on Tesla volatility. Therefore, no conclusions can be made about negative tweets from the model and better tools are needed to fit negative tweets into the model. Daily S&P 500 volatility seems to be the control variable with the most explanatory power on Tesla's daily volatility. This is to be expected because the aggregation of stocks that S&P 500 includes represents a credible average of systematic risk in the market. Tesla being a U.S. equity shares a significant portion of that risk. The VIX variable indicates that when the markets expect a higher

near term volatility the Tesla stock seems to stabilize itself. The reason for this stabilization is unknown and this could be an avenue of exploration for researchers.

The results obtained from the model are insufficient to prove the stated research question: does the increasing perceived and operational reliability of the Tesla stock contribute to Elon Musk's Tweets having a decreasing effect on its price volatility. However, the integration of machine learning generated variables in econometric models offers a new horizon for researchers and economists to explore. The use of AI tools combined with improved econometric methodologies will help us tackle more interesting questions increasing the real world applicability of economics.

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