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SOCIAL MEDIA COMMUNICATION AND ITS IMPACT ON FINANCIAL ASSETS: FRESH EVIDENCE FROM PRESIDENT TRUMP'S FIRST PRESIDENCY (2017-2021)

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Abstract

We investigate the link between Trump tweet sentiments and financial assets. We employ daily data for a set of assets including stocks, gold, crude oil, the Baltic Dry Index, and Bitcoin. The sample period spans from January-2017 to January-2021. Emotions relate to tweets encompassing sentiment, irony, hate speech, and offensive language. We analyse text using the Robustly Optimized BERT Pretraining Approach to extract sentimental indices linked to former US President Donald Trump's tweets. Tweets have an impact both on asset returns and their volatility, whereby tweets that bear positive (negative) emotions increase (decrease) returns and decrease (increase) volatility. Our findings survive several robustness tests, including the consideration of traditional social media information and the period before Trump's presidency.

Keywords: Trump's tweets; asset prices; RoBERTa sentiment analysis; ARMA-GARCH models, ARMA-EGARCH models

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INTRODUCTION

Market participants invest only if they feel optimistic about the prospects of their investments. They also realize that market expectations can change either by endogenous factors and fundamentals (e.g., talented leadership, resource exploration licenses, access to funding, number of patents), or by exogenous factors (e.g., trade openness, foreign conflicts, political environment, foreign subsidies). The only way to collect information on both these endogenous and exogenous events is through information shared either from traditional or emerging channels. In testament to that, a link has long been identified among the various channels of information, market sentiment, and financial markets (Dougal et al., 2012). For instance, the efficient market hypothesis recognizes the role of information accessible to investors on price formation (Fama, 1965). In turn, it can be argued that investors' emotional state affects both investments and prices (Shiller, 2003).

Linkages between traditional media outlets and stock markets can be found in the work of authors, such as Fang and Peress (2009), Engelberg and Parsons (2011), and (Dougal et al., 2012). At the same time, social media platforms have emerged as a dynamic alternative to traditional media outlets, such as newspapers or broadcasts, and they play an important role in shaping public opinion. Unlike newspapers and journals, social media offer a platform for social action, commentary, and influence. In fact, effects may even be in opposite directions. For instance, Jiao et al. (2020) provide evidence that traditional broadcasts are typically associated with decreases of stock market volatility, while social media forums with respective increases.

With American President Donald Trump frequently using social media platforms, such as 'X' (former Twitter) as his primary communication channel, his tweets attracted considerable attention from the financial press. Trump has had the power to affect not only US economic policy, but also both domestic and foreign financial markets. However, unlike official news from the White House and other government agencies, his tweets could reflect his own sentiment and personal views. Kaissar (2017) stresses that the impact of presidential tweets on stock prices may not be entirely anticipated by market participants. By contrast, stock markets may consider tweets as new information relevant to firms and investors. According to Ewalt (2016) and Gibbs (2017), the US President holds a unique position with extended powers and is able to influence policies relevant to firms and markets, including government contracts, trade tariffs, and government bailouts. In this sense, Trump's own views about political affairs travelling on the 'X' platform, may be perceived by investors as including information about future actions and political decisions that might have a strong impact on markets. In other words, presidential tweets may form unexpected news (events) with the potential to affect investment activity.

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Some studies explore the link between Trump tweets and stock market performance (Klaus and Koser, 2021), while other focus on the sentiment analysis of his tweets (Abdullah and Hadzikadic, 2017; Yaqub, 2020). It may be the case that some of these tweets may only constitute noise exerting a minimum (if any) impact on stock markets; Tetlock (2007) and Barber and Odean (2008) stress that market participants will eventually buy the stocks that draw their attention. In this setting, we assume that US President Trump's tweets direct draw investors' attention towards the firm or market mentioned in the tweet, stimulating a response from market participants.

Motivated by the aforementioned framework and the interaction between social media activity and financial markets, the contribution of this paper is twofold. First, it adds to the theory of sentiment formation and to the growing literature on the effects of social media on financial assets. We accomplish this by investigating the effects of Trump's tweet sentiments on the price and volatility of various financial assets, such as the S&P500, gold prices, oil prices, the Baltic dry index, as well as cryptocurrency prices, using daily data. In this regard, we investigate the impact of investor sentiment related to Trump tweets by utilising machine-learning methods, on all main markets. Second, we contribute methodologically to the existing machine-learning applications literature by introducing an application of RoBERTa; that is, one of the most significant transfer learning models in the field of Natural Language Processing (NLP) and artificial neural networks in general, and thereby looking into new ways for solving financial and economic issues relating to the impact of social media. Essentially, we test for sentiment formation by examining both the context and content of messages posted by a particular user who happened to be the President of the US.

Main findings indicate that President Trump's tweets significantly affect both the returns and the associated volatility of the assets under investigation. We find that tweets that convey a positive message (i.e., that bear positive emotions) positively affect asset returns and reduce asset volatility, while the reverse holds. The responses regarding the sign and the magnitude of the impact are qualitatively similar across the empirical methods employed in this study.

The structure of the paper comprises the following sections. Section 2 discusses the empirical literature and the emergent hypotheses. Section 3 introduces the high-frequency data used in this study, including a short description of the variables and an overview of the statistical model. Section 4 reports the empirical findings and discusses whether there is evidence to either support or refute our hypotheses. Section 5 provides of series of robustness checks that support the validity of our findings. Finally, Section 6 concludes with implications for policymakers.

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LITERATURE REVIEW

Opinion Leaders, Sentiment Formation and the Stock Market

The focal point of our study is the impact of US President Trump's Twitter activity on the stock market. According to Mehra et al. (2006) opinion leaders can have a disproportionate role in influencing others or reducing information-asymmetries (whereby specific information would have been complexed to reach a wider audience). Social media offer precisely that. An uncontrollable flow of private information being diffused by the public instead of other specific channels, which can become readily available. On a related note, Williams and Reade (2016) argue that social media satisfy the conditions for removing information costs about the markets.

Sentiment formation was initially researched as the outcome of news and media coverages (Cutler et al., 1989; Tetlock, 2007, Engelberg and Parsons, 2011), earnings or dividends announcements (Barberis et al., 1998; Dasilas and Leventis, 2011), chat messages (Antweiler and Murray, 2004), online investment forums (Chen et al., 2014), and was interpreted as an overaction or an underreaction to real stock prices. Kalampokis et al. (2013) argue that social media help us form sentiment on many social areas, such as financial markets, disease outbreaks and product sales. Researchers believe that institutional traders are less prone to noise trading than small traders (Lemmon and Portniaguina, 2006). In general, social media make investors be more active (Ali, 2018).

Relevant research on the effects of social media on the stock market depends on algorithms that extract overall sentiment from 'big data'. Chen et al. (2014) use a negative words list to analyse investment-related website articles and their comments. Siganos et al. (2014) use the Gross National Happiness index constructed by Facebook, based on positive and negative words in the status updates of Facebook users. Azar and Lo (2016) use a polarity score based on the positive, negative, and objective meanings in a tweet, while Bartov et al. (2018) classify tweets as positive or negative. In their recent work, Nishimura et al. (2021) explore the US stock market outcomes from US President Trump tweets and their relevant influence. Their findings indicate that Trump's tweeting positively and significantly affects the volatility and jumps, while the response of realised volatility to tweets is greater than multidimensional volatility because of the jump component in realised volatility.

Furthermore, in a similar strand of the literature, using machine learning methodology, Kinyua et al. (2021) go even further to suggest that influencers with political power and followers strongly affect financial markets. The influence can be both within the US financial markets (Colonescu, 2018) and financial markets in the People's Republic of China (Guo et al., 2021), the European Union (Klaus and Koser, 2021), and the Russian Federation (Afanasyev et al., 2021). Not all information carries the same impact (Gjerstad et al., 2021), and not all information

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can influence investor sentiment (Brooks et al., 2003). Therefore, the following hypothesis emerges:

Hypothesis 1: Trump tweet sentiments affect S&P index returns and their associated volatility.

Trump Tweet Sentiments, Oil Prices, Precious Metals and the Baltic Dry Index

Yu et al. (2008) highlight that certain events can draw increased attention and influence the variability of oil prices on the short-term horizon (Smales, 2014; Piñeiro-Chousa et al., 2018) on gold returns. Headlines news from newspapers' home pages and information that is publicly shared, exert an influence on crude oil prices (Yu et al., 2005; Li et al., 2019). Our sample period covers the COVID-19 crisis; that is, a period for which Akhtaruzzaman et al., 2021 suggest that gold has not persistently acted as safe haven.

In turn, Geman ans Smith (2012) stress the need to investigate the Baltic Dry Index (BDI), as it represents global economic trade through shipping. According to Makridakis et al. (2020), uncertainty in the shipping market has increased so much that we can no longer ignore it. The industry has long been protected by low taxation; however, changes are imminent, and these further include the positive attitude of the International Marine Organisation (IMO) towards the promotion of green fuels and the adoption of blockchain technologies to digitalise procedures and handle bureaucracy. Examining the effect of information on freight rates will help understand whether the sentiment formation theory is present in a capital-intensive industry.

The majority of scholars who attempted to forecast the trend of this index, find that the BDI follows a random walk making predictions rather difficult (Kavussanos and Nomikos, 1999; Kavussanos and Alizadeh-M, 2001; Batchelor et al., 2007; Papailias et al., 2017; Tsioumas et al., 2017; Makridakis et al., 2020). The role of political influencers might be indicative of a change in market dynamics, as technology now propagates information faster and to a broader audience. This is particularly important as influencers begin to affect international corporations (Wagner et al., 2018) and sectors with or without favorable ties (Child et al., 2021). It follows that we need to consider how social media information can affect shipping prices. Considering both commodities, crude oil and gold, and the Baltic Dry Index, the following hypotheses emerge:

Hypothesis 2: Trump tweet sentiments affect both crude oil and gold prices, as well as their associated volatility.

Hypothesis 3: Trump tweet sentiments affect the Baltic Dry Index, as well as its associated volatility.

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Trump's Tweet Sentiments and Cryptocurrencies

Cryptocurrencies have unlocked peer-to-peer transactions that do not require bank authorisation and rely on blockchain technology to avoid moral hazards and adverse selection. Shen et al. (2019) report the influence from several social media on cryptocurrencies' following-day trading volume and realised volatility. Similar evidence has been reported in connection with cryptocurrency price returns and volume activity in the cryptocurrency markets (Huynh, 2021).

Mai et al. (2018) explore the dynamic relationship between social media and cryptocurrencies and find that not all posts are the same. Some have stronger impact on mitigating information asymmetries and depend more on followers. Choi (2021) argues that the strongest impact between social media and cryptocurrencies occurs in the short-time horizon. Nonetheless, certain tweets may attract particular attention to the extent of information propagation. Urquhart (2016) postulates that we could not see any influence on cryptocurrencies in the past, as there was not a critical mass of investors. More recently though, this appears not to be the case anymore as there is a growing number of institutional investors that include cryptocurrencies in their portfolios. Guégan and Renault (2021) pose the argument that we cannot accurately capture any effect from social media. It is therefore essential to test whether the sentiment formation theory is also relevant for cryptocurrencies. The following hypothesis emerges:

Hypothesis 4: Trump tweet sentiments impact on Bitcoin prices and their associated volatility.

METHODOLOGY

Based on previous work (Filippou et al., 2020; Ajjoub et al., 2021), we access President Trump's tweets through a well-established open database. The Trump InterArchive is a dataset that includes 53,871 tweets across the time interval 2010-2021; 39,784 tweets from 2010 to 2017 and 14,087 from 2017 to 2021. In this study and in terms of the baseline analysis, we focus only on the first presidential period of President Trump, i.e., between January 20th, 2017, and January 20th, 2021. We focus on tweets with economic-financial content to maximise the quality and amount of relevant information in our initial raw dataset. Accordingly, we apply general pre-processing methods, text normalisation and filtering to the initial dataset to prune it by conserving as much relevant information as possible. Given that the empirical analysis is based on the employment on daily observations across financial markets, while President Trump provided more than one Tweet per day in several cases, each day makes use of all those daily Tweets.

When it comes to sentiment extraction, the model 'learns' to extract the sentiment of a given text by training and validating on a labelled dataset; thus, the model

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attempts to asymptotically imitate the human labelling through iterative procedures and optimisation methods. In contrast, social media platforms are databases of raw text without any additional information regarding, among other elements, sentiment, and consequently, machine-learning models have no a priori knowledge to consume to 'learn' iteratively the hyperspace, where each sentiment category is linearly separable from the others by a hyperplane. In our work, the variable creation on the extracted sentiment is accomplished through Twitter-RoBERTa (Barbieri et al., 2020) (emotion, hate, irony, offensive, sentiment).

Twitter-RoBERTa was created due to the absence of a transparent, robust, and standardised evaluation protocol regarding NLP for social media. Therefore, Barbieri et al. (2020) propose a new evaluation framework, TWEETEVAL, consisting of seven Twitter-specific heterogenous classification tasks: emotion recognition, emoji recognition, irony detection, hate speech detection, offensive language identification, sentiment analysis and stance detection (see Table 1 below).

Table 1: The Online Communication Classification

Labels and instances in training, validation, and test are set for each dataset. The specific statistics of each target domain in the stance detection task are included at the bottom (Barbieri et al., 2020). RoBERTa was trained on 60M English tweets (using automatic labelling provided by Twitter).

Task	Training	Validation	Test
Emoji prediction	45,000	5,000	50,000
Emotion recognition	3,257	374	1,421
Hate speech detection	9,000	1,000	2,970
Irony detection	2,862	955	784
Offensive language identification	11,916	1,324	860
Sentiment analysis	45,389	2,000	11,906
Stance detection	2,620	294	1,249

In our task, we use the following RoBERTa variations to analyse Trump's tweets: emotion recognition, irony detection, hate speech detection, offensive language identification, and sentiment analysis. We employ the RoBERTa variant to extract 13 indexes out of Trump's tweets. Consequently, and therefore we delve deeper than traditional dictionary-based and binary (positive, negative) sentiment approaches, by introducing more flexibility and depth in our study. An example of RoBERTa-processing can be found in the Appendix of the study (Figure A1).

In terms of the financial data under investigation in this study, the Refinitiv dataset used in this study includes high-frequency observations on a daily interval basis of transaction prices

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on crude oil prices measured both in Brent FOB prices and WTI prices (both oil price series are denoted in dollars per barrel), S&P500 prices, gold spot prices (measured in US dollar per ounce), Bitcoin prices, and the Baltic Dry Index, spanning the period 2017-2021, resulting 1,004 observations. At this point we need to mention that although certain markets, such as cryptocurrencies are open on a 24/7 basis, including holidays, we match their observations to those markets who operate all days excluding weekends and holidays. Descriptive statistics are provided below in Table 2.

Table 2: Descriptive Statistics

Variables	Mean	SD	Min	Max	Skewness	Kurtosis	Jarque-Bera
Anger	0.46	0.38	0.01	0.98	0.96	6.17	2,269.63
Joy	0.17	0.26	0.00	0.97	0.93	5.61	2,198.07
Optimism	0.25	0.27	0.00	0.96	0.89	5.98	2,274.93
Sadness	0.11	0.16	0.01	0.98	0.92	6.25	2,559.38
Hate	0.08	0.12	0.01	0.98	0.94	6.18	2,714.81
Irony	0.52	0.28	0.02	0.99	0.97	5.94	2,669.54
Offensive	0.23	0.19	0.02	0.90	0.91	6.31	2,548.93
Negative	0.37	0.35	0.00	0.98	0.95	6.53	2,874.09
Neutral	0.30	0.24	0.01	0.96	0.92	7.43	3,095.64
Positive	0.33	0.38	0.00	0.99	0.89	7.11	2,986.58
S&P500	2,901.09	325.35	2,237.4	3,851.85	0.76	0.07	2,984.61
Oil(Brent)	57.90	13.49	9.12	86.07	-0.70	0.58	30,767.62
Oil(WTI)	53.09	11.59	8.91	77.41	-0.73	1.01	25,441.19
Bitcoin	7,959.9	5,312.5	887	40,666,7	2.38	9.95	4,348.44
Gold	1431.5	233.9	1,192	1969	1.05	-0.25	12,200.92
Baltic Dry Index	2,430.3	125.0	2,090.4	2,805.1	0.10	-0.08	6,186.02
Obs.	1,000						

SD = standard deviation.

At this point, it is important to clarify our assumptions behind the measure of the Tweets variable. This variable takes only binary or multidimensional forms. In this work, we consider the latter format as more realistic and representative, since in this way, a given tweet can encapsulate many emotional states at the same time, not just one from each category. More specifically, the available emotional categories are: 1) emotion (anger, joy, optimism, sadness), 2) hate-speech (no hate-speech, hate-speech), 3) irony (no irony, irony), 4) offensive speech (not offensive, offensive), and 5) sentiment (negative, neutral, positive). In the cases of emotion and sentiment, RoBERTa applies the softmax function, in order to form its final decision:

$$\sigma(z) = \frac{e^{z_j}}{\sum_{j=1}^{K} -e^{z_j}}$$

Where, σ: $R^K \rightarrow (0,1)^K$ *when* $K > 1$

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The softmax function maps an input vector z_j in the interval (0,1), thus transforms it into a probability distribution, where all of its components sum to one. In the cases of hate-speech, irony and offensive speech, which are binary variables, RoBERTa applies the sigmoid function (logistic function):

$$S(z) = \frac{1}{1 + e^{-(z)}}$$

Turning to our primary concern, if we consider tweets as a discrete variable, this implies that any given tweet could be described from only one component from each category, for instance, a tweet cannot contain joy and optimism simultaneously. By contrast, the multidimensional form of this variable, provides us with a more realistic view, given that it allows a tweet to be described by the probabilities of each tweet to belong to all available categories. More specifically, this format illustrates the notion that a tweet can be described by a probability distribution, which reflects the likelihood of a tweet to belong to any component of each category, thus it encapsulates information from all available indices. All things considered we employ the multidimensional form of variable tweets as one of the inputs to the econometric analysis. The scores were constructed in a manner that match the daily observations of financial data.

Next, we utilize the ARMA-GARCH (ARMAX) framework recommended by Connor et al. (2006). This model allows for considering US president Trump's tweets as a variable that affects the mean of assets returns and their associated volatilities. An ARMA (p, q) returns process also calculates errors. That is, for returns, r_t, the following specification is used:

$$r_t = \mu_0 + \sum_{i=1}^{q_1} a_1 rt_{t-1} + \sum_{i=1}^{q_2} a_2 u_{t-1} + b(tweets)_t + \eta_t \quad (1)$$

Where, the first sum represents the autoregressive (AR) component and the second sum the moving average (MA) component, with tweets representing the five alternative measures of the tweets' sentiment and emotion. Finally, η_t is the error term. In addition, within the ARMA-GARCH(1, 1) framework, the equation of conditional volatility turns out to be:

$$h_t = f_1 + f_2 h_{t-1} + f_3 \eta_{t-1}^2 + f_4 (tweets)_t \quad (2)$$

In the interests of robustness, we further consider the asymmetric character of asset returns. To this end, the exponential GARCH (EGARCH) model, proposed by Nelson (1991), is also applied. The EGARCH model is based on a logarithmic expression of conditional variance. Nelson (1991) argues that this modelling approach is suitable for testing market leverage. The specifications for conditional variance yields:

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$$log(h_t) = \omega + a\, log(h_{t-1}) + b \left| \frac{\eta_{t-1}}{\sqrt[2]{h_{t-1}}} \right| + \sum_{k=1}^{r} c_k \frac{\eta_{t-k}}{\sqrt[2]{h_{t-k}}} \quad (3)$$

Where, Equation (3) is the logarithmic conditional variance and the leverage effect is exponential instead of quadratic, and the conditional variance forecast is guaranteed to be nonnegative. The EGARCH model is different from the standard GARCH models in two main respects (Engle and Ng, 1993): i) the EGARCH model allows good news and bad news to have a different (asymmetric) impact on volatility, while the standard GARCH model does not, and ii) the EGARCH model allows big news to have a greater impact on volatility than the standard GARCH model. The presence of leverage can be tested by the hypothesis that $c_k > 0$. The effect is asymmetric if $c_k \neq 0$.

Table 3: Unit Root Tests

	Levels	First differences
S&P500	-1.35(4)	-6.71(3)***
Oil(Brent)	-1.30(3)	-6.64(2)***
Oil(WTI)	-1.32(3)	-6.68(2)***
Gold	-1.31(4)	-6.75(3)***
Baltic Dry Index	-1.38(3)	-6.71(2)***
Bitcoin	-1.25(4)	-6.89(3)***

The numbers in parentheses denote the lag length used to obtain white noise residuals.

The lag length was selected using the Akaike Information Criterion.

***: p≤0.01.

Table 3 presents the stationarity properties of the series involved in the study based on the unit root test provided by Elliott et al. (1996). In particular, all series employed in the study are integrated of order one (i.e., stationary in their first differences). On a final note, it would be instructive to note that we employ the following ARMA specifications for the mean equation depending on the asset under consideration. Oil (Brent): ARMA(1, 0), Oil (WTI): ARMA(1, 0), Bitcoin: ARMA(2, 0), Gold: ARMA(2, 0), Baltic Dry Index: (1, 0) and S&P500: ARMA(1, 0). The selection of the model has been based on the Akaike criterion.

RESULTS AND DISCUSSION

In the first step of the empirical analysis, we make use of the linear version of the ARMA-GARCH model (as described in Equations (1) and (2)), based on the five alternative measures

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of the Trump tweets' sentiment. A detailed presentation of the results can be found in the Appendix of the study, in Tables A1 to A20. The Tables in the Appendix comprise the full spectrum of findings, also including the coefficients for the idiosyncratic elements of the GARCH models (i.e., ARCH/GARCH effects). In this regard, we proceed with a constructive summary of the main findings regarding the impact of tweets on the mean and the volatility equation of the variables of interest. This is given below in Table 4.

Table 4: ARMA-GARCH estimates (tweets in mean equation)

Emotion	Oil (Brent)	Oil (WTI)	Bitcoin	Gold	Baltic Index	S&P500
Anger	-0.109*** [0.00]	-0.099*** [0.01]	-0.086** [0.02]	-0.074** [0.02]	-0.093*** [0.01]	-0.122*** [0.00]
Joy	0.079** [0.02]	0.089** [0.02]	0.083** [0.02]	0.109*** [0.00]	0.104*** [0.00]	0.136*** [0.00]
Optimism	0.114*** [0.00]	0.103*** [0.00]	0.098*** [0.01]	0.119*** [0.00]	0.091*** [0.00]	0.123*** [0.00]
Sadness	-0.123*** [0.00]	-0.112*** [0.00]	-0.094** [0.02]	-0.128*** [0.00]	-0.120*** [0.00]	-0.132*** [0.00]
Hate	-0.148*** [0.00]	-0.147*** [0.00]	-0.116*** [0.01]	-0.149*** [0.00]	-0.148*** [0.00]	-0.156*** [0.00]
Irony	-0.141*** [0.00]	-0.145*** [0.00]	-0.125*** [0.00]	-0.156*** [0.00]	-0.155*** [0.00]	-0.159*** [0.00]
Offensive	-0.148*** [0.00]	-0.152*** [0.00]	-0.134*** [0.00]	-0.163*** [0.00]	-0.160*** [0.00]	-0.166*** [0.00]
Negative	-0.157*** [0.00]	-0.158*** [0.00]	-0.145*** [0.00]	-0.168*** [0.00]	-0.168*** [0.00]	-0.175*** [0.00]
Neutral	-0.036[0.31]	0.040[0.28]	0.044[0.27]	0.038[0.30]	0.047[0.24]	-0.050[0.23]
Positive	0.107*** [0.00]	0.113*** [0.00]	0.094** [0.02]	0.108*** [0.00]	0.099*** [0.01]	0.126*** [0.00]

Figures in brackets denote p-values.

**: p≤0.05; ***: p≤0.01.

Looking at the sign of the effect, except for "joy", "optimism" and "positive sentiment", all other emotions have a negative impact on asset returns. This is a rather anticipated outcome which confirms our initial hypotheses regarding the likelihood of an impact of tweets on all relevant series and further illustrates the crucial role of sentiment and the difference between a positive and a negative tweet. Turning to the magnitude of the effect, as far as negative tweets are concerned, we note that in all cases "negative sentiment", "hate", "offensive language", as well as "irony" have the most influence. Emotions of "sadness", "anger", they also have a negative impact, albeit, to some lesser extent. As far as "neutral sentiment" is concerned, we do not find any significant results.

We next turn to the impact of tweets on the conditional volatility equation, whereby a negative sign indicates a decrease in volatility and vice versa. These findings are presented in Table 5. We notice that tweets reflecting "joy", "optimism" and "positive sentiment" they all result in less volatility in all series under investigation. By contrast, all tweets that bring out a negative tone, they almost all (i.e., "neutral" sentiment aside) manage to significantly increase volatility in all series under investigation. Again, this is a rather anticipated outcome.

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Table 5: ARMA-GARCH estimates (tweets in conditional volatility equation)

Emotion	Oil (Brent)	Oil (WTI)	Bitcoin	Gold	Baltic Index	S&P500
Anger	0.092***[0.00]	0.104***[0.00]	0.116***[0.00]	0.131***[0.00]	0.119***[0.00]	0.134***[0.00]
Joy	-0.097***[0.00]	-0.105***[0.00]	-0.091***[0.01]	-0.098***[0.00]	-0.105***[0.00]	-0.137***[0.00]
Optimism	-0.092***[0.00]	-0.088***[0.00]	-0.082***[0.01]	-0.113***[0.00]	-0.097***[0.00]	-0.120***[0.00]
Sadness	0.116***[0.00]	0.115***[0.00]	0.108***[0.00]	0.129***[0.00]	0.119***[0.00]	0.134***[0.00]
Hate	0.138***[0.00]	0.139***[0.00]	0.119***[0.00]	0.138***[0.00]	0.134***[0.00]	0.144***[0.00]
Irony	0.140***[0.00]	0.145***[0.00]	0.125***[0.00]	0.142***[0.00]	0.141***[0.00]	0.148***[0.00]
Offensive	0.146***[0.00]	0.153***[0.00]	0.136***[0.00]	0.149***[0.00]	0.147***[0.00]	0.155***[0.00]
Negative	0.155***[0.00]	0.159***[0.00]	0.148***[0.00]	0.157***[0.00]	0.156***[0.00]	0.163***[0.00]
Neutral	0.036[0.30]	0.052[0.26]	0.047[0.27]	0.051[0.26]	0.055[0.24]	0.048[0.27]
Positive	-0.091**[0.02]	-0.102***[0.00]	-0.095**[0.01]	-0.114***[0.00]	-0.094**[0.02]	-0.129[0.00]

Notes: Figures in brackets denote p-values. **: p≤0.05; ***: p≤0.01.

For the purposes of robustness, we then consider the EGARCH modelling approach, to confirm the prior results and to further account for asymmetric volatility. These results are presented in Tables 6-8.

Table 6: ARMA-EGARCH estimates (tweets in mean equation)

Emotion	Oil (Brent)	Oil (WTI)	Bitcoin	Gold	Baltic Index	S&P500
Anger	-0.121***[0.00]	-0.127***[0.00]	-0.090**[0.02]	-0.106***[0.00]	-0.096**[0.02]	-0.146***[0.00]
Joy	0.106***[0.00]	0.119***[0.00]	0.094**[0.02]	0.112***[0.00]	0.095**[0.02]	0.130***[0.00]
Optimism	0.095**[0.02]	0.105***[0.00]	0.090**[0.02]	0.114***[0.00]	0.093**[0.02]	0.137***[0.00]
Sadness	-0.137***[0.00]	-0.146***[0.00]	-0.094**[0.02]	-0.131***[0.00]	-0.106***[0.00]	-0.142***[0.00]
Hate	-0.122***[0.00]	-0.134***[0.00]	-0.105**[0.02]	-0.129***[0.00]	-0.103**[0.02]	-0.142***[0.00]
Irony	-0.120***[0.00]	-0.132***[0.00]	-0.111***[0.00]	-0.122***[0.00]	-0.108***[0.00]	-0.140***[0.00]
Offensive	-0.126***[0.00]	-0.136***[0.00]	-0.107***[0.00]	-0.128***[0.00]	-0.112***[0.00]	-0.145***[0.00]
Negative	-0.130***[0.00]	-0.139***[0.00]	-0.112***[0.00]	-0.130***[0.00]	-0.114***[0.00]	-0.149***[0.00]
Neutral	-0.044[0.24]	-0.041[0.26]	-0.035[0.30]	-0.039[0.29]	-0.028[0.35]	-0.044[0.25]
Positive	0.139***[0.00]	0.148***[0.00]	0.122***[0.00]	0.149***[0.00]	0.124***[0.00]	0.157***[0.00]

Figures in brackets denote p-values. **: p≤0.05; ***: p≤0.01.

Table 7: ARMA-EGARCH estimates (tweets in conditional volatility equation)

Emotion	Oil (Brent)	Oil (WTI)	Bitcoin	Gold	Baltic Index	S&P500
Anger	0.088***[0.00]	0.098***[0.00]	0.092***[0.00]	0.119***[0.00]	0.098***[0.00]	0.131***[0.00]
Joy	-0.089**[0.02]	-0.099**[0.02]	-0.090**[0.02]	-0.105***[0.00]	-0.093**[0.02]	-0.117***[0.00]
Optimism	-0.093***[0.00]	-0.101***[0.00]	-0.085***[0.01]	-0.107***[0.00]	-0.095***[0.00]	-0.134***[0.00]
Sadness	0.121***[0.00]	0.130***[0.00]	0.102***[0.00]	0.132***[0.00]	0.109***[0.00]	0.139***[0.00]
Hate	0.128***[0.00]	0.139***[0.00]	0.111***[0.00]	0.125***[0.00]	0.119***[0.00]	0.145***[0.00]
Irony	0.125***[0.00]	0.132***[0.00]	0.118***[0.00]	0.140***[0.00]	0.117***[0.00]	0.148***[0.00]
Offensive	0.131***[0.00]	0.139***[0.00]	0.114***[0.00]	0.136***[0.00]	0.115***[0.00]	0.150***[0.00]
Negative	0.136***[0.00]	0.144***[0.00]	0.116***[0.00]	0.141***[0.00]	0.120***[0.00]	0.155***[0.00]
Neutral	0.026[0.28]	0.029[0.26]	0.024[0.30]	0.035[0.24]	0.019[0.36]	0.038[0.23]
Positive	-0.135***[0.00]	-0.148***[0.00]	-0.124***[0.00]	-0.155***[0.00]	-0.124***[0.00]	-0.164***[0.00]

Figures in brackets denote p-values. **: p≤0.05; ***: p≤0.01.

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Table 8: ARMA-EGARCH Estimates (gamma coefficient in conditional volatility equation)

Emotion	Oil (Brent)	Oil (WTI)	Bitcoin	Gold	Baltic Index	S&P500
Anger	-0.087** [0.00]	-0.089*** [0.00]	-0.096*** [0.00]	-0.098*** [0.00]	-0.109*** [0.00]	-0.120*** [0.00]
Joy	-0.077*** [0.00]	-0.074*** [0.00]	-0.079*** [0.00]	-0.083*** [0.00]	-0.089*** [0.00]	-0.091*** [0.00]
Optimism	-0.097*** [0.00]	-0.094*** [0.00]	-0.088*** [0.01]	-0.092*** [0.00]	-0.093*** [0.00]	-0.097*** [0.00]
Sadness	-0.108*** [0.00]	-0.099*** [0.00]	-0.088*** [0.01]	-0.094*** [0.00]	-0.091*** [0.00]	-0.093*** [0.00]
Hate	-0.085*** [0.00]	-0.090*** [0.00]	-0.085*** [0.00]	-0.091*** [0.00]	-0.090*** [0.00]	-0.094*** [0.00]
Irony	-0.089*** [0.00]	-0.093*** [0.00]	-0.087*** [0.00]	-0.095*** [0.00]	-0.096*** [0.00]	-0.093*** [0.00]
Offensive	-0.086*** [0.00]	-0.090*** [0.00]	-0.089*** [0.00]	-0.093*** [0.00]	-0.094*** [0.00]	-0.094*** [0.00]
Negative	-0.089*** [0.00]	-0.093*** [0.00]	-0.091*** [0.00]	-0.096*** [0.00]	-0.097*** [0.00]	-0.097*** [0.00]
Neutral	-0.085*** [0.00]	-0.090*** [0.00]	-0.088*** [0.00]	-0.093*** [0.00]	-0.094*** [0.00]	-0.095*** [0.00]
Positive	-0.091*** [0.00]	-0.092*** [0.00]	-0.094*** [0.00]	-0.094*** [0.00]	-0.095*** [0.00]	-0.096*** [0.00]

Figures in brackets denote p-values. **: p≤0.05; ***: p≤0.01.

In both Tables 6 and 7 we document that the results obtained from the ARMA-EGARCH modelling approach are qualitatively similar to those obtained by the ARMA-GARCH approach, in terms of all signs, magnitudes, and statistical significance. Finally, in Table 8, we note that the gamma coefficient of the model is persistently negative and statistically significant for all assets under investigation. This practically implies that the gamma coefficient measures asymmetry in response to return shocks.

On general principles, the findings are in line with the existing relevant literature. Sentiments and the role of media platforms can provide useful insight with regard to political and economic developments. Most existing studies of the finance persuasion focus mainly on the linkages between Trump's tweets and stock market returns, although there has been limited evidence with regard to linkages between tweets and stock market volatility, or gold, or Bitcoin. Nonetheless, these areas, including research on the linkages between tweets and the oil market or the Baltic Dry Index, are all rather insufficiently examined.

We begin by noting that, the potential effect of former US President Trump's tweets on public sentiment, as well as economic activity, has recently drawn considerable attention. In point of fact, many recent studies both in the field of politics and economics have investigated the repercussions of using social media platforms to inform the public about political views and decisions; that is, a practice which was widely adopted during Trump's Presidency. In an interesting study, Hornsey et al. (2020) highlight that Trump's tweets about the vaccination against COVID-19 had a substantial impact among Trump voters, effectively resulting in them becoming more worried about vaccination. Furthermore, Sahin et al. (2021) raise the issue of discursive governance; that is, when politicians make use of social media and bypass formal institutions in order to promote their political agenda and invoke policy change.

Turning to financial markets per se, the findings of our study corroborate arguments that have recently been reported in the relevant strand of the literature. In their study of US

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presidential elections, Marinc et al. (2021) record the unprecedented use of media platforms, such as Twitter, by most candidates for the Oval Office and point out the positive response from cumulative abnormal returns (CARs) when tweets bear a positive linguistic tone. In a similar manner, we also find that tweets reflecting "joy", "positive sentiment" and "optimism" increase asset returns and decrease asset volatility. What is more, Klaus and Koser (2021) are able to identify a time-varying and heterogeneous effect – depending on the tone and context of the tweets, on European Financial Markets and raise the question of how access to Twitter messages relates to market efficiency. Gjerstad et al. (2021) provide evidence that President's tweets increase trading and uncertainty in the US stock market, while when the topic revolved around "trade war", both the US and the Chinese stock markets declined, with the price of gold moving to the opposite direction.

In addition, the negative impact of Trump's tweets on stock market volatility has been reported by Nishimura et al. (2021). Our study extends such findings by considering different conditions of emotions, whereby tweets that convey a positive message do in fact diminish volatility in the stock market. Finally, as far as Bitcoin is involved, we cannot report any differences between the response of the stock market and Bitcoin to tweets (Wen et al., 2022). In another recent study, Huynh (2021) provides evidence that Trump's tweets can have a dynamic impact on the Bitcoin market.

Overall, this present work investigates the theory of sentiment formation, where the role of social media starts having a rising and contemporaneous role not only on sentiment itself, but also on financial assets (Siganos et al., 2014; Azar and Lo, 2016). The findings exhort that Trump tweet sentiments have an influencing role in S&P500 prices and the associated volatility ($\boldsymbol{H_1}$), which corroborates the prior literature on the association of Trump tweet sentiments with stock prices (Chen et al., 2014; Sun et al., 2016; Beckers, 2018; Colonescu, 2018; Afanasyev et al., 2021; Guo et al., 2021; Klaus and Koser, 2021). Investigating the effect of Trump tweet sentiments on oil prices and their volatility ($\boldsymbol{H_2}$) helps us identify whether the effect we identified in the first hypothesis persists in energy prices. The results support the second hypothesis and prior research, which investigates similar effects (Yu et al., 2005; Li et al., 2019; Narayan and Narayan, 2019). Similarly, the Trump tweet sentiments – prices and volatility association ($\boldsymbol{H_2}$) is per the role of Trump tweet sentiments on gold prices (Smales, 2014; Piñeiro-Chousa et al., 2018). Concerning the third hypothesis, no prior investigation has explored it between Trump tweet sentiments and the Baltic Dry Index prices and the associated volatility ($\boldsymbol{H_3}$). In this setting, we practically shed new light upon the proposition of previous researchers regarding the difficulty of predicting any effects on the Baltic Dry Index (Kavussanos and Nomikos, 1999; Kavussanos and Alizadeh-M, 2001; Batchelor et al., 2007; Papailas et al., 2017; Tsioumas et

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al., 2017; Makridakis et al., 2020). The findings support the articulated hypothesis. Finally, Trump tweet sentiments have influenced Bitcoin prices and its associated volatility (***H_4***). Supporting the fourth hypothesis aligns with previous research from Mai et al. (2018), Shen et al. (2019), and Choi (2021), but not Guégan and Renault (2021).

Robustness Checks

Adding a Conventional News Source

Certain studies have analyzed news articles to explore how and to what extent information found on journalistic type of media is explicitly integrated as a source in journalistic content (Bane, 2017; Hine, 2020; Lukito et al., 2020; among others). Nevertheless, the consensus of the relevant literature is that social media message postings and Tweets tend to have a limited capacity to provide reliable predictions about future market prices or these predictions have limited and short-lived predictive power (Tetlock, 2007; Sabherwal et al., 2008).

This section considers adding a conventional news source to the analysis; in particular, the methodology takes explicitly into account tweets from the New York Times and jointly analyze their effects. This could potentially allow a comparison between social and traditional media. In case that Trump's tweets are still shown to have a market effect, a stronger case could be made that the sentiments of the president affect markets above and beyond exogenous events already reported in the news. Using a desktop program called Tweetcatcher with access to the Twitter API, certain tweets coming from the New York Times (NYT) newspaper have been collected in the same sample window. The data were collected by Twitter Search API, where a search query consists of the financial market tag associated with the markets under consideration. Then, the same methodology as before was used to extract the sentiments associated with those NYT tweets.

The new findings are reported in Tables 9 and 10 for the mean and volatility of market prices, respectively. They clearly state that although the news sentiments exert an impact of financial prices, albeit significant only in certain cases and at 10 percent, the role of Trump's sentiments remains substantial strong.

Table 9: ARMA-EGARCH estimates (tweets in mean equation-adding NYT tweets)

Emotion	Oil (Brent)	Oil (WTI)	Bitcoin	Gold	Baltic Index	S&P500
Anger	-0.108***[0.00]	-0.119***[0.00]	-0.077**[0.03]	-0.090***[0.00]	-0.084**[0.02]	-0.125***[0.00]
Anger NYT	-0.046*[0.09]	-0.042*[0.10]	-0.037[0.11]	-0.041*[0.10]	-0.032[0.12]	-0.064*[0.06]
Joy	0.097***[0.01]	0.105***[0.00]	0.088**[0.02]	0.103*** [0.00]	0.090**[0.02]	0.123***[0.00]
Joy NYT	0.038*[0.10]	0.035[0.12]	0.044*[0.09]	0.041*[0.09]	0.033[0.13]	0.052*[0.09]
Optimism	0.089**[0.02]	0.094***[0.01]	0.083**[0.03]	0.102***[0.00]	0.081**[0.03]	0.116***[0.00]

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OptimismNYT	0.038[*][0.09]	0.032[*][0.10]	0.025[0.14]	0.039[*][0.10]	0.024[0.16]	0.052[*][0.09]
Sadness	-0.128[***][0.00]	-0.131[***][0.00]	-0.089[**][0.03]	-0.122[***][0.00]	-0.094[***][0.01]	-0.133[***][0.00]
SadnessNYT	-0.054[*][0.09]	-0.103[***][0.00]	-0.044[*][0.10]	-0.062[*][0.09]	-0.032[0.11]	-0.067[*][0.09]
Hate	-0.113[***][0.00]	-0.125[***][0.00]	-0.088[**][0.03]	-0.116[***][0.00]	-0.091[**][0.02]	-0.128[***][0.00]
Hate NYT	-0.052[*][0.09]	-0.061[*][0.08]	-0.035[*][0.10]	-0.053[*][0.09]	-0.039[*][0.10]	-0.042[*][0.10]
Irony	-0.104[***][0.00]	-0.124[***][0.00]	-0.102[***][0.00]	-0.114[***][0.00]	-0.093[**][0.02]	-0.129[***][0.00]
Irony NYT	-0.055[*][0.09]	-0.047[*][0.10]	-0.040[*][0.10]	-0.046[*][0.10]	-0.035[0.11]	-0.053[*][0.09]
Offensive	-0.119[***][0.00]	-0.125[***][0.00]	-0.093[**][0.02]	-0.115[***][0.00]	-0.109[***][0.00]	-0.128[***][0.00]
OffensiveNYT	-0.046[*][0.10]	-0.051[*][0.09]	-0.033[0.12]	-0.038[*][0.10]	-0.037[0.12]	-0.063[*][0.08]
Negative	-0.122[***][0.00]	-0.127[***][0.00]	-0.104[***][0.00]	-0.119[***][0.00]	-0.103[***][0.00]	-0.128[***][0.00]
NegativeNYT	-0.051[*][0.09]	-0.052[*][0.09]	-0.032[0.12]	-0.040[*][0.10]	-0.034[*][0.10]	-0.052[*][0.09]
Neutral	-0.034[0.16]	-0.032[0.17]	-0.024[0.24]	-0.031[0.17]	-0.019[0.28]	-0.031[0.18]
Neutra NYT	-0.013[0.39]	-0.012[0.40]	-0.013[0.35]	-0.011[0.40]	-0.005[0.49]	-0.006[0.48]
Positive	0.123[***][0.00]	0.140[***][0.00]	0.114[***][0.00]	0.133[***][0.00]	0.109[***][0.00]	0.132[***][0.00]
Positive NYT	0.063[*][0.08]	0.058[*][0.09]	0.045[*][0.10]	0.058[*][0.09]	0.037[0.11]	0.052[*][0.10]

Figures in brackets denote p-values. *: p≤0.10; **: p≤0.05; ***: p≤0.01.

Table 10: ARMA-EGARCH estimates (tweets in conditional volatility equation-adding NYT tweets)

Emotion	Oil (Brent)	Oil (WTI)	Bitcoin	Gold	Baltic Index	S&P500
Anger	0.072[***][0.01]	0.085[***][0.00]	0.077[***][0.01]	0.095[***][0.00]	0.082[***][0.00]	0.109[***][0.00]
Anger NYT	0.029[0.21]	0.046[*][0.09]	0.030[*][0.10]	0.043[*][0.10]	0.041[*][0.10]	0.045[*][0.09]
Joy	-0.076[**][0.03]	-0.084[**][0.02]	-0.072[**][0.03]	-0.089[**][0.02]	-0.080[**][0.03]	-0.093[***][0.01]
Joy NYT	-0.024[0.13]	-0.035[*][0.09]	-0.027[0.12]	-0.038[*][0.09]	-0.028[0.12]	-0.030[*][0.10]
Optimism	-0.081[***][0.01]	-0.083[**][0.02]	-0.070[**][0.03]	-0.089[***][0.01]	-0.083[**][0.02]	-0.103[***][0.00]
OptimismNYT	-0.029[0.14]	-0.031[*][0.10]	-0.033[*][0.10]	-0.027[0.15]	-0.031[*][0.10]	-0.035[*][0.09]
Sadness	0.102[***][0.00]	0.105[***][0.00]	0.081[**][0.03]	0.112[***][0.00]	0.086[**][0.02]	0.109[***][0.00]
SadnessNYT	0.035[*][0.10]	0.024[0.13]	-0.028[0.12]	0.035[*][0.10]	0.024[0.14]	0.030[*][0.10]
Hate	0.109[***][0.00]	0.112[***][0.00]	0.090[**][0.02]	0.105[***][0.00]	0.093[***][0.01]	0.124[***][0.00]
Hate NYT	0.040[*][0.09]	0.043[*][0.09]	0.024[0.14]	0.029[0.13]	0.025[0.15]	0.038[*][0.10]
Irony	0.106[***][0.00]	0.111[***][0.00]	0.095[***][0.01]	0.108[***][0.00]	0.091[***][0.01]	0.124[***][0.00]
Irony NYT	0.047[*][0.09]	0.042[*][0.09]	0.026[0.13]	0.029[0.12]	0.024[0.14]	0.039[*][0.10]
Offensive	0.106[***][0.00]	0.110[***][0.00]	0.091[**][0.02]	0.113[***][0.00]	0.090[**][0.02]	0.115[***][0.00]
OffensiveNYT	0.046[*][0.09]	0.039[*][0.10]	0.022[0.17]	0.027[0.12]	0.018[0.25]	0.035[0.12]
Negative	0.122[***][0.00]	0.119[***][0.00]	0.091[**][0.02]	0.114[***][0.00]	0.095[***][0.01]	0.131[***][0.00]
NegativeNYT	0.049[*][0.08]	0.042[*][0.09]	0.024[0.14]	0.022[0.19]	0.018[0.24]	0.029[0.17]
Neutral	0.015[0.38]	0.013[0.24]	0.010[0.42]	0.021[0.33]	0.009[0.48]	0.027[0.31]
NeutralNYT	0.004[0.58]	0.005[0.65]	0.000[0.82]	0.003[0.64]	0.000[0.86]	0.010[0.65]
Positive	-0.115[***][0.00]	-0.122[***][0.00]	-0.096[**][0.02]	-0.129[***][0.00]	-0.093[**][0.02]	-0.129[***][0.00]
PositiveNYT	-0.041[*][0.08]	-0.040[*][0.08]	-0.024[0.18]	-0.038[*][0.09]	-0.036[*][0.10]	-0.041[*][0.08]

Notes: Figures in brackets denote p-values. *: p≤0.10; **: p≤0.05; ***: p≤0.01.

Is it Particular About Trump or Trump Being the President?

This section considers additional robustness tests by using Trump tweets before he became president in comparison to those during his first presidency period. The non-presidency period comes from 2010 to 2016, except in the case of Bitcoin where available data start from October 2014. The new results for the mean and the volatility of financial prices are reported in Tables 11 and 12, respectively. Wald F-test provide formal test support for indicating that Trump's Tweets over the period prior to his presidency were exerting a different and weak

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impact on those prices (statistically significant only at 10%), while the effect was statistically insignificant for oil (Brent), gold, and Bitcoin prices.

Table 11: ARMA-EGARCH estimates

(tweets in mean equation-Trump's presidency vs Trump's non-presidency periods)

Emotion	Oil (Brent)	Oil (WTI)	Bitcoin	Gold	Baltic Index	S&P500
Anger	-0.109*** [0.00]	-0.099*** [0.00]	-0.086** [0.02]	-0.074** [0.02]	-0.093*** [0.01]	-0.122*** [0.00]
Anger NP	-0.027[0.18]	-0.039* [0.10]	-0.030[0.16]	-0.032[0.15]	-0.046* [0.09]	-0.057* [0.07]
	Wald test[0.00]					
Joy	0.079** [0.02]	0.089** [0.02]	0.083** [0.02]	0.109*** [0.00]	0.104*** [0.00]	0.136*** [0.00]
Joy NP	0.032[0.15]	0.046* [0.09]	0.026[0.19]	0.029[0.17]	0.044* [0.10]	0.059* [0.07]
	Wald test[0.00]					
Optimism	0.114*** [0.00]	0.103*** [0.00]	0.098*** [0.01]	0.119*** [0.00]	0.091*** [0.00]	0.123*** [0.00]
Optimism NP	0.033[0.15]	0.038* [0.10]	0.022[0.16]	0.034[0.14]	0.046* [0.08]	0.059* [0.07]
	Wald test[0.00]					
Sadness	-0.123*** [0.00]	-0.112*** [0.00]	-0.094** [0.02]	-0.128*** [0.00]	-0.120*** [0.00]	-0.132*** [0.00]
Sadness NP	-0.035[0.15]	-0.061* [0.06]	-0.039[0.15]	-0.032[0.17]	-0.051[0.08]	-0.069* [0.07]
	Wald test[0.00]					
Hate	-0.148*** [0.00]	-0.147*** [0.00]	-0.116*** [0.01]	-0.149*** [0.00]	-0.148*** [0.00]	-0.156*** [0.00]
Hate NP	-0.036[0.14]	-0.058* [0.08]	-0.031[0.17]	-0.033[0.16]	-0.050* [0.08]	-0.059* [0.08]
	Wald test[0.01]					
Irony	-0.141*** [0.00]	-0.145*** [0.00]	-0.125*** [0.00]	-0.156*** [0.00]	-0.155*** [0.00]	-0.159*** [0.00]
Irony NP	-0.027[0.19]	-0.049* [0.09]	-0.030[0.18]	-0.026[0.20]	-0.057* [0.07]	-0.062* [0.06]
	Wald test[0.00]					
Offensive	-0.148*** [0.00]	-0.152*** [0.00]	-0.134** [0.00]	-0.163*** [0.00]	-0.160*** [0.00]	-0.166*** [0.00]
Offensive NP	-0.026[0.19]	-0.053* [0.08]	-0.028[0.20]	-0.018[0.23]	-0.060* [0.06]	-0.068* [0.06]
	Wald test[0.00]					
Negative	-0.157*** [0.00]	-0.158*** [0.00]	-0.145*** [0.00]	-0.168*** [0.00]	-0.168*** [0.00]	-0.175*** [0.00]
Negative NP	-0.032[0.16]	-0.054* [0.08]	-0.026[0.22]	-0.030[0.20]	-0.049* [0.09]	-0.066* [0.06]
	Wald test[0.00]					
Neutral	-0.036[0.31]	-0.040[0.28]	-0.044[0.27]	-0.038[0.30]	-0.047[0.24]	-0.050[0.23]
Neutral NP	-0.009[0.44]	-0.005[0.45]	-0.004[0.49]	-0.013[0.40]	-0.019[0.39]	-0.026[0.36]
	Wald test[0.00]					
Positive	0.107*** [0.00]	0.113*** [0.00]	0.094** [0.02]	0.108*** [0.00]	0.099*** [0.01]	0.126*** [0.00]
Positive NP	0.033[0.32]	0.048* [0.07]	0.029[0.35]	0.028[0.36]	0.055* [0.07]	0.060* [0.06]
	Wald test[0.00]					

NP denotes the non-presidency period. Figures in brackets denote p-values.

*: p≤0.10; **: p≤0.05; ***: p≤0.01.

Table 12: ARMA-EGARCH estimates

(tweets in conditional volatility equation- Trump's presidency vs Trump's non-presidency periods)

Emotion	Oil (Brent)	Oil (WTI)	Bitcoin	Gold	Baltic Index	S&P500
Anger	0.092*** [0.00]	0.104*** [0.00]	0.116*** [0.00]	0.131*** [0.00]	0.119*** [0.00]	0.134*** [0.00]
Anger NP	0.027[0.28]	0.049* [0.08]	0.031[0.15]	0.033[0.14]	0.048* [0.08]	0.064* [0.06]
	Wald test[0.00]					
Joy	-0.097*** [0.00]	-0.105*** [0.00]	-0.091*** [0.01]	-0.098*** [0.00]	-0.105*** [0.00]	-0.137*** [0.00]
Joy NP	-0.022[0.30]	-0.041* [0.09]	-0.024[0.28]	-0.028[0.25]	-0.040* [0.08]	-0.059* [0.07]
	Wald test[0.00]					
Optimism	-0.092*** [0.00]	-0.088*** [0.00]	-0.082*** [0.01]	-0.113*** [0.00]	-0.097*** [0.00]	-0.120*** [0.00]
Optimism NP	-0.025[0.28]	-0.043* [0.09]	-0.031[0.26]	-0.026[0.28]	-0.042* [0.08]	-0.055* [0.07]
	Wald test[0.00]					

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Sadness	0.116***[0.00]	0.115***[0.00]	0.108***[0.00]	0.129***[0.00]	0.119***[0.00]	0.134***[0.00]
Sadness NP	0.029[0.26]	0.039*[0.10]	-0.026[0.29]	0.034[0.15]	0.045*[0.08]	0.060*[0.06]
	Wald test[0.01]					
Hate	0.138***[0.00]	0.139***[0.00]	0.119***[0.00]	0.138***[0.00]	0.134***[0.00]	0.144***[0.00]
Hate NP	0.023[0.28]	0.045*[0.08]	0.022[0.29]	0.026[0.24]	0.048*[0.08]	0.066*[0.06]
	Wald test[0.00]					
Irony	0.140***[0.00]	0.145***[0.00]	0.125***[0.00]	0.142***[0.00]	0.141***[0.00]	0.148***[0.00]
Irony NP	0.035[0.21]	0.046*[0.08]	0.024[0.33]	0.022[0.34]	0.049*[0.08]	0.059*[0.07]
	Wald test[0.01]					
Offensive	0.146***[0.00]	0.153***[0.00]	0.136***[0.00]	0.149***[0.00]	0.147***[0.00]	0.155***[0.00]
Offensive NP	0.027[0.29]	0.043*[0.09]	0.020[0.34]	0.025[0.30]	0.057*[0.07]	0.066*[0.06]
	Wald test[0.01]					
Negative	0.155***[0.00]	0.159***[0.00]	0.148***[0.00]	0.157***[0.00]	0.156***[0.01]	0.163***[0.00]
Negative NP	0.019[0.40]	0.045*[0.08]	0.021[0.36]	0.026[0.30]	0.058*[0.07]	0.069*[0.06]
	Wald test[0.00]					
Neutral	0.036[0.30]	0.052[0.26]	0.047[0.27]	0.051[0.26]	0.055[0.24]	0.048[0.27]
Neutral NP	0.006[0.55]	0.012[0.46]	0.003[0.59]	0.000[0.67]	0.010[0.51]	0.014[0.47]
	Wald test[0.01]					
Positive	-0.091**[0.02]	-0.102***[0.00]	-0.095***[0.01]	-0.114***[0.00]	-0.094**[0.02]	-0.129***[0.00]
Positive NP	-0.033[0.18]	-0.042*[0.08]	-0.022[0.28]	-0.028[0.25]	-0.046*[0.08]	-0.062*[0.06]
	Wald test[0.00]					

NP denotes the non-presidency period. Figures in brackets denote p-values.

*: p≤0.10; **: p≤0.05; ***: p≤0.01.

CONCLUSION

This study investigated the effects of former President Trump's tweets on a set of assets including the capital market (S&P500), commodities (Brent oil, WTI crude oil, gold), cryptocurrencies (Bitcoin), as well as the Baltic Dry Index. It added to the existing literature regarding the sentiment formation theory and the impact of social media on finance and market sentiment.

Prominent among our approach was the fact that we employed the RoBERTa application; that is, one of the most significant transfer learning models in the field of Natural Language Processing (NLP) to distinguish between different types of emotions conveyed via tweets. More particularly, it considered the following broader emotional categories: 1) emotion (anger, joy, optimism, sadness), 2) hate-speech (no hate-speech, hate-speech), 3) irony (no irony, irony), 4) offensive speech (not offensive, offensive), and 5) sentiment (negative, neutral, positive).

It then applied the econometric methodology which was predicted upon GARCH-family models. The main findings suggested that President Trump's tweets during his first presidency had a significant impact on both the returns and the volatility of the assets included in the study. It also found that tweets that bore positive emotions had a positive impact on asset returns and a negative impact on asset volatility (i.e., volatility declined). It also highlighted that tweets that bore negative emotions had the exact opposite effect as far as both returns and volatility were

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concerned. The gamma coefficient that was obtained from the ARMA-EGARCH-X model further indicated that positive tweets affected the assets of our study less as opposed to negative tweets. Finally, the findings retained their consistency after considering certain robustness checks, such as the inclusion of traditional social information, such as the New York Times newspaper tweets and the period before Trump's presidency.

The empirical findings confirm the significance of the tweets of powerful figures on the mean and the volatility components of financial markets. Within the domain of asset pricing research, the results point to the special compensation by investors for bearing extra risk. Consequently, this paper calls attention to tweet information released by influential political, or business figures in real-world investments. Venues for further inquiry might include comparisons among politicians who have adopted social media platforms as one of their main communication channels. Considering the impact of social media platforms on international currencies and, hence, on international trade, might also be a relevant way to take research further in this field.

Potential limitations are related to the absence and the comparison of a similar analysis with other presidents, as well as a more extended sample of asset prices, such as housing prices. Nevertheless, such limitations open up new venues for further future research.

Declaration of interests

The authors have no conflict of interest to declare

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