

Digital Expression Under Financial Risk

Joshua Midha

West Windsor Plainsboro High School South

Abstract

This paper dives into what financial factors provoke social media expression. The term expression, in this paper, is being defined as the act of sharing relevant information regarding a set topic. By estimating facets such as the correlation between risk and communication, we find social media expression about investments correlates to volatility in the financial markets. It is evident from decades of research in loss aversion and prospect theory that human reaction to price change triggers heuristics and biases. It has also been proven that social media heavily alters basic human behavior such as emotional expression in users. Financial decision making, political perception and other factors which are dependent on outside characteristics are altered on social media. With the prevalence of outside nudges, heuristics, and biases plaguing the digital age, it is essential to understand how social media behavior is affected by financial, ethical, and cultural factors. In essence, this study compares different financial measures to the amount of Tweets (measure of social media expression) regarding a set subject.

Keywords: Tweets, Behavioral Finance, Expression, Risk

Introduction:

With social media's ubiquity in our society, we see the effects on behavior (Kumar 2016). A couple key factors seen in social media user's decision making factors involve a higher exposure to biases, more data but less informed decisions, and distractions. These aspects of behavior carry over to an investor's decision making processes. In the last few years, the average age of investors is also heavily decreasing, slowly moving towards a generation raised on social media. (Arifuzzaman 2014). The faster we can understand social media behavior, the more opportunities we have to use it to our advantage.

The impact of stock price volatility on investor behavior has been evident since the late 1990s (Oslen 1998). Past research in the fields of uncertain financial decision making or risky financial decisions have highlighted tremendous progress for helping investors make better decisions (Shiller 1990). Building up from Richard Olsen's initial investigation that volatility leads to more risk in decision making, this paper links digital behavior to financial activity. More so, speculative behavior based on uncertain prices and high variance is a topic which this paper aims to decipher.

There have also been recent uncoverings that highlight the change in financial behavior caused by social media and the dawn of the digital age as a whole (Ge 2010). An infamous study conducted by Bollen et al and corrected by Lachanski et al, highlighted how Twitter's community mood predicted the stock market (Bollen 2010) (Lachanski and Pav 2016). The

value of information is different and so is the mere perception of it. Unlike other studies, this study aims to ignore sentiment. Though mood is an important figure to consider, this study simply highlights numerical expression: Tweets. By understanding community action without sentiment, it opens a lot more leeway for conceptualizing multiple users' reaction to stock market changes. This study provides an opportunity to get a better understanding of why and when a user presses the "Tweet" button.

Testing Methodology:

The research design of this process is split into 3 main parts. The Tweets, the Stocks, and the Measures. The Tweets were calculated in 3 trials using a program described later on in this section. Each trial yielded different results, thus the mean of all 3 trials was taken for a final figure. Second, for the Stocks; there were 4 stocks analyzed throughout this paper; \$TSLA, \$GMC, \$AMC, \$AAPL. These stocks were carefully selected as to their history. \$AAPL is one of the most consistent stocks which is still active in the media (Kunnathur 2017). Thus, the usage of this would act as a control in comparison to the other, more volatile stocks. Next up I had \$AMC and \$GME, both became infamous for the WallStreetBets short squeeze of Jan 2021. These filled social media and were trending on Twitter for weeks straight (Twitter 2021). The measure of these already popular stocks which were riding on high variance throughout these calculations. The last stock, \$TSLA, was being used due to its social media presence. Tesla's dominance over social media has been only growing for the last year, and their stock is reflective of that (Tiwari 2017). These 4 stocks are representative of the popular markets seen with the newer generation of traders; the same generation which is constantly expressing themselves on social media (Arifuzzaman 2014). In the stocks themselves, I analyzed and calculated the measures/Tweets for each of them 4 times each. For example, for Tesla, I calculated all factors (Tweets, Volume, Volatility, etc) at 1/28/21 from 13:00-15:00; 1/27/21 from 12:00-14:00; 2/1/21 from 15:00-17:00; and 9/2/2021 from 14:00-16:00. The purpose of calculating 4 times was to have further consistency within the results. In the charts, 4 dates for each stock are analyzed. During each of those 4 dates, 3 trials for the Tweets were conducted and the average was used for further calculations and graphing.

As for calculating the stock-price measures; all data regarding the stocks analyzed were collected from TradingView, which is a platform for traders and investors to share live/full featured charts on Stock, Futures, and Forex analyses. The date, price change, mean historical volatility (MHV, calculated in %), volume, and times were then collected. To scale down data, I divided the average amount of Tweets by the volume of the stock and did the same for MHV. I dubbed the mean tweets over volume as the "Tweet Ratio". And referred to the MHV/Volume as MHV/Vol. To calculate MHV (X_m), this paper used the provided formula: $(X_1+X_2)/2=X_m$. X_1 represents the historic volatility at the start time, and X_2 is the historic volatility at the end time. Once I had (X_m), I divided it over the volume to get our MHV/Vol. The Tweet Ratio, a measure to scale down the amount of Tweets by dividing it by the volume at the time, was also calculated in a similar process. After running the aforementioned script three times, and collecting data for every individual trial, the mean of the trials was calculated and utilized for the ratio. The equation for the mean tweets was as follows (Y =amount of Tweets in a trial); $(Y_1+Y_2+Y_3)/3=Y_m$ Once the mean tweets were calculated using Excel, I scaled down to calculate the Tweet Ratio by dividing (Y_m) by the Volume.

All graphs and data were organized, analyzed, and created using R Studio. I calculated all tweets, stock factors, and processes in a 2-hour interval. For example, I calculated the number of tweets for “\$BFT” in 2 hours.

This paper utilizes the Tweepy API and a basic Python code written below to count the number of Tweets on a Twitter page during a specified time. To gather insights about the reaction to stock price changes, I made a parameter on the Twitter search filter to state a “\$” followed by the ticker symbol (i.e; \$PLTR). This narrows the product down to time (D, H, M, S), the name of the search query, and the total count. All times are in UTC (per the platform used to calculate stock-price measures). Additionally, the Tweepy API interval was maintained to 15 minutes by using the Basic Twitter Developer packages which did not use 500,000/month limitations.

```
import tweepy
import datetime
import time

twitter_keys = {
    'consumer_key': 'xxxxxx',
    'consumer_secret': 'xxxxxxxx',
    'access_token_key': 'xxxxxxxxxx',
    'access_token_secret': 'xxxxxxxxxx'
}

auth = tweepy.OAuthHandler(twitter_keys['consumer_key'], twitter_keys['consumer_secret'])
auth.set_access_token(twitter_keys['access_token_key'], twitter_keys['access_token_secret'])

api = tweepy.API(auth)

start_date = datetime.datetime(Year, Mon, Day, Hour, Min, Sec)
end_date = datetime.datetime(Year, Mon, Day, Hour, Min, Sec)

search_string = "$tickersymbol"

tweet_count = 0

current_results = []

from tweepy import Cursor

pages = Cursor(api.search,
               q=search_string,
               result_type="recent",
               "get_total_items.py" 56L, 1630C
```

Result:

Our first analyzed ticker was GameStop. The 4 selected dates were hand picked to represent major gains and drops in the stock’s history. Also, considering a lot of the aforementioned reasoning behind the picking of these was the short squeeze, the volatility was taken into account beforehand. For example, \$GME on 1/28/21 from 12:00-14:00 was selected due to the aftermath of the short squeeze, which increased the volatility of the stock. Where as 1/25/2021 from 14:00-16:00 was taken since it was before the squeeze itself. This would highlight the

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moments leading up to the squeeze. The table below includes all the information collected on the stock other than the Tweet Ratio, and MHV/Vol. See Table 1:

Name/Date	Price Change	Start Time	End Time	Volume	MHV	AVG TWEETS
1/28/2021	-\$247.52	12:00	14:00	58815800	423.025	20,288.33
1/27/2021	\$176.49	13:00	15:00	93396700	278.785	24,348.67
1/25/2021	\$60.72	14:00	16:00	177874000	318.87	38,132.33
1/28/2021	-\$168.76	14:30	16:30	58815800	532.66	70,405.33

Table 1

After running the script to return the average tweets from the 3 trials for the dates and times, I calculated the Tweet Ratio and the MHV/Vol. Here is where the pattern began; after plotting the MHV/Vol in comparison to the Tweet Ratio as (x,y) coordinates on R Studio, I saw the Tweet Ratio rise with the MHV/Vol. See Table 2 for data and Figure 1.1 for graph.

Name/Date	MHV/Vol	Tweet Ratio
1/28/2021	7.19E-06	3.45E-04
1/27/2021	2.98E-06	2.61E-04
1/25/2021	1.79E-06	2.14E-04
1/28/2021	9.06E-06	1.20E-03

Table 2

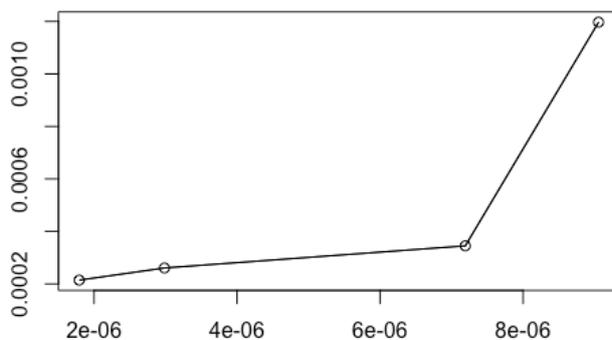


Figure 1.1

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After observing the previous pattern, I went on to analyze the second ticker: \$AMC. This stock accompanied GameStop during the short squeeze so I wanted to make sure that the instance with GME was not an abnormality. Below are the labeled tables. Table 3 shows the measured increments.

Name/Date	Price Change	Start Time	End Time	Volume	MHV	AVG TWEETS
1/27/2021	\$17.59	12:00	14:00	2174000	190.595	61671.66667
1/28/2021	-\$6.83	12:00	14:00	537000	279.57	74322.33333
2/1/2021	-\$2.34	14:00	16:00	3096000	92.61	85543
1/27/2021	\$5.87	17:00	19:00	2071000	440.01	93965.33333

Table 3

I then went on to carry through with the calculations for MHV/Vol and Tweet Ratio as shown in the following table (Table 4). I also plotted the results in a similar (x,y) fashion, and yielded the same results (Figure 1.2).

Name/Date	MHV/Vol	Tweet Ratio
1/27/2021	8.77E-05	2.84E-02
1/28/2021	5.21E-04	1.38E-01
2/1/2021	2.99E-05	2.76E-02
1/27/2021	2.12E-04	4.54E-02

Table 4

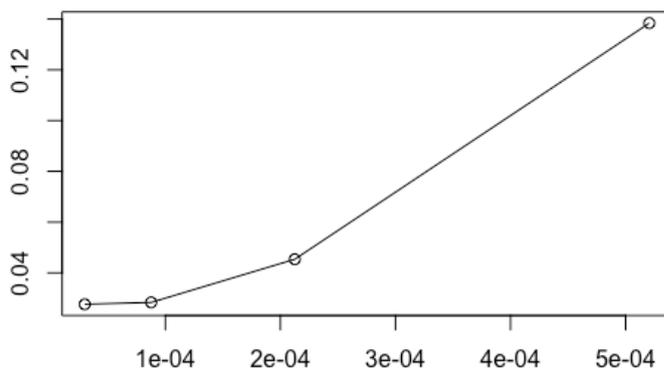


Figure 1.2

To ensure these results were not only fit to the stocks involved with the short squeeze, I analyzed a popular stock which was barely affected by the WallStreetBets situation. I followed \$AAPL using the same techniques as the previous example. The 4 selected dates in this case were 3 mainly acting as measures of consistency. Thus $\frac{3}{4}$ had a relatively minimal price change

and lower volatility. But September 2, 2020 was used as a measure to see how a Tweet regarding a consistent stock at a high volatility would differ. Measured increment are shown in Table 5.

Name/Date	Price Change	Start Time	End Time	Volume	MHV	AVG TWEETS
9/2/2020	-\$13.78	13:00	15:00	1862000	18.3	18,255.33
12/22/2020	\$2.40	12:00	14:00	2520000	10.005	18,167.33
1/4/2021	-\$3.22	14:00	16:00	1099000	14.09	17,993.33
1/25/2021	\$4.27	13:00	15:00	1695000	15.93	18,110.33

Table 5

Like I conducted with past examples, I went on to plot in (x,y) format and saw a very similar result. Despite having a lower volatility as compared to the other stocks, the Tweets were proportional (shown in Table 6 and Figure 1.3). Also, though the Sep 2 results were not drastic, they followed a similar pattern of growth. We see an increase in the amount of tweets with an increase in MHV, but the amount increased is exponentially larger as MHV grows.

Name/Date	MHV/Vol	Tweet Ratio
9/2/2020	9.83E-06	9.80E-03
12/22/2020	3.97E-06	7.21E-03
1/4/2021	1.28E-05	1.64E-02
1/25/2021	9.40E-06	1.07E-02

Table 6

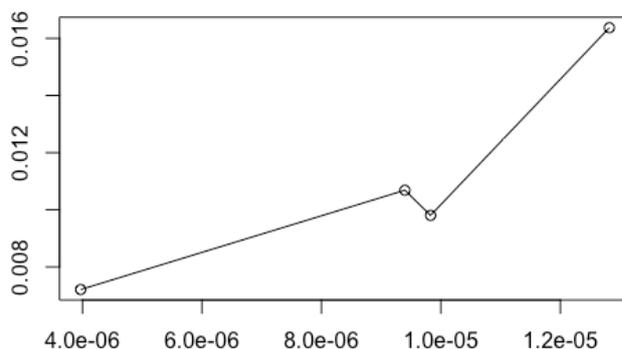


Figure 1.3

Finally, I measured a popular stock who not only holds a very prevalent social media presence, but also has been one of the most volatile S&P 500 stocks this year. \$TSLA dominates Twitter so I wanted to see how the amount of Tweets for this giant differ during different volatility levels. Our measured increments are in Table 7 below.

Name/Date	Price Change	Start Time	End Time	Volume	MHV	AVG TWEETS
3/10/2021	-\$38.10	15:00	17:00	198000	29.9	80485.66667
3/5/2021	-\$49.62	14:00	16:00	101700	33.41	66656
3/1/2021	\$16.72	13:30	15:30	89400	15.76	44799.66667
2/10/2021	-\$27.85	14:00	16:00	107708	9.3	40938.66667

Table 7

I then ran the previously used (x,y) plotting format and MHV/Vol with Tweet Ratio calculations as highlighted in Table 8 and Figure 1.4. Following the patterns recognized in the past stocks, the Tweet Ratio grew with the MHV/Vol as shown in the graph.

Name/Date	MHV/Vol	Tweet Ratio
3/10/2021	0.00015101	0.40649327
3/5/2021	0.00032852	0.65541790
3/1/2021	0.00017629	0.50111484
2/10/2021	0.00008634	0.38008938

Table 8

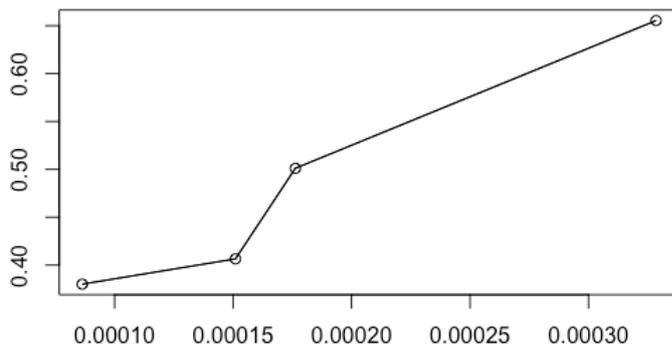


Figure 1.4

Conclusion:

The results found in this paper highlight how social media expression follows the volatility of a stock. In essence, users discuss a stock more when it is more volatile. The applications of this data to areas such as nudging, post intervals, Digi-age short squeezes, and several other profound platforms are endless. For example, with a large majority of investors using Twitter (along with other social media platforms like Discord, Reddit and TikTok) as a platform for discussion, overall Tweets will increase when a popular stock is volatile. If outlets which use Twitter to spread important information understand this, they can space out posting to low volatility periods in order to emphasize their Tweet. Or, this study may prove useful to Twitter

for handling the efficiency of their platform during periods where volatility for popular stocks is high (i.e; the surplus of Tweets during the WallStreetBets Short Squeeze in late January of 2021). The application of this study into nudging is even more advanced, behavioral economists can use these moments of Tweet surplus which lead to information overload to their advantage. Users are exposed to more information, thus giving more opportunities for potential nudges.

The main conclusion presented through the data highlights that as σ_1 (MHV/Vol) increases, σ_2 (Tweet Ratio) follows. This would show that as stock is more volatile and the higher variance is measured, the more likely people are to use social media to share about it. It has been evident in the past that basic human behaviors are altered in uncertain or anxious situations (Dutton & Aron 1974). Though volatility is not risk, it is the primary measure for risk in the short term (Lothian 2014). This study is representative of risk behavior in the digital age, and how communication is different during uncertainty.

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