The Effects of Trump’s Tweets on Daily Financial Volatility

Team Raina

Objective

The unprecedented use of Twitter by President Donald Trump has had significant social and political effects since the beginning of his presidential campaign. JP Morgan even created the Volfefe index to quantify his tweets’ growing effects on U.S. bond yields. As an extension, this project explores the impact of his tweets’ daily sentiment volatility on the volatility of a range of financial series, mostly focusing on economic indices, tech stocks, and exchange rates. Along the way, we also conduct exploratory analyses that yield interesting insights as possible grounds for further investigation.

Fundamental Analyses

Prior to regression analyses, fundamental analyses are conducted on cleaned the texts to understand the characteristics of the tweets and identify constantly tweeted terms versus those tweeted in specific months. TFIDF Vectorizer is utilized to only extract relevant terms and the 5 most common n-grams for each month. As seen in Figure 1, topics like ‘fake news’ and ‘witch hunt’ prevail throughout the year. Some interesting and month-specific n-grams are ‘mueller report’, ‘north korea’, and ‘crooked Hilary’. Such an analysis is useful when identifying where Trump’s attention lies each month.

```
(1,
 [('fake news', 35),
  ('border security', 29),
  ('southern border', 29),
  ('united states', 18),
  ('white house', 17)]),
(2,
 [('border security', 15),
  ('united states', 15),
  ('fake news', 15),
  ('north korea', 13),
  ('kim jong', 10)]),
(3,
 [('fake news', 28),
  ('crooked hillary', 14),
  ('witch hunt', 14),
  ('north korea', 13),
  ('united states', 12)]),
(4,
 [('fake news', 29),
  ('united states', 28),
  ('mueller report', 20),
  ('southern border', 18),
  ('new york', 17)]),
(5,
 [('united states', 36),
  ('witch hunt', 35),
  ('fake news', 31),
  ('north korea', 25),
  ('billion dollars', 24)]),
(6,
 [('fake news', 49),
  ('witch hunt', 40),
  ('united states', 38),
  ('news media', 24),
  ('north korea', 22)]),
(7,
 [('fake news', 53),
  ('united states', 49),
  ('witch hunt', 41),
  ('news media', 24),
  ('fake news media', 23)]),
(8,
 [('fake news', 61),
  ('united states', 35),
  ('witch hunt', 26),
  ('america great', 24),
  ('hillary clinton', 22)]),
(9,
 [('fake news', 45),
  ('north carolina', 32),
  ('president trump', 29),
  ('witch hunt', 27),
  ('new york', 24)]),
(10,
 [('united states', 44),
  ('fake news', 40),
  ('witch hunt', 31),
  ('adam schiff', 27),
  ('nancy pelosi', 22)]),
(11,
 [('united states', 30),
  ('tax cuts', 23),
  ('fake news', 23),
  ('crooked hillary', 12),
  ('america great', 12)]),
(12,
 [('fake news', 40),
  ('border security', 34),
  ('united states', 20),
  ('america great', 20),
  ('witch hunt', 18)])]
```

Figure 1. N-grams For Each Month

Methodology

Independent Variable: Twitter Sentiment Volatility

The data for calculating daily sentiment volatility is scraped from the Trump Twitter Archive using Selenium. After obtaining 9855 tweets dated from November 1st, 2017 to October 21, 2019, we exclude Retweets and URLs using Regex and derive an aggregate positive and negative sentiment for each tweet based on the established NRC Emotional Lexicon. Initially, we tried to clean and normalize the texts as much as possible; however, such a conservative approach is proven to be unnecessarily limiting the quality of the post-processed texts, therefore not providing meaningful insights. Next, for all tweets on a given day, we calculate the volatility of positive and negative sentiments to obtain our regressors. We take each day as previous day 16:30 EST - current day 16:30 EST to ensure that the day in question is more consistent with trading hours. The sentiment volatility for each day is calculated using the following formula:

$$\sqrt{\frac{\sum\ (Positive\ (Negative)\ Sentiment - Average\ Positive\ (Negative)\ Sentiment)^{2}}{Number\ of\ Tweets}}$$

Dependent Variables: Financial Volatility

Our dependent variables come from querying Yahoo Finance API, through which we obtain economic indices (S&P 500, NASDAQ, DJI, Shanghai Composite, Hang Seng Index), 13-week T-Bill, tech stocks (Amazon, Apple, Facebook, Google, Tesla, Intel), Dow Jones Commodity Index, and exchange rates (US-CNY, GBP, JPY). For each financial series, we calculate daily volatility and exclude 99.9% quantile outliers so the outliers do not skew our regression estimates.

Regression Analysis

Next, we run OLS regression using **statsmodels.api** to derive coefficient estimates for the equation $Y = a + bX_1 + cX_2$, where the dependent variable is financial volatility for a specific financial series and the independent variables are positive and negative sentiment volatilities, respective. Our observations are daily for a span of two years, excluding null values.

	pos_coef	neg_coef	rsquared	pos_tval	neg_tval
SP500	34.080404	34.436983	0.617805	6.953976	5.250529
NASDAQ	113.752212	108.638912	0.649142	7.615416	5.434613
DJI	298.947634	329.744531	0.603572	6.497173	5.354962
SSEC	41.203710	79.919859	0.580913	4.610071	6.681523
HSI	308.412677	744.528774	0.569975	3.926131	7.082124
TB13w	0.020319	0.039784	0.525276	4.095453	5.991939
AMZN	38.520422	36.742125	0.614602	7.073852	5.041719
AAPL	4.397529	3.497026	0.679504	8.742729	5.195012
INTC	0.929475	1.201926	0.713749	7.718272	7.457777
GOOG	24.086712	19.958208	0.706565	9.179054	5.683180
FB	3.341800	5.227988	0.711900	6.962837	8.139352
DJCI	5.318423	5.492244	0.697561	8.230198	6.350775
USDCNY	0.022697	0.030768	0.633481	6.277064	6.358220
GBPUSD	0.012014	0.017636	0.673908	6.588192	7.226450
USDJPY	0.907324	0.716359	0.659544	8.378537	4.942949
TSLA	7.993243	12.620015	0.629492	5.744780	6.777347

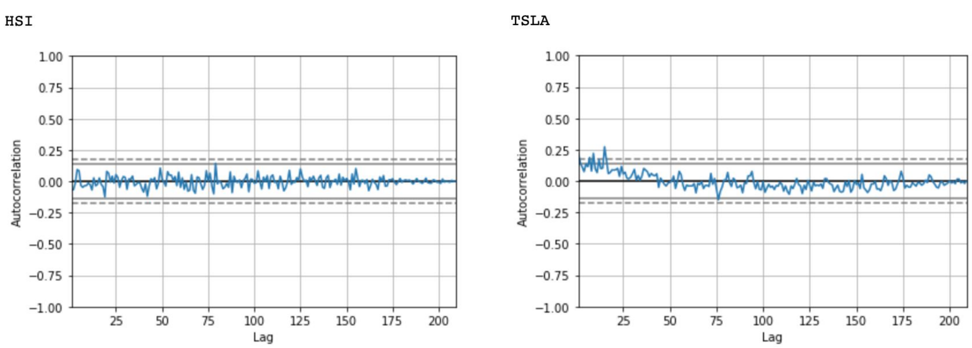
Figure 2. OLS Regression Result

Variable	ADF Statistic	p-value
Vol_Pos	-14.405807	8.361590e-27
Vol_Neg	-10.093067	1.109016e-17
SP500	-5.966517	1.981838e-07
NASDAQ	-5.125389	1.246134e-05
DJI	-4.690119	8.782378e-05
SSEC	-3.347534	1.288288e-02
HSI	-15.439929	2.873986e-28
TB13w	-7.280996	1.500557e-10
AMZN	-6.337651	2.804828e-08
AAPL	-7.613404	2.224206e-11
INTC	-5.857000	3.481172e-07
GOOG	-11.133000	3.246893e-20
FB	-13.414503	4.308677e-25
DJCI	-11.888448	5.946456e-22
USDCNY	-5.446066	2.708862e-06
GBPUSD	-2.629593	8.703388e-02
USDJPY	-4.110106	9.319348e-04
TSLA	-2.142393	2.278132e-01

Figure 3. ADF Test Result

Figure 2 shows regression results with the corresponding t-statistics and p-values. For all our financial series, we reject the null hypothesis of no effect of sentiment volatility on financial volatility at the 99% confidence level. To investigate the statistical soundness of our time-series regression, we also conduct an Augmented Dickey-Fuller (ADF) test using **statsmodels.tsa.stattools.** This is to test whether our time series of volatilities are random walks, which might bring about a case of spurious regression, causing us to incorrectly reject the null. *Figure 3* presents the results of the ADF test, where we reject the null of a random walk for all variables except GBPUSD and TSLA. In fact, the currencies on a whole exhibit weaker confidence in rejecting the null of a random walk. A further point of exploration might be to see if there are signs of volatility persistent in currencies relative to other financial assets.

One interesting anomaly is the volatility of Tesla. Our ADF test implies that we cannot reject the null of a random walk of Tesla; this becomes especially evident as we plot the autocorrelation plots for S&P500 and Tesla's volatilities as presented in *Figure 4*. The diagrams imply that, unlike HSI volatility, the recent lags of Tesla volatility are statistically significant predictors of instantaneous volatility, a particularly intriguing phenomenon that warrants further investigation. However, it is also not entirely surprising given the unique nature of Tesla as seen in events over the past year.



Significance Level	Critical Values
1%	-3.462
5%	-2.876
10%	-2.574

Figure 4. Autocorrelation Plots (HSI vs TSLA)

Further Analyses

1. **Complexity Analysis: Which Tweets Are Actually Trump's?**
   To augment our analysis, we attempted to figure out which tweets were originally written by Trump himself, as there exist reports that his social media director also has access to his account. We conduct a difference-in-means test to show that, on average, his tweets contain more words on average on Sundays and Mondays, as well as between the early hours of 5am-7am. We then segment the tweets along with these day and hour groups and conduct a text complexity analysis using the ratio of unique words (vocabulary) to number of words as a proxy. It seems to suggest that Trump's tweets in the early morning show a distinctly lower level of vocabulary complexity.

	Vocab	Avg word length	Avg sent length	ratio of Vocab to number of words
Sun/Mo	6508	4	17	0.087696
Other Days	9943	4	17	0.060489

	Vocab	Avg word length	Avg sent length	ratio of Vocab to number of words
5am-7am	6091	4	17	0.083313
Other Hours	3156	4	16	0.167214

Figure 5. Complexity Analysis according to day and hour subsets

2. **Stocks Are Most Volatile on Wednesdays**
   Another interesting sub-study was to see if there were trends in which days had the most volatility in stock prices. Interestingly, as *Figure 6* shows, the US market indices and major tech stocks had Wednesday (Day=2) as the most volatile day, contrary to what financial theory might predict.

3. **Name-Entity Detection**
   We also conducted named-entity detection and affection scoring for Trump's tweets. After identifying the 'persons' within each tweet, we ranked each the 'persons' based on the extent of negative/positive affect scoring for the corresponding tweet to get an idea of which 'persons' were associated with the most extreme sentiment as expressed in Trump's tweets. This provides us with a proxy as to which issues were most pressing for Trump, and we depict the evolution of pertinent issues across the months in 2019. An example of the most negative name-entity is displayed below (*Figure 7*), and more for negative and positive pairs for each month are included in the Jupyter notebook.

	Variable	most_vol	_	_	_	_	least_vol
0	SP500	2	3	4	1	0	-
1	NASDAQ	2	4	3	1	0	-
2	DJI	2	3	4	1	0	-
3	SSEC	0	3	2	1	4	6
4	HSI	1	2	3	0	4	6
5	TB13w	4	3	0	2	1	-
6	AMZN	2	1	4	3	0	-
7	AAPL	1	2	3	4	0	-
8	INTC	3	2	4	0	1	-
9	GOOG	2	1	0	4	3	-
10	FB	2	0	1	3	4	-
11	DJCI	2	3	0	4	1	-
12	USDCNY	2	6	3	1	0	4
13	GBPUSD	1	4	3	2	0	6
14	USDJPY	2	3	4	0	1	6
15	TSLA	4	0	3	2	1	-

Figure 6. Most to Least Volatile Day Per Indicator

```
[['Barack Obama', -0.8555],
 ['Dangerous', -0.8044333333333333],
 ['Corrupt Adam Schiff Congressman Michael McCaul', -0.7506],
 ['Failing Campaign', -0.6996],
 ['James Clapper', -0.6908],
 ['Green Beret', -0.6597],
 ['Angela Merkel', -0.6249],
 ['Katie', -0.6249],
 ['Got Early Account', -0.6239],
 ['Volodymyr Zelensky', -0.6239],
 ['Impeach Schiff', -0.6239],
 ['Shifty Adam Schiff', -0.60934],
 ['Devin Nunez', -0.5984],
 ['Bad', -0.5615916666666666],
 ['Treason', -0.55765],
 ['Trump Fundraising Haul Shows Impeachment Backfiring', -0.5267],
 ['Uber Left Elizabeth Warren', -0.4939],
 ['Kellyanne Conway', -0.4767],
 ['Steve Mnuchin', -0.4767],
 ['Hunter Biden', -0.475325]]
```

Figure 7. Most Negative Name-Entity (Most Recent Month)

4. Dispersion Plot

The preceding analysis was then complemented by a lexicon dispersion plot which traced the frequency distribution of particular words across the 2 years. As expected, we see parallel clusters of frequency for word groups such as {impeach, schiff, biden}, {korea, kim} and, most recently, {turkey, syria}. We also observe interest trends such as how frequency distribution serves as a proxy for how much he views a particular democratic candidate as a viable threat, and also his decreasing emphasis on issues such as 'tax', plausibly due to its unattractiveness as a topic for the 2020 election.

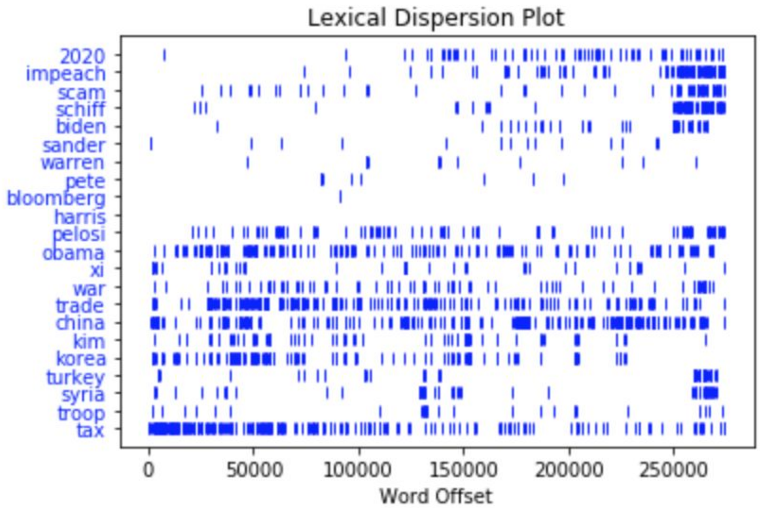


Figure 8. Dispersion Plot