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Donald Trump, investor attention and financial markets

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Abstract

Information attracts attention but attention is costly. Social media has been at the forefront of information dissipation due to the sheer number of users propagating information in a fast but cheap way. We look into one specific case where Donald Trump's tweets on companies have had an effect on retail investors whose only source of information is internet. We find that retail investor attention spikes as indicated by surge in Google Search Volume Index following Donald Trump's tweets, irrespective of the tone in the tweet. We also find that Trump's tweets result in retail investors selling off stock when retail investor attention is low: retail investors sell stocks, and institutional investors buy them at later date. Finally, we analyze the daily abnormal returns of the stocks following the tweets and find that attention and tone of the tweet are opposing factors when determining abnormal returns following the tweet.

Keywords: *Investor's attention; Twitter; Retail Investors; Trading; Google SVI; Donald Trump.*

1. Introduction

When information is released, it ought to be quickly incorporated into the asset prices in efficient markets. A necessary condition for this process is attention: only when investors pay attention, newly released information can be incorporated into the asset price. However, retail investors in particular can only give attention to a few stocks in the equity universe at a given point in time since attention is costly. Kahneman (1973) was the first to raise the issue of limited attention, and Barber and Odean (2008) discuss how ignoring “right” information and paying attention to “wrong” information leads to suboptimal choices.

Investor attention can be broadly divided into retail investor attention and institutional investor attention. Institutional investors have under their arsenal a vast channel of resources to investigate stocks (e.g., Ben-Rephael et al. (2017)). In contrast, this paper focuses on retail investor attention triggered through social media, and studies its effect on equity prices. Related studies use either indirect or direct proxies of retail investor attention. Indirect proxies include absolute 1-day returns (Barber and Odean (2008)), DOW highs (Yuan (2015)) , trading volume (Gervais et al. (2001)), advertising expenses (Grullon et al. (2004)), the frequency of newspaper articles on a stock (Fang and Peress (2009)) or the appearance of a company in the New York Times (Yuan (2015)). One challenge of indirect proxies is that it is difficult to argue causally. E.g., does high trading volume cause attention, or does attention cause high trading volume? To counter this, recent studies use direct proxies for attention. These include the number of times investors login to their trading account (Sicherman et al. (2016)), the activity of investors in a brokerage account data set (Gargano and Rossi (2018)), Google search volume (SVI, Drake et al. (2012) and Vozlyublennaia (2014)), abnormal Google search volume (ASVI, Da et al. (2011)), and the Baidu index (Zhang and Wang (2015)).

So, what triggers investor attention for a particular stock? There is general consensus that media are particularly responsible for triggering investor attention. Busse and Green (2002) show that investors pay attention to morning television programs, and trade accordingly later in the day. Gurun and Butler (2012) investigate the slant of local newspapers in U.S for the local firms to satisfy the local readers. Information via social media spreads very quickly and widely, which differentiates the medium from conventional dispersal methods. Among social media platforms, Twitter is arguably among the most successful. Not only traders and important investors regularly discuss ideas and stock picks. Also, companies which are more active on Twitter have lower information asymmetry (Blankespoor et al. (2014)).

Besides this firm-initiated information, the impact of prominent figures on social media seems to be very powerful. Anger and Kittl (2011) refer to people who possess this power as "super hubs, influencers or alpha users", representing a minority of users whose communication via Twitter reaches a widely spread and alert audiences. In this regard, the tweets of President of USA, Donald Trump plays a unique role. As of 25th February 2019, he has 58.6 million followers on Twitter. Apart from commenting on political events, President Trump also focuses on companies: Between December 2016 and January 2018, he submitted more than 50 tweets on various companies. The tone of these tweets ranges from quite harsh (Nordstrom) to extremely supportive and encouraging (Ford).

The important question then arises that how do the investors react to them? Do the tweets trigger investor attention, especially the retail investor attention? We answer these questions by using the ASVI as measure for attention. Any spike in ASVI will correspond to investor attention getting triggered. In Figure 1, we plot the average ASVI on the companies Donald Trump tweets. The x-axis denotes -15 to +15 days from the day of the tweet (0). The left panel gives the results for tweets with a negative tone, the right panel for tweets with a positive tone. We use the categories “All Categories” and “Financial Market” as our categories in Google Trend, and look for either the company name or the stock ticker. The main focus in our paper is the combination of “All Categories” and stock ticker, depicted in the blue dotted line. We find that Donald Trump’s tweets cause a significant spike in investor attention irrespective of the tone in the tweet. The attention level remains high for the day of the tweet and the following day. As expected, we find that negative tweets (left in Figure 1) create far higher attention than positive ones (right in Figure 1).

Once it is established Trump’s tweets have a strong effect on attention, we analyze subsequent trading behavior. Barber and Odean (2008) find that attention affects the retail investors more than the institutional investors. Also, it has greater impact in inducing the investors to buy rather than sell. Da et al. (2011) find that an increase in SVI leads to increased orders and trading volume by retail individual traders. In contrast, we only find an effect of negative tweets, which causes retail investors to sell off their holdings. This effect is stronger when attention prior to the tweet is already low, which is in line with Barber and Odean (2008). However, the effect we document is more long-lived and spreads out over several days. Finally, we look how the returns for the stock behave post the spike in attention and given the trading behavior of various market participants. Da et al. (2011) find that more internet search on the company lead to more upwards price pressure for the following 2 weeks.

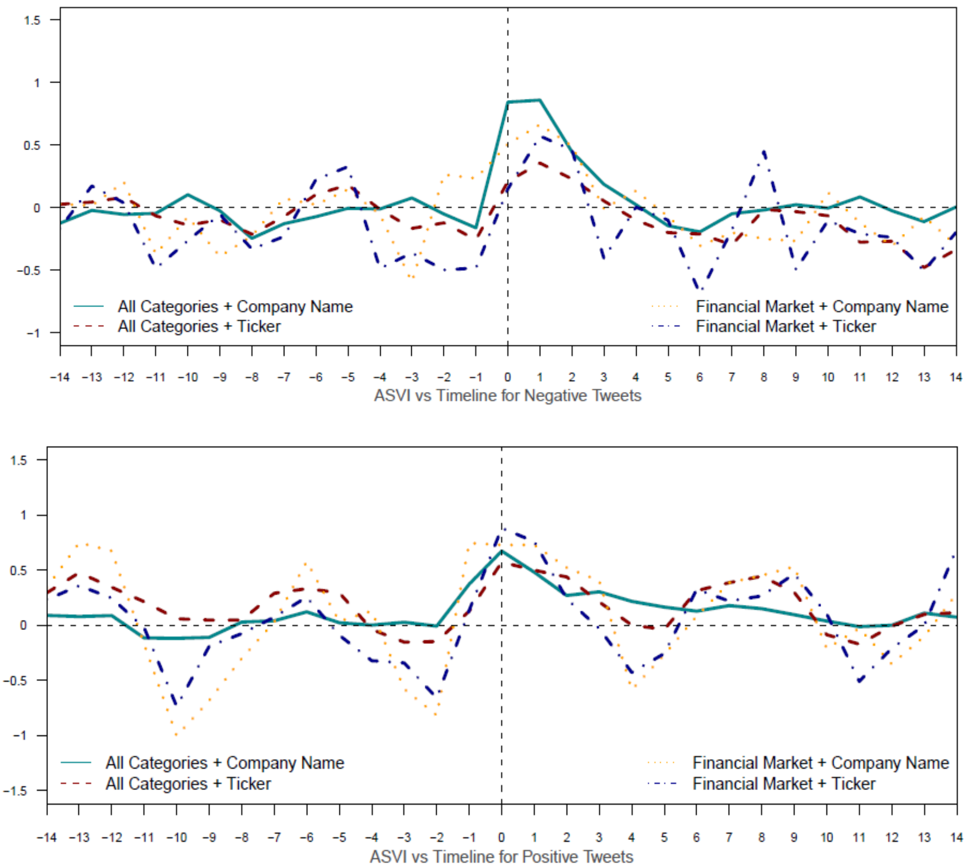

Figure 1. Average ASVI vs the days from Donald Trump's tweets.

Our study contributes to the existing literature in multiple ways. First, it studies the effect of social media on investor attention and the resulting trading behavior. Second, the paper provides evidence on the differential effect of tone on attention. Third, it provides guidance to retail investors on the detrimental wealth effects of herding due to non-fundamental information.

The rest of the paper is organized as follows. In section 2, we discuss the data sources and variables created from these sources, as well as the methodology. In section 3, we show that President Trump's tweets grab attention and lead to different trading reactions based on prior attention. We also describe the tweets' impact on stock returns. Finally, we conclude in Chapter 4.

2. Data and Research Design

We collect all messages of President Trump from Twitter between December 2016 and January 2018. We identify company-related tweets, and assign a positive or negative tone identifier (manually). This leaves us with 45 tweets, out of which 28 have a positive and 17 have a negative tone. Next, we collect the stock tickers of the companies on which the tweet was made, and Daily Google Search Volume for these tickers from Google Trends. Tick data comes from the NYSE Trade and Quote (TAQ) database via Wharton Research Data Services (WRDS). Daily price and volume data come from Thomson Reuters Datastream.

We first test whether there is a surge in attention following Donald Trump's tweets on the companies. We derive ASVI from SVI of the stock tickers as in Da et al. (2011):

$$ASVI_t = log(SVI_t) - log[Med(SVI_{t-1}, \dots, SVI_{t-56})]. \tag{1}$$

We then test the effect of tweets on attention through the following pooled regression model:

$$ASVI_{t,i} = \alpha + \beta * D_{t,i} + \gamma * CV_{t,i} + \varepsilon, \tag{2}$$

where $ASVI_{t,i}$ is the ASVI measure for the tweet on company i on day t after the tweet. $D_{t,i}$ is a dummy variable which takes on a value of 1 on the day t for the tweet for company i, and 0 otherwise. $CV_{t,i}$ are control variables and include log of market capitalization, number of analysts followed and dollar turnover of the stock. Second, we test for the impact of the tweet on buy-sell imbalance for different investor groups (retail and institutional). Buy-sell imbalance captures the buying or selling pressure for these groups, since a negative buy-sell imbalance suggests selling pressure by a particular class of investors. To measure this effect, we create a $Order_{t,i,j}$variable given by:

$$Order_{t,i,j} = \frac{B_{t,i,j} - S_{t,i,j}}{B_{t,i,j} + S_{t,i,j}} \tag{3}$$

$B_{t,i,j}(S_{t,i,j})$ is the buy (sell) initiated dollar volume for the company i on day t for the trader class j. We calculate the buy or sell initiated trade following the Lee and Ready (1991) algorithm. Referring to Lee and Radhakrishna (2000), we define our trader classes as small, medium, and large. We then test the effect of Trump's tweets on buy-sell imbalance via the following pooled regression model:

$$Order_{t,ij} = \alpha + \beta_1 * Order_{t-1,i,j} + \beta_2 * D_{t,i} + \varepsilon \tag{4}$$

where $Order_{t,i,j}$ is the buy-sell imbalance for day t , the tweet on company i and trader class j. $D_{t,i}$ is as in equation (2). Third, we look at abnormal daily stock returns. We calculate abnormal daily return as in Zhang et al. (2016), and estimate model (5) with abnormal returns via the following pooled regression model:

$$AR_{t,i} = \alpha + \beta_1 * D_{t,i} + \varepsilon \tag{5}$$

where $AR_{t,i}$ is the abnormal return for day t for the tweet on company i. We re-run the regressions separately for tweets with positive and negative tone. Also, to check the effect of attention, we additionally separate the data into top half and bottom half based on the attention the stock receives on the day of the tweet, and run separate regressions for the resulting sub-samples.

3. Results

We now look into the effect of the tweets on retail investors' attention.

3.1. Tweets and Attention

The regression analysis is done for the tweets as described in (2). As can be seen in Table 1, the coefficient for the day coefficient T0 (day of the tweet) and T1 (one day after the tweet) is positive and statistically significant in all cases. Hence, tweets increase attention for the stock. logMktCap, logTurnOver and logAnalysts are the log of market capitalization, dollar turnover and number of analysts followed for the stocks respectively.

Table 1: Dependent variable: ASVI "All categories" and stock tickers.

	All tone	Positive tone	Negative tone
T0	0.401***	0.327***	0.517***
T1	0.357***	0.339***	0.376**
T2	0.060	0.019	0.122
T3	0.034	0.032	0.016
T4	0.146	0.116	0.183
T5	0.079	0.085	0.054
logMktCap	-0.091***	-0.113***	-0.133***
logTurnover	0.058	0.013	0.169**
logAnalysts	-0.090	0.010	-0.295**
Observations	720	464	256
R2	0.069	0.065	0.129
Adjusted R2	0.057	0.047	0.097
Res. Std. Error	0.543 (df = 710)	0.539 (df = 454)	0.529 (df = 246)
F Statistic	5.859*** (df = 9; 710)	3.520*** (df = 9; 454)	4.039*** (df = 9; 246)

Note: *p<0.1; **p<0.05; ***p<0.01

This is in line with Drake et al. (2012) who find a surge in ASVI on the day of the event and post-event day. Comparing the differences between the columns, we observe that negative tweets have a 50% higher impact on attention than positive ones. Investors' attention is thus more drawn when the tone of the tweets is negative than when it is positive. The impact of the control variables is as expected: larger companies and those covered by more analysts are more transparent, resulting in overall lower search volume. High attention goes to those stocks for which investors might have to spend some effort, smaller ones followed by a small number of analysts. Turnover is positively associated with attention, but only for negative tweets.

3.2. Attention and Buy-Sell Imbalance

We now explore the impact of the tweets on buy-sell imbalance via the attention channel. We only focus on negative tweets, because the results are significant. We run the regression separately for all three trader types (small, medium, and large), and for tweets in high and low attention environments. We define a low attention environment by a below-median ASVI for the company on the day of the tweet (bottom), and a high attention environment by an above-median ASVI for the company on the day of the tweet (top). Table 2 shows the estimation results for equation (4). prevI1, prevI2 and prevI3 are the buy-sell imbalance for small, medium and large traders respectrively for 1 day before the tweet. T0 is the dummy variable which is 1 for the day of the tweet and 0 otherwise. T1 is the dummy variable which is 1 for the day of the tweet and 0 otherwise and so on.

Table 2: Dependent variable: Buy-Sell imbalance for different trader groups, following negative tweets.

	Small-Bottom	Medium-Bottom	Large-Bottom	Small-Top	Medium-Top	Large-Top
prevI1	0.575***			0.788***		
prevI2		0.361***			0.655***	
prevI3			-0.049			0.058
T0	-0.023	-0.035	0.144	-0.051	-0.066	-0.036
T1	-0.060*	-0.071	-0.070	-0.024	-0.021	-0.084
T2	-0.023	-0.019	-0.024	0.024	0.007	0.092
T3	-0.061*	-0.051	0.137	-0.024	0.001	0.071
T4	-0.016	0.046	0.113	-0.039	-0.027	-0.064
T5	0.031	-0.051	0.124	-0.030	0.010	0.136
T6	-0.091**	-0.022	0.440***	0.013	0.049	-0.032
T7	-0.071**	-0.104**	0.040	-0.031	-0.055	0.024
T8	0.025	-0.011	-0.004	0.031	0.067	-0.028
T9	-0.007	-0.012	0.555***	0.010	0.028	0.166
T10	-0.021	-0.032	0.121	-0.040	-0.014	-0.079

Note: *p<0.1; **p<0.05; ***p<0.01

For high attention stocks, buy-sell imbalance is not affected by tweets. This is interesting, since attention usually creates buying pressure. One possible explanation is the negative tone, which may counteract the attention-based buying pressure (Tetlock (2007)). However, when repeating the analysis for positive tweets, we do not find a positive impact either. In contrast, Table 2 shows that small and medium traders increase their selling pressure following the tweets in low attention environments. At the same time, there is buying pressure from institutional investors: large traders move in to buy the stock.

Turning towards the economic interpretation of the results of Table 2, we find that small traders sell off stocks of companies following a tweet, whereas large traders buy in (for negative tweets in a low-attention environment). This result is in line with Barber and Odean (2008), who find that retail traders sell and large traders buy stocks on low attention days. We observe a staggered introduction of this pattern: Large traders strategically defer their trades. Apparently, institutional investors trade more as a reaction to retail traders' behavior.

3.3. Attention and Daily Returns

Last, we analyze abnormal returns. We run regression with daily abnormal returns as our dependent variable and the dummy day variables as the independent variable. We focus on positive tweets first, and find a positive and significant abnormal return of around 0.2% for 2, 3 and 6 days post the tweet. As the market incorporates the tweets, investors start purchasing stocks. In contrast, negative news seems to have no price impact. As in Table 2, we separate the sample into a high and low attention environment subsample based on the ASVI on the day of the tweet. The results for the tweets are in Table 3 after running equation (5). The left panel gives the results for tweets with a negative tone, the right panel for tweets with a positive tone. T0 is the dummy variable which is 1 for the day of the tweet and 0 otherwise. T1 is the dummy variable which is

Table 3: Dependent variable: Daily Returns, following positive tweets.

	Negative Tweets			Positive Tweets	
	Top ASVI Tweets	Bottom ASVI Tweets		Top ASVI Tweets	Bottom ASVI Tweets
T0	0.003	0.0004	T0	-0.002	-0.001
T1	-0.0002	0.003*	T1	0.001	0.0003
T2	0.002	0.001	T2	0.003**	0.001
T3	-0.001	0.001	T3	0.003**	0.001
T4	0.0003	0.001	T4	0.003**	-0.002*
T5	0.001	0.001	T5	0.002*	0.0003
T6	0.003	-0.001	T6	0.001	0.002**
T7	-0.002	-0.001	T7	-0.001	0.0001
T8	0.001	0.001	T8	0.001	-0.0001
T9	-0.001	-0.001	T9	0.0004	-0.001
T10	0.001	-0.0003	T10	-0.001	-0.0002
Observations	128	128	Observations	224	224
R2	0.073	0.050	R2	0.102	0.047
Adjusted R2	-0.015	-0.040	Adjusted R2	0.055	-0.002
Res Std. Err. (df = 116)	0.005	0.004	Res. Std. Err (df = 212)	0.004	0.004
F Stat (df = 11; 116)	0.825	0.555	F Stat(df = 11; 212)	2.181**	0.960

Note: *p<0.1; **p<0.05; ***p<0.01

For the positive tweets, from 2 to 5 days after the tweet, stocks show an abnormal return of 0.2% to 0.3% in the high attention environment. For the low attention environment, we obtain a significant return of around -0.2% 4 days after the tweet, which reverses on day 6 post the tweet. Next we repeat the exercise for negative tweets. We only get a +0.3% abnormal return for the first day after the tweet in the low attention environment. There is no significant abnormal return for the high attention environment. This may be due to the offsetting effects of attention and tone: negative tone should result in a negative return (Tetlock (2007)), but high attention should result in positive returns (Barber and Odean (2008)). Both the phenomena seem to act in opposite to each other resulting in almost no change in the abnormal returns for the stocks.

4. Conclusion

Attention is costly and retail investors react differently once their attention is grabbed. In recent years, social media has played an important role in grabbing investor attention for stocks. News about a stock dissipate fast and cheap thus reaching a wide audience. In this regard, we check for a particular activity which is gathering investor attention through social media: Company-related tweets by President Trump. We find that his tweets cause a significant spike in attention on and directly after the day of the tweet. Tweets with a negative tone create 50% more attention than tweets with a positive tone.

We then analyze how different trader groups react to the trades. In line with the lower attention, positive tweets do not affect buy-sell imbalance. Negative tweets, however, result in retail investors selling off, and institutional investors buying in later days. The effect is stronger in low attention environments. Our study is the first to document this effect: the selling pressure created through the negative tone dominates the (hypothesized) buying pressure through increased attention. Institutional investors take advantage of this behavior by retail investors, and buy up the stocks that retail investors sell. As a result, retail investors lose out to institutional investors. It can be seen that while retail investors are selling during negative tweets, there is slight price rise on 1 day after the tweet and no fall after that. It is important therefore that retail investors maintain caution when President Trump tweets about a given company.

Similarly, for positive tweets, when checked through the window of attention for days following the tweet, high ASVI stocks show good abnormal returns whereas low ASVI positive tweet stocks show no significant abnormal returns. This is in line with existing literature that high attention results in abnormal returns. Negative tweets on a whole do not show any significant returns post the tweet. Thus it is important that the retail investors do not sell off their stocks post the tweet if there is negative news about a company because there is no significant fall in stock prices which happen after the tweet. It is also important to analyze as to why some stocks get higher attention than the others to make more incisive analysis.

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