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# A Longer-Term evaluation of Information releases by Influential market Agents and the Semi-strong market Efficiency

Pankaj Agrawal<sup>\*, §</sup> and Rajat Agarwal<sup>§</sup>  
(Pre-print version)

*This paper is an evaluation of long-term cumulative returns (CAR's) based on Twitter broadcasts by highly influential market agents. We look at the information content of Elon Musk, CEO of SpaceX, Tesla and Twitter Inc. and the former US President Donald Trump. The principal objectives of this research are twofold: 1.) To assess whether markets are semi-strong form efficient and consequentially whether or not returns can be derived from strategies based on such sporadic tweet releases (abstracting from 'news'). For this purpose, event studies are conducted on multiple companies which were targeted by Musk and Trump tweets. A control group of all Dow Jones companies with earnings releases on Twitter is utilized. We find there appears to be a "pre-post-Twitter-drift" when the release is by exceedingly influential market personalities. The cumulative abnormal returns remain significant over long durations. This indicates that markets are not entirely semi-strong form efficient regarding social media releases and that trading on such tweets may be profitable (even after factoring in varying market phases). 2.) The paper introduces a new theme: long term CAR's of market information events. The paper also notes whether the tweet was during regular market hours or after-market hours.*

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**Keywords:** market efficiency, semi-strong, investor sentiment, event study, CARs, Musk, Trump, overreaction, Twitter, Tweets, social media, extended trading hours, control, after-hours

**JEL Classification:** G41; G17; C10; C18; B41

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<sup>§</sup> This work is independent, any personal views and academic conclusions expressed are entirely those of the authors (driven by publicly available data) and do not reflect the views of any institution, including the authors' employers.

# A Longer-Term evaluation of Information releases by Influential market Agents and the Semi-strong market Efficiency

## 1 Introduction

Elon Musk, CEO of Tesla Inc. and former US President Donald Trump have demonstrated (Cano-Morin et al., 2023) that a social media platform such as Twitter can be a significant media and public relations platform. Their tweets (information posts) have often been market moving, albeit for a perceived short amount of time (Benedikt, Seigner, Milanov, Lundmark and Shepherd, 2023) and corporations have been using them to signal the quality of earnings releases (Tao, Zhang and Wang, 2023). Occasionally, President Trump had been even singling out specific companies and criticizing them for not conforming to his agenda. In such cases, investors had been taking a mostly defensive stance towards Trump-tweets and preparing measures for preventing losses to their portfolios. Asset management firms were “making sure someone, anyone, is awake in the middle of the night for fear that a Trump tweet could have negative effects” on their portfolio (Shubber, 2017). Tesla Inc. and Twitter Inc. (private as of 2022) investors know of the instantaneous price action that can be brought about by Musk’s twitter activity (Kraaijeveld and Smedt, 2020; Stokanovic et al., 2022).

While this makes tweets by such agents as Musk or Trump volatility inducing events (Huynh, 2021) and a threat to investors, they could also be possibly seen as *an alpha opportunity*. Specifically, Musk-tweets or Trump-tweets could be harnessed by investors as a potentially new source of public information (Heavy et al., 2020) and thereby be used as basis for trading strategies<sup>1</sup>. Zinoviev et al. (2023) research the so called “Musk effect” that “significantly impact(s) Wall Street,” in their work they form a unique fourteen cluster of influence zones based on quantifying over 9.9 million tweets. Tesla and the US Presidency feature in their centrality nodes, they also quantify the impact of the “Musk Effect” on Main Street.

Furthermore, being a novel source of public information and seemingly having an impact on financial markets, Musk/Trump-tweets also present an opportunity for finance academics to assess the validity of the Efficient Market Hypothesis (EMH). Ever since Eugene Fama (1970) introduced the EMH, there has been considerable academic discussion about which form of market efficiency truly prevails in the financial markets, whether markets are efficient at all, if professional stock analysts do in fact have an informational edge and if investors over rely on them (Bruce, 2002).

The following work capitalizes on the opportunity the Musk/Trump-tweets present and aims at contributing to the academic discussion about the efficiency of financial markets. Specifically, the following research questions are addressed: Firstly, are financial markets semi-strong form efficient? Secondly, could returns can be derived from strategies based on Musk/Trump-tweets? We also evaluate long term CARs (250-day window vs the classic 20-day window of returns), to see if there is informational persistence and carryover to longer term excess returns (Bordalo et al., 2022). Most of the tweets are categorized as during or after the regular trading hours (with respect to US exchanges located on the east coast).

In order to answer these questions, a testable research hypothesis is derived from the current academic literature on market efficiency in section 2. Thereafter, the empirical event study methodology for testing the hypothesis is presented in section 3. Section 4 deals with the

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<sup>1</sup> Such as going short in stocks with negatively themed tweets or long in stocks with positively themed tweets.

sample and data used during the empirical analysis while section 5 and 6 concludes the analysis by presenting and discussing the primary findings.

## 2 Theory and Supporting Literature

### 2.1 The Efficient Market Hypothesis

The theory of market efficiency and the academic discussion around it have been decisively shaped by the works of Eugene Fama who introduced the Efficient Market Hypothesis (EMH) in 1970. A brief review is provided here for a wider audience, some of whom could, at times, use the terms interchangeably. According to Fama's hypothesis, each piece of information concerning a specific asset is *immediately and without any bias* incorporated into the price of the respective asset. The current security price thus correctly reflects all available information. However, depending on what is included in the “*all available information*,” three versions of the EMH can be distinguished (Clarke, Jandik and Mandelker, 2001).

1. Weak-form efficiency: The weak form EMH asserts that the current price fully incorporates information contained in the *past history of prices and trading volume*. Thus, investors should not be able to realize profits by analysing past prices and then trading on them. If this hypothesis were true, technical analysis (identifying patterns in historical price/volume data) would not have any merit. Runs tests, autoregressive tests (AR( $\rho$ )) and filter tests have dispelled that prices have memory, though there has been some evidence to the contrary in informationally segmented markets (Diallo et al., 2021).

$$X_t = \sum_{i=1}^p \vartheta_i X_{t-i} + \varepsilon_t$$

An example of a stationary (AR( $\rho$ )) process of order  $\rho$  for a prices  $X_t$  would be the parameter  $|\vartheta| = 1$ , with  $\varepsilon_t$  being the error term.

2. Semi-strong-form efficiency: The semi-strong-form EMH suggests that the current price fully incorporates *all publicly available information*. The publicly available information includes the historical prices and volume data, but it also includes other sources of public financial and non-financial information e.g. news reports, financial statements, company filings, macroeconomic information and essentially all information which is accessible to other investors as well. Based on this definition of market efficiency, no investor (not even specialized fund managers) should be able to consistently realize profits using any information that is readily accessible to other individuals. Also, since newly published public information would be processed instantaneously, trading strategies based on this information as trading signals should have no merit. Tweets belong to such information type and we use a control set versus Musk/Trump tweets to research if there is residual information in their tweets. For an asset whose path is determined as a stochastic process  $X_t$  the change in its value over a very small increment of time  $dt$  is given by

$$dX_t = \mu X_t dt + \sigma X_t dW_t$$

$$[X]_t = \int_0^t \sigma^2 X_t^2 dt$$

$X_t$  follows a Weiner process  $W_t$  (Geometric Brownian Motion).

3. Strong-form efficiency: The strong-form market efficiency defines the broadest concept of priced-in information. In addition to all public information, it *also incorporates all private information* (which has not yet been divulged to the public), as being reflected in the current market price. This form of market efficiency implies that investors and even company insiders (such as directors or executives) should not be able to realize profits consistently using non-public information about the asset (it is also unlawful). The market price would already be reflecting such private information. Grossman and Stiglitz (1980) presented the 'efficient markets paradox' where they state "that perfectly informationally efficient markets are an impossibility, for if markets are perfectly efficient, the return to gathering information is zero, in which case there would be little reason to trade and the markets would eventually collapse." In their model, the demand for the risky asset, by the informed trader is  $X_I$ , and if the demand by each uninformed trader is  $X_U$ , then the market clearing condition is:

$$\lambda X_I + (1 - \lambda)X_U = x$$

where  $x$  is the supply of the stock (risky asset) with the distribution  $\sim N(\mu_x, \sigma_x^2)$ , where  $\mu$  and  $\sigma$  are the first and second moments of the distribution of  $x$ , and the fraction of informed traders denoted by  $\lambda$ . However, because information is costly, there has to be a return to gathering that information, so an informationally efficient market would be impossible.

## 2.2 A Review of Supporting Literature

The academic literature on the market impact of Twitter based informational releases is limited in timespan, by the formation of the platform in itself (2006). Since then, a number of studies have linked Twitter releases to a variety of financial events. Bollen et al. (2011) find that Twitter mood predicts the value of the Dow Jones index to a certain extent. Ranco et al. (2015) evaluate the effects of Twitter sentiment on stock price returns and, "find a relatively low Pearson correlation and Granger causality between the corresponding time series over the entire time period," we utilize their historical dataset to develop a control for this study (using Earnings announcements for the constituents of the Dow Jones index). Broadstock and Zhang (2019) use intraday high frequency stock returns for a sample of US companies and find that price dynamics are susceptible to social-media sentiment pricing factors. Burggraf et al. (2020) report that tweets related to the US-China trade war negatively predict S&P 500 returns and positively predict the VIX (implied volatility on the S&P 500). Gu and Kurov (2020) find that Twitter sentiment provides information about analyst recommendations, price targets and quarterly earnings. Nicolau et al. (2020) even find that, "participation of public personalities (such as Donald Trump) in social media can have repercussions on the market value of their country's tourism industry." Ajjoub et al. (2021), differentiate between Trump's tweets about media and non-media firms and explore the impact of "old" vs "new" news based on whether the former President repeated information already known to the market." Gjerstadt et al. (2021), find that Trump tweets impacted financial markets, and that the Chinese stock market responded to these tweets negatively, while the price of gold responded positively; Guo et al. (2021) also found a similar effect on China's capital markets. Klaus and Koser (2021) developed the Volfefe index and found that the "Trump Tweet factor contributes to the prediction of European stock market returns." Shahzad et al. (2022), highlights Elon Musk as a key person who has an influential role, "through social media on the formation of bubbles, which matters to the decision-making of crypto traders and market efficiency." Ante (2022)

and Sevic et al. (2022), demonstrate the impact Musk has on cryptocurrencies and also the valuation of Tesla stock.

The validity of the EMH has been examined extensively in numerous studies before. The weak-form was often tested by identifying patterns in past stock prices and anticipating future stock price movements based on these patterns. Brock, Lakonishok and LeBaron (1992) for instance argue against the weak-form EMH, and show that technical indicators do provide some incremental information for predicting prices and can be exploited by primitive tools such as the moving average operator. Lo, Mamaysky and Wang (2000) extend the scope of these results by uncovering additional technical indicators which extrapolate from past stock prices. However, subsequent research (Neely, Weller and Dittmar, 1997) showed that the gains from such strategies were insufficient to cover transaction costs. Consequently, these findings are mostly consistent with weak-form market efficiency.

Other studies have aimed to validate the semi-strong form EMH. For that, researchers have conducted two types of studies. The first type aims at *indirectly* validating the hypothesis by analysing the possible returns from trading strategies based on public information. Jensen (1968) for instance finds that mutual funds achieved a risk-adjusted performance of approximately zero percent per year. Malkiel (1995) supports these findings by showing that equity funds, too, consistently underperformed the broad market (S&P 500) on average from 1971-1991. These findings strongly support the semi-strong form EMH as they show that investors and even specialized fund managers are unable to derive consistent returns based on public information; possibly because new public information gets immediately priced in.

The second body of literature aims at *directly* validating the hypothesis by assessing the time and speed at which new information gets incorporated into asset prices. Fama, Fisher, Jensen and Roll (1969) for example discovered that stock prices almost instantaneously reacted to stock split news and that no abnormal stock price performance was observable after the announcement. Keown and Pinkerton (1981) noticed a similar behaviour during the announcement of takeover attempts. This is evidence in favour of the semi-strong form as markets seem to instantaneously process new information and any subsequent trading on this information yielded no abnormal returns after the event.

Other researchers, however, have pointed to evidence which disputes the claim that new public information is almost immediately processed, thereby opposing the semi-strong hypothesis. A widely-cited example is the “post-earnings-announcement drift” (Ball and Brown, 1968) where stock prices appear to respond to earnings for up to an entire year after they were announced. Chan (2003) observes this phenomenon also for certain cases of non-financial news. We will show later in the paper that there appears to be a “pre-post-Twitter-drift” when the release is by exceedingly influential market personalities. Goldsticker and Agrawal (1999) find that the dilutive effect of executive stock options on EPS growth rates is not trivial and that it persists. Jurdi (2022) finds that alpha opportunities across various markets remain for investors from forecasting the risk premium, resulting from the inefficient market pricing of predictors; and misestimation of betas as seen on finance web portals (Waggle et al., 2010). Moreover, studies highlight the existence of other anomalies which prevent new information to be processed in an unbiased way. Behavioural characteristics, for instance, lead to an initial under- reaction or over-reaction by investors while processing new information. Thus, this information is processed inefficiently and does not conform with the semi-strong hypothesis.

Studies on the strong-form of market efficiency show (Rozeff and Zaman, 1988) that trading on private or inside information consistently yields significant returns, which is evidence

against strong-form efficiency. However, it is not entirely surprising, as insider trading (trading on private information) is prohibited by law in all relevant jurisdictions.

More recently, Chamberlain et al. (2023) focus on equities with high short-interest and report that "the return-news sentiment relationship is stronger for firms with a high short interest ratio, for small firms, and particularly for firms that are both small and heavily shorted." Liu and Popova (2023) find Trump's tweets (related to lower interest rates) to be a proxy for threats to central bank independence and create exchange rate volatility. Twitter in its own way is part of the information release ecosystem integrated with the global economy and press freedom is integral to its growth (Nguyen et al., 2020).

### 2.3 Deriving the Research Hypothesis

The literature review above suggests that Twitter based informational releases impact corporations as well as capital markets. There is also evidence to the contrary with respect to the weak-form and the strong-form of the EMH. The following research hypothesis is derived in order to validate the semi-strong EMH as pertaining to the Musk/Trump-tweets. Essentially, no abnormal returns should be realized after that information is published.

#### Research hypothesis

**H<sub>0</sub>:** *Prices should immediately react to new information contained in the Musk/Trump-tweets and no subsequent returns should be realized from trading on that information.*

**H<sub>A</sub>:**  $\nless \text{not } H_0$

This hypothesis is tested using the research design and methodology presented in the following section. By evaluating this hypothesis, the following work aims to contribute to the current academic discourse about the semi-strong form by providing new evidence for or against it.

## 3 Research Design and Methodology

### 3.1 Research Design

The research hypothesis from section 2.3 contains two testable elements: 1. the speed at which the information of the Musk/Trump-tweet is processed and 2. the returns from trading on Musk/Trump-tweets. The first component can be tested by conducting event studies on assets affected by Musk/Trump-tweets while the second component can be tested by both event studies as well as simulating trading strategies. Therefore, in the following analysis, the event study methodology is employed as it covers both components of the research hypothesis.

Event studies capture the impact of an event (Musk/Trump-tweet in this case) through so-called abnormal returns ( $u_{it}$ ). They are essentially the excess of realized returns ( $r_{it}$ ) over what returns would have been if the event had not occurred ( $r_{it}^n$ ):

$$u_{it} = r_{it} - r_{it}^n, \text{ where } i \text{ refers to the asset and } t \text{ is the time subscript} \quad (\text{eq. 1})$$

Thus, if an event had an impact on asset returns, the realized return would differ strongly from the return if the event had not occurred, leading to large abnormal returns around the event period. Identifying the precise timing of the abnormal returns allows to validate the research hypotheses: e.g. observing abnormal returns over more than one period would suggest a slow and non-instantaneous processing of information. Long term CARs are computed at  $t = +250$

trading days, in addition to the usual  $t = \pm 10$  day window. At the suggestion of a reviewer, we constructed a 'control group' CAR study, that was independent of Musk/Trump activity and time independent, yet based on twitter releases of earnings. It comprised of Dow Jones index companies to see if their financial tweet releases had a return drift associated with them (additional discussion and output is in the results section).

### 3.2 Computing Abnormal Returns

Abnormal returns are computed and observed over a period (event window) during which the event could have an impact on the asset prices. Since information leakage could occur prior to the event or the event may not be processed immediately and entirely, the event window is not merely a single point in time but rather an interval of time points around the event time ( $t = 0$ ). Following the well-established methodology of Brown and Warner (1985), the event window is set to start 30 periods before the event ( $t = -30$ ) and end 30 periods after the event ( $t = +30$ ) in the following analysis. Fama, Fisher, Jensen and Roll (1969) describe three steps (later on improved by Brown and Warner (1980)) for computing abnormal returns. Each of the steps is described in detail below.

Step 1: Since only realized returns, which already contain the impact of the event, are observable, returns which would have been realized if the event had not occurred remain unobserved. Therefore, the normal returns during the event window,  $r_{it}^n$ , have to be estimated before abnormal returns can be computed. This is done by calibrating a model which best describes returns during “normal times” over an estimation window prior to the event window.

Step 2: Once the model has been calibrated over the estimation window, the estimated model parameters are used to predict the normal returns over the event window,  $\hat{r}_{it}^n$ . It is assumed that the estimated coefficients from step 1 are constant over the estimation and event window.

Step 3: Lastly, after estimating the normal returns, the abnormal returns can be computed as:

$$u_{it} = r_{it} - \hat{r}_{it}^n \quad (\text{eq. 2})$$

To better assess the aggregate effect of the event over time, the cumulative abnormal return (CAR) can be calculated as well. The  $q$ -period CAR is simply the sum of the abnormal returns over  $q$  periods within the event window. e.g. the 3-period CAR starting at  $t = -20$  is given by:

$$CAR_{i,3} = u_{i,-20} + u_{i,-19} + u_{i,-18} \quad (\text{eq. 3})$$

Long term CARs are computed at  $t = +250$ , where the count is in trading days, not calendar days. The long term CAR results are presented as aggregated visuals in the Appendices.

### 3.3 Normal Return Models

A variety of models have been proposed to estimate normal returns for step 1. Among various models, the one used most widely for estimating expected or “normal” returns is the market model. According to this model, the normal return to asset  $i$  at time  $t$  can be expressed as a linear function of the returns from a portfolio of all marketed assets ( $r_{mt}$ ) which can be estimated by ordinary least squares regression:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \epsilon_{it} \quad (\text{eq. 4})$$

with  $E(\epsilon_{it}) = 0$ ,  $Cov(\epsilon_{it}, \epsilon_{i,t-s}) = 0$  and  $Cov(\epsilon_{it}, r_{mt}) = 0$

The market model with  $\beta_i$  as the asset's systematic risk response factor to the index returns, has increasingly been replaced by the Fama and French (1996) FF3-factor model. This multi-factor model is a linear regression of the return of asset  $i$  on the market return, the “small-



minus-big” portfolio return and the “high-minus-low” portfolio return. These regressors account for additional systematic risk factors besides the market risk  $\beta_m$ :

$$r_{it} = \alpha_i + \beta_{m,i} r_{mt} + b_{SMB,i} SMB_t + b_{HML,i} HML_t + \epsilon_{it} \quad (\text{eq. 5})$$

Although this FF3-factor model is theoretically superior to the single factor model, experience with multi-factor models also suggests (Campbell, Lo and MacKinley, 1997) that they only give modest improvements of the  $R^2$  compared to the market model. Agrawal, Gilbert and Harkins (2022) show that alternate (to 5-year monthly) return frequency and the window interval length affects  $\beta_i$  estimations, and that some matching with holding periods may be optimal. However, as elaborated below (section 3.4), selecting models with a high  $R^2$  for normal returns can significantly improve the accuracy of the results.<sup>2</sup> Thus for the sake of accuracy over convenience (Agrawal (2023) provides a visually intuitive GRS geometric test for portfolio efficiency), the FF3-factor model from (eq. 5) is chosen to model the normal returns over the event periods.

### 3.4 Testing Abnormal Returns

Since the normal returns over the event window will be estimates, they will feature some estimation uncertainty. More precisely,  $\text{var}(\hat{r}_{it}^n) = \text{var}(\epsilon_{it})$  where  $\epsilon_{it}$  is the residual from (eq. 4) or (eq. 5). This uncertainty (Valadkhani, 2023) translates directly into uncertainty when calculating the abnormal returns. More specifically:

$$\text{var}(u_{it}) = \text{var}(r_{it} - \hat{r}_{it}^n) = \text{var}(\epsilon_{it}) \quad (\text{eq. 6})$$

Using this expression for the variance of abnormal return  $u_{it}$ , a  $t$ -test can be constructed to test for statistical significance<sup>3</sup> of individual abnormal returns:

$$t\_stat = \frac{u_{it}}{\sqrt{\text{var}(\epsilon_{it})}} \quad (\text{eq. 7})$$

The cumulative abnormal return can also be tested with a  $t$ -test. Due to historically low autocorrelation in returns (Campbell, Lo and MacKinley, 1997), it can be fairly assumed that the returns are uncorrelated across time. With this assumption, the variance of the CAR simplifies as follows:

$$\text{var}(CAR_q) = \text{var}\left(\sum_{t=0}^q u_{it}\right) = \sum_{t=0}^q \text{var}(u_{it}) = q \text{var}(u_{it}) = q \text{var}(\epsilon_{it}) \quad (\text{eq. 8})$$

Using the variance expression above, the  $t$ -test to test the significance of the CAR is constructed as follows:

$$t\_stat = \frac{CAR_q}{\sqrt{q \text{var}(\epsilon_{it})}} \quad (\text{eq. 9})$$

As can be seen from (eq. 7) and (eq. 9), the variance of the residuals from the normal returns model,  $\text{var}(\epsilon_{it})$ , is crucial for testing the hypothesis of no abnormal returns (or no CAR): The smaller this variance, the easier it is to reject a false null hypothesis.<sup>4</sup> We also applied the non-parametric Corrado-Zivney (1992) test to ensure robustness.<sup>5</sup>

<sup>2</sup> Theoretically, instead of specifying complex models to estimate normal returns, these returns could simply be set equal to a constant e.g. the mean over the estimation window. However, this would yield a very low  $R^2$  and thus lead to inconclusive results when performing inferential tests. Refer to section 3.4 for more details.

<sup>3</sup> The null-hypothesis being that  $u_{it} = 0$

<sup>4</sup> Since  $R^2 = \frac{SSE}{SST} = 1 - \frac{SSR}{SST} = 1 - \frac{\text{var}(\epsilon)}{\text{var}(y)}$ , a high  $R^2$  implies a low  $\text{var}(\epsilon)$

<sup>5</sup> The Corrado and Zivney test statistic is given as:

$$z = \sqrt{L_2} \left( \frac{\overline{K_{T_1+1, T_2}} - 0.5}{S_{\bar{K}}} \right) \quad \text{with} \quad \overline{K_{T_1+1, T_2}} = \frac{1}{L_2} \sum_{t=T_1+1}^{T_2} \bar{K}_t$$

### 3.5 Testing the Research Hypothesis

Testing the abnormal returns and the CAR is the primary way to test the EMH using event studies. If the Musk/Trump-tweet would indeed be instantaneously processed by the market, one should only observe abnormal returns on the event day exclusively. Abnormal returns on any other day close to the event would indicate that markets gradually, instead of instantaneously, process new information. Accordingly, one should observe constant cumulative abnormal return after the event takes place if prices were to adjust immediately.

The research hypothesis from section 2.3 (and thus the semi-strong form EMH) would consequentially be rejected if significant abnormal returns occurred at other days besides the event day and if the cumulative abnormal return is increasing in magnitude.

## 4 Sample and Data

The sample for the analysis presented in section 3 contains companies listed on US Stock Exchanges<sup>6</sup> which Musk/Trump targeted in their tweets during a trading day. Companies addressed on non-trading days are excluded because the closest observable return would be too far away from the event to still consider it as an immediate market reaction to the Tweet event. Elon Musk, as of April 2022, had mentioned at least 12 listed companies (non-overlapping and excluding crypto assets) with market moving material. As of July 2019, Donald Trump had singled out multiple companies resulting in 32 company/events in total and addressed them in his tweets after being elected the president of the United States in November 2016. Exhibit 1 illustrates the sample constituents and relevant meta-information for the event study, methods utilizing web harvesting algorithms were also applied to create machine readable data (Aggrawal, 2009).

**Exhibit 1: Companies Addressed by Donald Trump's-Tweets in the Event Study Sample**

Company name (Ticker)	Theme of Tweet	Event (t = 0)	Event window (t = - 30 till t = + 30)
Rexnord (RXN)	Shifting production to Mexico and terminating American workers	05/12/16	21/10/16 19/01/17
Lockheed Martin (LM)	F-35 costs are out of control	12/12/16	28/10/16 26/01/17
Boeing (BA)	Cost of Air Force One replacement too high	22/12/16	09/11/16 07/02/17
General Motors (GM)	Making Chevy Cruze in Mexico is wrong	03/01/17	17/11/16 15/02/17
Ford (F)	Expanding US production plant	09/01/17	23/11/16 22/02/17

For any  $i$  where  $L_{i,2}$  denotes the number of non-missing  $AR_{i,t}$  during the event window and for any  $t$ , we denote the number of non-missing scaled ranks  $K_{i,t}$  by  $N_t$ .

<sup>6</sup> These companies are included as 1. Fama and French factors are used and 2. The US President only has executive and legislative power over the jurisdiction. Companies listed in the US are assumed to have significant US operations, which is why they are more likely to be affected by Trump-actions than non-US-operating companies.

Nordstrom (JWN)	Daughter treated unfairly by Nordstrom	08/02/17	23/12/16 23/03/17
Toyota Motors (TM)	Producing cars in Mexico for sale in US	06/01/17	22/11/16 21/02/17
Alphabet (GOOG)	Google should be investigated	16/07/19	31/05/19 30/08/19
Various	Various	6/01/17 to 16/07/19	t-30 (CAR's end 12/31/2022)
*To conserve space, the full list is shown in the Appendix		*List shows Tweet release time	RTH, AH      Regular/ After Trading Hour

For the analysis in section 5, return data on the 41 (32 Trump + 12 Musk) company/events in the sample is retrieved from March 29<sup>th</sup> 2012 to December 31<sup>st</sup> 2022 through the CRSP dataset (via the Wharton Research Database Services, WRDS, 2023). The values of the Fama and French factors (market, size and value) for the normal returns regression are queried at the same frequency and for the same time period through the Ken French Data Library<sup>i7</sup> (hosted at Dartmouth College).

## 5 Results and Discussion

### 5.1 Normal Returns Model Calibration

As discussed in section 3, the FF3-factor model was calibrated iteratively to each of the companies by performing OLS over the respective estimation windows.

$$E(R_i) = R_f + \beta_{m,i}(R_m - R_f) + \beta_{s,i}(R_s - R_l) + \beta_{v,i}(R_v - R_g) \quad (\text{eq. 10})$$

Where:  $i, f, m, s, l, v, g$  are the return subscripts for the  $i^{\text{th}}$  company, the risk-free rate and the market, small, large, value and growth factor loadings respectively. Also,  $\beta_{v,i}$  is the response coefficient of stock  $i$  to the value factor  $v$ .

This return generating mechanism invokes the Gaussian distribution for the return random variable  $x$ , with the mean and variance  $\sim N(\mu, \sigma^2)$ .

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad (\text{eq. 11})$$

The cumulative distribution function (CDF  $\gamma(z)$ ) of a standard normal distribution with  $\mu=0, \sigma^2=1$  is the integral of the PDF given above from minus infinity to a value of  $z$  and is given by:

$$\gamma(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-x^2/2} dx \quad (\text{eq. 12})$$

<sup>7</sup> [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

Exhibit 2 summarizes the estimation results. Each column represents an estimation for the respective company. As can be seen from that table, with an  $R^2$  of up to 51.1%, the FF3-factor model is able to explain a significant amount of variation in the asset returns (also by inspecting the return overlaps in Exhibit A-1 in Appendix A). The coefficients from these calibrated models were therefore used to predict the normal returns over the event windows. Based on these normal returns, the abnormal returns (market adjusted) over the event window were computed. We also apply non-parametric methods to evaluate the robustness of these statistical outcomes (Exhibit B-9).

**Exhibit 2: FF3-Factor Normal Returns Model Estimation Results**

<i>Dependent variable: Daily realized returns over the estimation window</i>							
	Rexnord (RXN)	Boeing (BA)	General Motors (GA)	Ford (F)	Nordstrom (JWN)	Toyota Motors (TM)	Lockheed Martin (LMT)
MKT	1.207*** (0.070)	1.134*** (0.053)	1.028*** (0.061)	1.107*** (0.056)	0.907*** (0.107)	1.045*** (0.053)	0.648*** (0.042)
SMB	0.993*** (0.138)	-0.156 (0.103)	0.097 (0.111)	0.219** (0.103)	0.376** (0.190)	-0.146 (0.096)	-0.392*** (0.083)
HML	0.821*** (0.124)	0.071 (0.093)	0.366*** (0.104)	0.436*** (0.096)	0.321* (0.175)	0.165* (0.090)	-0.274*** (0.074)
Constant	-0.096 (0.066)	-0.030 (0.049)	-0.055 (0.056)	-0.109** (0.052)	-0.153 (0.098)	-0.060 (0.049)	0.042 (0.039)
Observations	441	441	441	441	441	439	441
$R^2$	0.483	0.511	0.414	0.497	0.164	0.477	0.365
Adjusted $R^2$	0.479	0.508	0.410	0.493	0.158	0.473	0.360
Residual S.E.	1.378 (df = 437)	1.032 (df = 437)	1.181 (df = 437)	1.091 (df = 437)	2.048 (df = 437)	1.023 (df = 435)	0.824 (df = 437)
F Statistic	135.967*** (df = 3; 437)	152.491*** (df = 3; 437)	102.761*** (df = 3; 437)	143.645*** (df = 3; 437)	28.476*** (df = 3; 437)	132.256*** (df = 3; 435)	83.626*** (df = 3; 437)

Note:

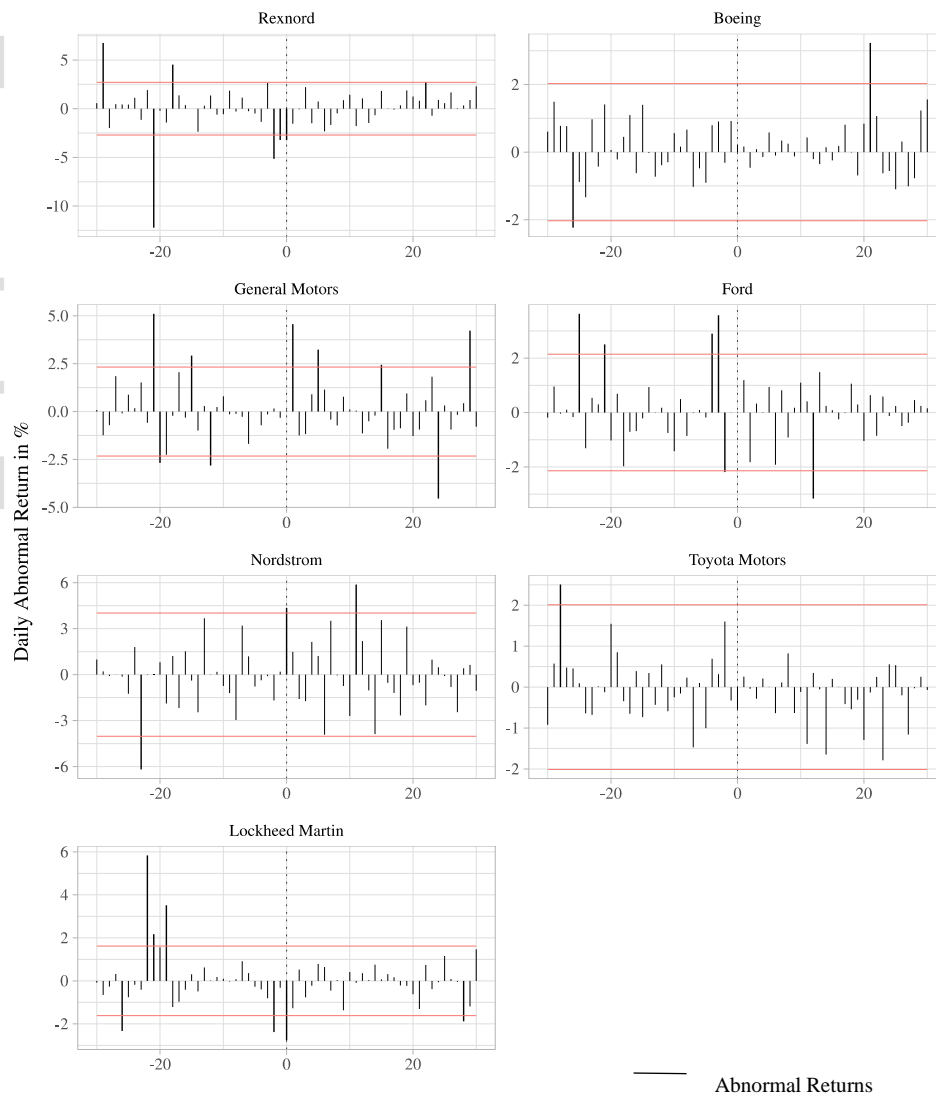
\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

## 5.2 Abnormal Return Analysis

Exhibit 3 illustrates the calculated abnormal returns (black bars) for each of the companies addressed by Trump-tweets starting 30 periods before the tweet and ending 30 periods after the tweet. The red bounds define the 95% confidence interval around 0. Thus, if the abnormal returns were significantly different than zero at the 5% significance level, they would lie outside the area surrounded by the red bounds. The Trump-tweet would thus have a significant effect on the asset returns during the day at which the significant abnormal return occurred. For abnormal returns lying within the lines, the hypothesis that the abnormal return is different than zero cannot be rejected at 5% significance level. In this case, the Trump-tweet would not have

**Exhibit 3: Abnormal Returns on Companies Addressed by Trump-Tweets**

had a significant effect on the asset returns.



Result 1: The first observation is that not all companies seem to be affected by Trump-tweets at or around the day of the tweet. Toyota Motors for instance has only one significant abnormal return, which is most likely not even linked to the event (as it occurs 28 periods prior to the

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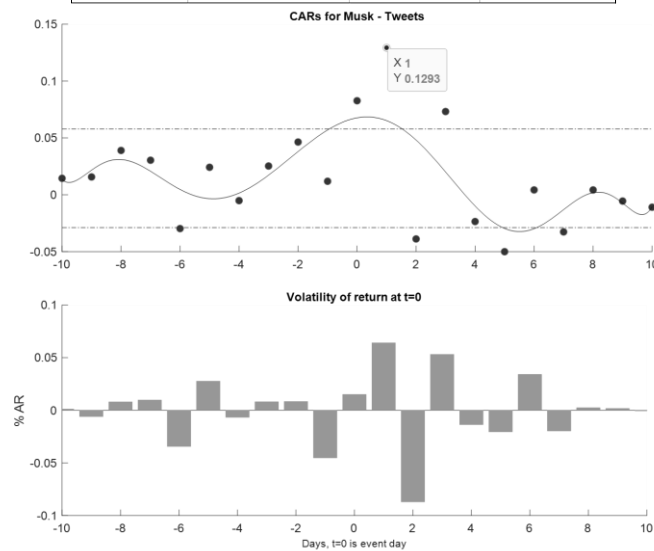
tweet). Similarly, Boeing has no significant abnormal returns immediately around the event day, while Lockheed Martin had negative days around 12/12/16, ten days prior to the Boeing tweet (it also had negative returns in that time frame, both having exposure to the defense aerospace industry in varying amounts, in any case social science research can only estimate and explain a small proportion of variability given a large number of factors that impact behavior).

It is also plausible that the tweet did not contain any new information. This could be the case if the content of the tweet was already anticipated by the market before the tweet was published, or the tweet was subsequent to a prior market event related to the company or the sector. Ford is an excellent example where this seems to be the case. While there are no significant abnormal returns observable at or after the tweet occurred, there are significant abnormal returns immediately before the tweet. This indicates that the information was in the market about the Ford event, before the tweet about it (a journalistic tweet in that sense).

Daily abnormal returns for Musk tweets (aggregated) are listed in Exhibit 4, where there is considerable positive return activity (2.4% to 12.93%) in the days leading to the actual release date. These returns adjusted for market action that day are significant for a number of days utilizing the non-parametric Corrado test. The associated graphical CAR (long term) is shown in Exhibit B-8, where the cumulative return runup to  $t=1$  is quite steep. For the +10 day window (Exhibi 4) there is disposition at about  $t=+4$  days, however for the longer term CAR the positive CAR persists beyond 200 days from the information release at  $t=0$ .

#### Exhibit 4: Daily Abnormal Returns on Companies Addressed by Musk-Tweets

Day Relative to Event	Mean Abnormal Return	t-statistic for Abnormal Returns	p-value (Corrado Signed Rank Test)
-10	0.0145	1.0628	0.4894
-9	0.0157	1.2931	0.2498
-8	<b>0.0390</b>	0.7220	0.1670
-7	<b>0.0304</b>	1.2201	0.2136
-6	<b>-0.0297</b>	<b>-2.1168</b>	<b>0.0236</b>
-5	<b>0.0242</b>	<b>2.0993</b>	<b>0.0532</b>
-4	-0.0051	-0.4955	<b>0.0843</b>
-3	0.0253	1.4913	0.0504
-2	<b>0.0464</b>	0.9833	0.2892
-1	<b>0.0119</b>	0.6872	0.3029
0	<b>0.0827</b>	0.9623	0.4317
1	<b>0.1293</b>	1.0353	0.4947
2	-0.0388	-0.9277	0.4947
3	0.0732	1.1712	<b>0.0415</b>
4	-0.0235	-0.7734	0.3604
5	-0.0500	-0.8787	0.3804
6	0.0043	0.6118	0.3956
7	-0.0326	-0.8057	0.2892
8	0.0043	0.2089	0.0727
9	-0.0055	-0.7404	0.4631
10	-0.0109	-0.6738	0.3555



\*There is positive return activity (2.42% to 12.93%, column 2) in the days leading to the actual release date. These returns adjusted for market action that day are significant at 90% and 95% (in bold) for a number of days utilizing the non-parametric Corrado test (*p-value* Corrado 0.0236, 0.0532, 0.0843\* (at 90% LOS only), 0.0415) as well. The 10-day window Musk-tweet CARs and their volatility can be seen in the exhibit above, while there is a runup before t=0 there is a return reaction at t=0, t=1, with subsequent selling. The long term Musk-tweet CARs can be seen in Exhibits B-8.

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Further research would be necessary to assess the source for this market anticipation. Did the market anticipate the Musk/Trump-tweet because insiders knew of the planned Musk/Trump-tweet and started trading based on this private information? This would constitute evidence for strong-form market efficiency. Or did the market anticipate the content of the Musk/Trump-tweet based on other public information (Brans, 2020) which got released prior to the tweet? This would suggest conformity with the semi-strong form of the EMH.

Result 2: The remaining companies are affected by Musk/Trump-tweets at or around the day of the tweet: Rexnord, Nordstrom, General Motors and Lockheed Martin. Musk/Trump-tweets therefore seem to have an impact on certain asset returns. The second observation with respect to these companies is that the abnormal return does not occur exclusively at the date of the event. Instead, it is mostly the case that the abnormal return at event date is preceded or followed by more abnormal returns (this is seen in the Musk-tweet CARs in Exhibits B-8 and B-9, which also includes the aggregate CARs and the Control group ARs).

These observations indicate some kind of a pre-post-tweet “return drift” and are in line with the findings of Ball and Brown (1968) and Chan (2003) who observe post-announcement drifts in abnormal returns. This result indicates that markets do not immediately process the new information of the Musk/Trump-tweet in its entirety but rather over several periods, with some of it even in the pre-release period (to be researched further, if there is information leakage or even educated anticipation). The reason for this phenomenon could again lie in the same behavioral factors described by the aforementioned researchers e.g. over-reaction or under-reaction to the new information.

This result constitutes some evidence against the semi-strong form of the Efficient Market Hypothesis, according to which prices should have adjusted immediately and abnormal returns only realized at the day of the tweet. The first component of the research hypothesis of this paper (that prices would immediately reflect the content of the Musk/Trump-tweets) can thus be rejected based on these findings, in other words there is a drift and it takes some time for the market agents to factor in the new information.

### 5.3 Cumulative Abnormal Return Analysis

The essential formulation of CAR's is:  $CAR_i = \sum_{t=T_1+1}^{T_2} AR_{i,t}$  and  $S_{AR_i}^2 = \frac{1}{M_i - P} \sum_{t=T_0}^{T_1} (AR_{i,t})^2$

$$WCAR = \sum_{i=1}^N \sum_{t=T_1+1}^{T_2} \omega_i AR_{i,t}, \text{ weighted CAR is } \omega_i = \frac{\left( \sum_{t=T_1+1}^{T_2} S_{AR_i,t}^2 \right)^{-0.5}}{\sum_{i=1}^N \left( \sum_{t=T_1+1}^{T_2} S_{AR_i,t}^2 \right)^{-0.5}} \quad (\text{eq. 13})$$

$S_{AR_i}$  denotes the sample standard deviation of the returns during the estimation window,  $M_i$  denotes the number of non-missing returns during the estimation window; for example,  $M_i = T_1 - T_0 + 1$  in case of no missing observations. Furthermore,  $P$  denotes the degrees of freedom in the return generating model ( $P = 3 + 1$  for the 3FF model).  $\omega_i$  is the weight attributed to the  $i^{\text{th}}$  company.  $AR_{i,t}$  is the abnormal return of firm  $i$  on day  $t$ .  $CAR_i$  is the cumulative abnormal return during the event window (Wolf, Schimmer, Levchenko, and Müller, 2014).

The second component of the research hypothesis (that trading on Musk/Trump-tweets should not yield significant return) is validated by analyzing Exhibit 5. It showcases the cumulative

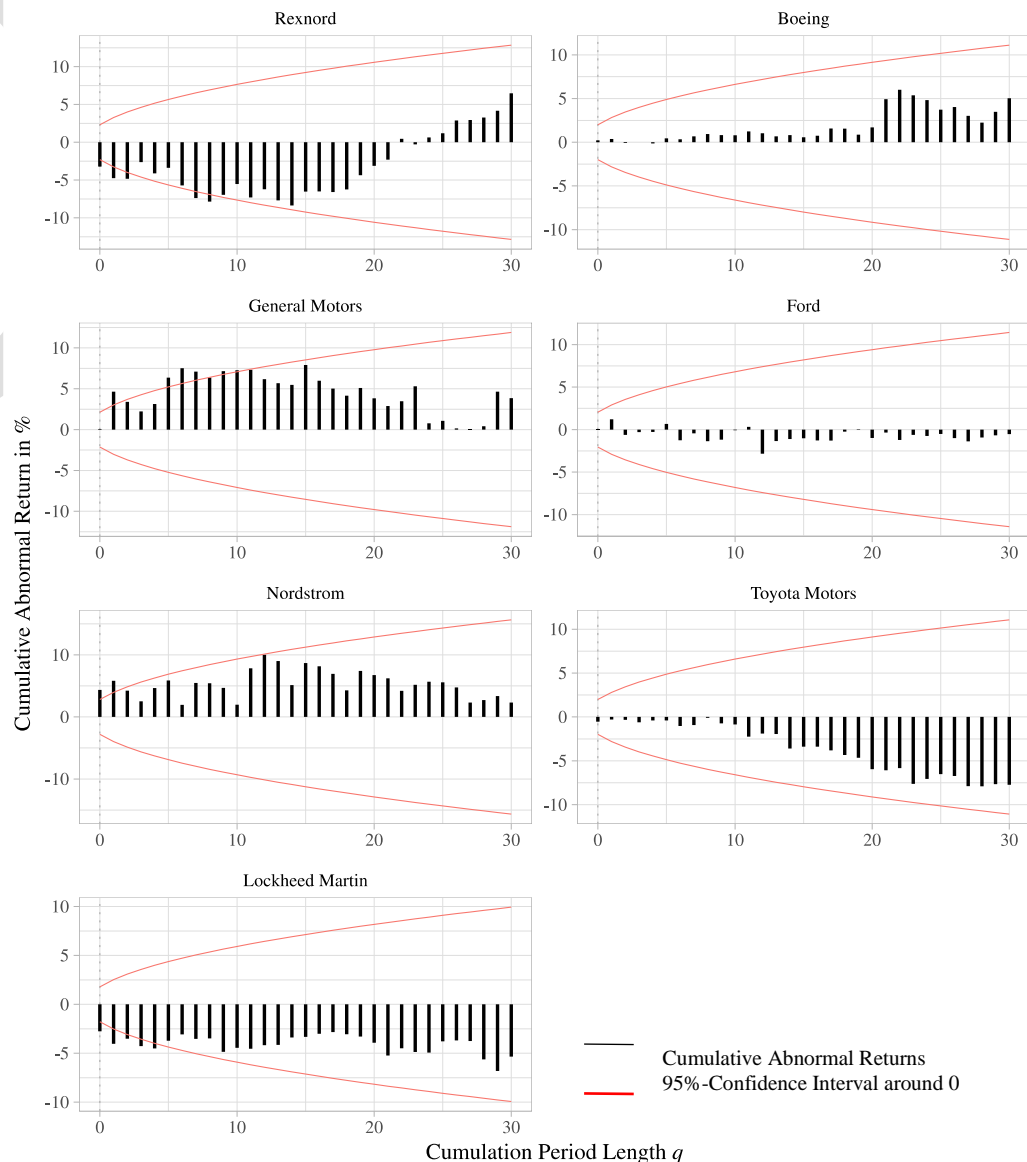


abnormal returns on the companies from Exhibit 3. The CAR begins at the date at which the Trump-tweet occurs and is computed up until the end of the event period. It therefore illustrates the aggregate effect of the Trump-tweet from the time it is published till the end of the event period. Again, the red bounds define the confidence interval around zero. CARs outside this band are significantly different than zero at the 5% significance level. Exhibit 4 and Exhibit B-8 shows the long term CARs for the information releases from Elon Musk.

Result 3: Here we see that the companies which had significant abnormal returns around the event day in Exhibit 3 also have significant cumulative abnormal returns. More interestingly, these cumulative abnormal returns are significant and also increasing in magnitude over several periods (e.g. 5 days for Lockheed Martin or 12 days for General Motors). Similar to result 2, this finding is also evidence against the semi-strong form of market efficiency as cumulative abnormal returns would not be increasing in magnitude if prices would react instantaneously

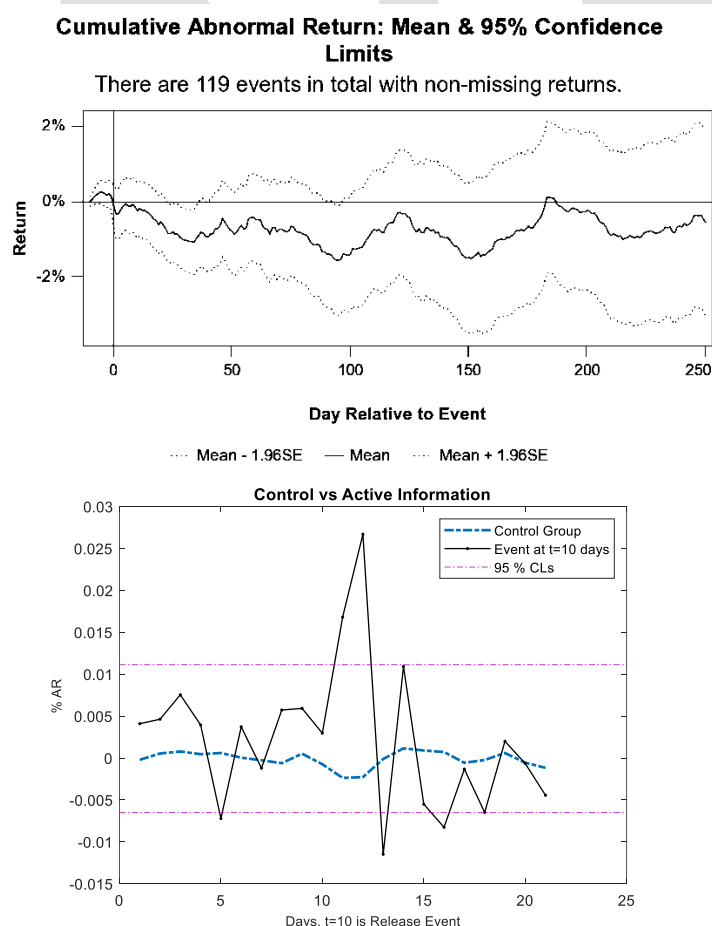
#### Exhibit 5: Cumulative Abnormal Returns on Companies Addressed by Trump-Tweets

to the new information. These results are therefore in contrast to those of Fama, Fisher, Jensen and Roll (1969) and Keown and Pinkerton (1981) who find immediate price adjustments after

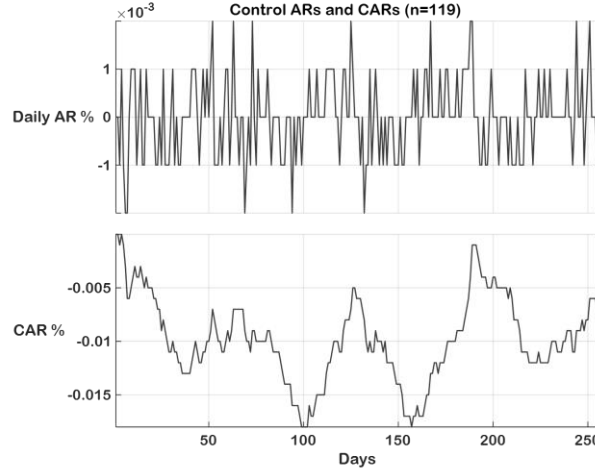


stock split and merger announcements, including seasonality effects (Agrawal and Skaves, 2015). Increasing CARs further means that the aggregate effect of the Musk/Trump tweet is not constant but rather increasing over time. Investors may therefore be able to realize returns from trading on Musk/Trump-tweets over a considerable duration. At the suggestion of a reviewer, we constructed a 'control group' CAR study, that was independent of Musk/Trump activity and time independent, yet based on Twitter releases of earnings. It comprised of Dow Jones index companies to see if their financial tweet releases had a return drift associated with them. We took the Earnings announcements of all available constituents of the Dow over a two-year period (Ranco et al. 2015),  $n=119$  events, and found a non-directional and neutral CAR ( $p$ -value 0.256)<sup>8</sup>. The output can be seen below in Exhibit 6. Even if either of Musk or Trump had return persistence, it would be indicative of an anomaly to the semi-strong EMH. The earnings announcements, even though on Twitter, did not produce any significant return drift.

**Exhibit 6: Cumulative and Abnormal Returns Control Group (n=119)**



<sup>8</sup> Numerical data output can be supplied upon request, not included due to space considerations.



\*The ARs and CARs of a large sample of non-Musk/Trump related Twitter earnings releases display no sustained CARs or daily ARs.

In Appendix B we have the aggregated CARs for over a longer term of 250 trading days, to see if the effect persists. For Trump-tweets we find a reversal effect, where the 'negatively toned' tweets outperformed the market (Exhibit B-1) and the 'positively toned' tweets underperformed (Exhibit B-2), over the longer 250 day period. Over the  $t+10$  day period there was a positive spike for both type of tweets followed by a gradual slide by day 10 (Exhibits B-3 and B-4 show the frequency and magnitude of the return response to this volatility). A majority of the 'negatively toned' tweets were in the extended trading hours and some in 'after-hours' (8:00PM too 7:00AM, excluding the weekends), where the market depth is thin and extreme downward pressure reverted in the RTH (Regular Trading Hours), please see Exhibit-B-6. This would be in agreement with the classic overreaction effect displayed in investor sentiment, as documented in the works of DeBondt and Thaler (1990). The long and short term performance of Musk's tweets remained positive (Choi, 2020 also finds bitcoin liquidity (Agrawal, 2014) was positively impacted on bitcoin tweet releases) for both estimation windows (Exhibit B-7 and B-8). Unlike Trump's companies, which were spread across various sectors, Musk's focus was on high growth, technology names, and even the poster child of the 'meme' stock phenomenon of 2021 – GameStop, in addition to Bitcoin (Ante, 2022; Shahzad et al., 2022). Musk had 60% of his tweets in the 'after-hours' (Exhibit B-7). In Exhibit B-5 and B-9 we present various tests of significance as applied to the return activity for  $(t-10, 0, t+10)$ , for the 'positively toned' tweets. While the positive  $AR$ 's at  $t=+1$  are as expected, it is not entirely clear why the  $t-7, t-6$  days had significantly negative days. We applied the non-parametric Corrado-Zivney test as well to ensure robustness, and it indicated significance during the event window. The Corrado and Zivney (1992) non-parametric ranked test statistic is given as:

$$Z = \sqrt{L_2} \left( \frac{\overline{K_{T_1+1, T_2}} - 0.5}{S_{\overline{K}}} \right) \quad \text{with} \quad \overline{K_{T_1+1, T_2}} = \frac{1}{L_2} \sum_{t=T_1+1}^{T_2} \overline{K}_t \quad (\text{eq. 14})$$

For any  $i$  where  $L_{i,2}$  denotes the number of non-missing  $AR_{i,t}$  during the event window and for any  $t$ , we denote the number of non-missing scaled ranks  $K_{i,t}$  by  $N_t$ . In Exhibit B-9 we also show the the aggregate CARs and the Control group ARs. It can be seen that Musk/Trump information releases on Twitter are volatility inducing and produce both short-term and also longer term ARs.

## 6 Concluding Remarks

The primary objective of this paper was to evaluate market efficiency, with regard to tweet releases from significant influencers, by testing the hypothesis that Musk/Trump-tweets

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(Klebnikov, 2021) would immediately get processed by the markets and that no sustained return was achievable, by trading on them. Conducting event studies on a set of company stock returns which were directly addressed by Musk/Trump-tweets provided the means to do so and presented evidence against the semi-strong form of market efficiency, both in the short term ( $t+10$ ) and the long term ( $t+250$  trading day window). Specifically, observing abnormal returns at several days around the event day and increasing statistically significant cumulative abnormal returns showed that Musk/Trump-tweets were not immediately processed by markets and that excess returns could subsequently be realized. This was not the case for the control group of  $n=119$  events, which were also financial Twitter releases but not Musk/Trump related. It could be that the control events did not influence agent sentiment to the extent it did for Musk/Trump, thus introducing a factor not fully captured by pricing models. This paper notes this anomaly and further research could be conducted to identify the factors behind the anomaly.

While these results are themselves some evidence against the semi-strong form of the Efficient Market Hypothesis (EMH), there is room for additional work on this topic. As a first step, the same analysis could be repeated with a larger sample of affected companies that include other significant influencers (Zinoviev et al., 2023 identify a cluster), however those that impact the financial markets *and* are Twitter active, are not in the same influence league as the two we looked at (Warren Buffett would be very influential but is not Twitter active). . Furthermore, as proposed at the beginning of section 5.2 the same analysis could be repeated while controlling for other events which occur during the event windows. This would allow assessing whether the tweets truly contain new information or whether the information was already processed at an earlier time in the market. Lastly, the same analysis could be repeated by using high frequency data rather than daily return data. The usage of such data would also allow obtaining cleaner results as the event window would be better isolated from other coinciding events. The present study provides a foundation for further research in the aforementioned direction.

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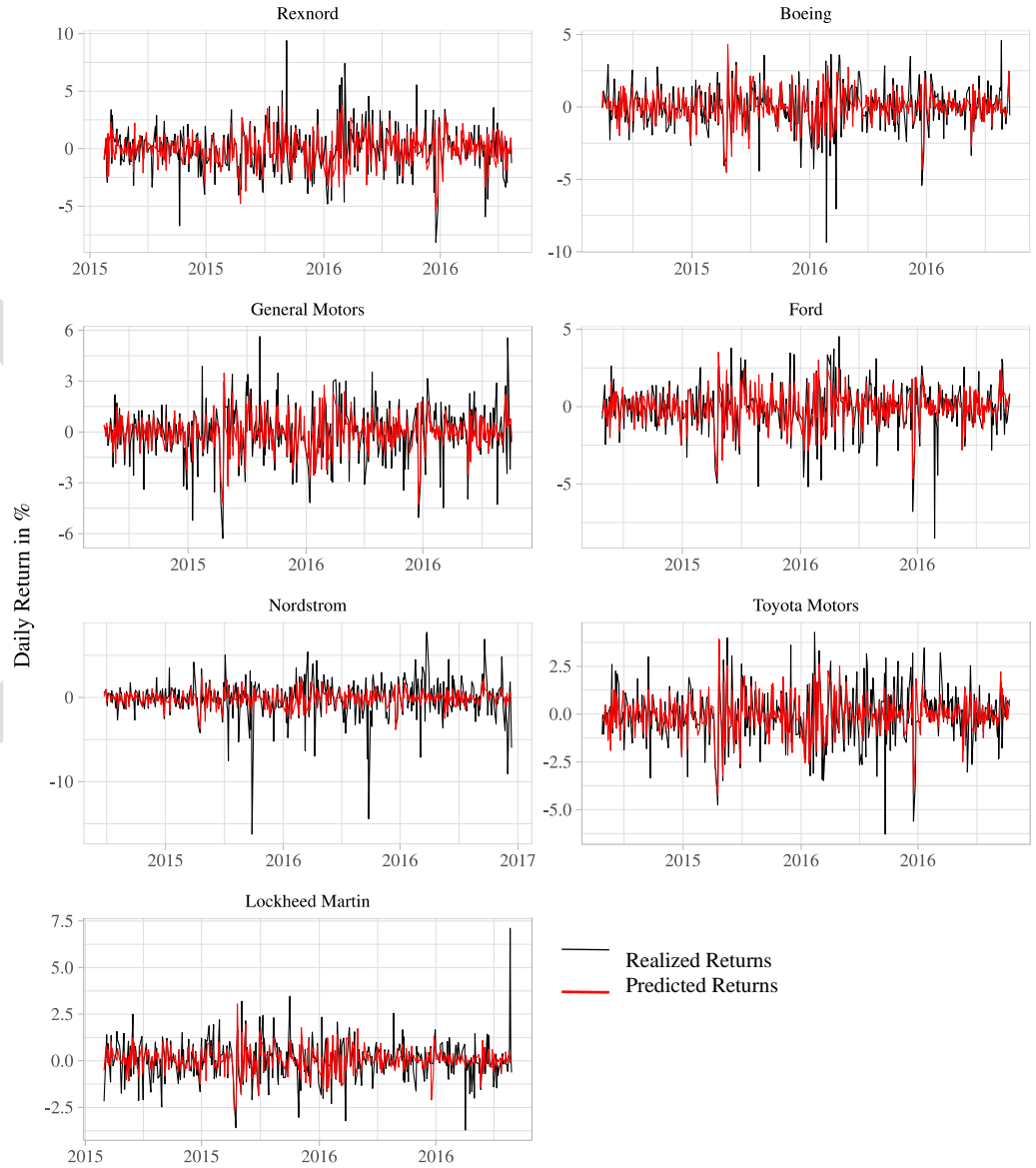
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# Appendix A

## Exhibit A-1: Predicted Values of FF3-Factor Normal Returns Model over Estimation Window

\*The FF3-factor model was calibrated iteratively by performing OLS regressions over the respective estimation windows.  $E(R_i) = R_f + \beta_{m,i}(R_m - R_f) + \beta_{s,i}(R_s - R_l) + \beta_{v,i}(R_v - R_g)$ , where:  $i, f, m, s, l, v, g$  are the return subscripts for the  $i^{\text{th}}$  company, the risk-free rate and the market, small, large, value and growth factor loadings respectively. The return generating mechanism is the Gaussian distribution for the return random variable  $x$ , is:



$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

$\beta_{v,i}$  is the response coefficient of stock  $i$  to the value factor  $v$ .

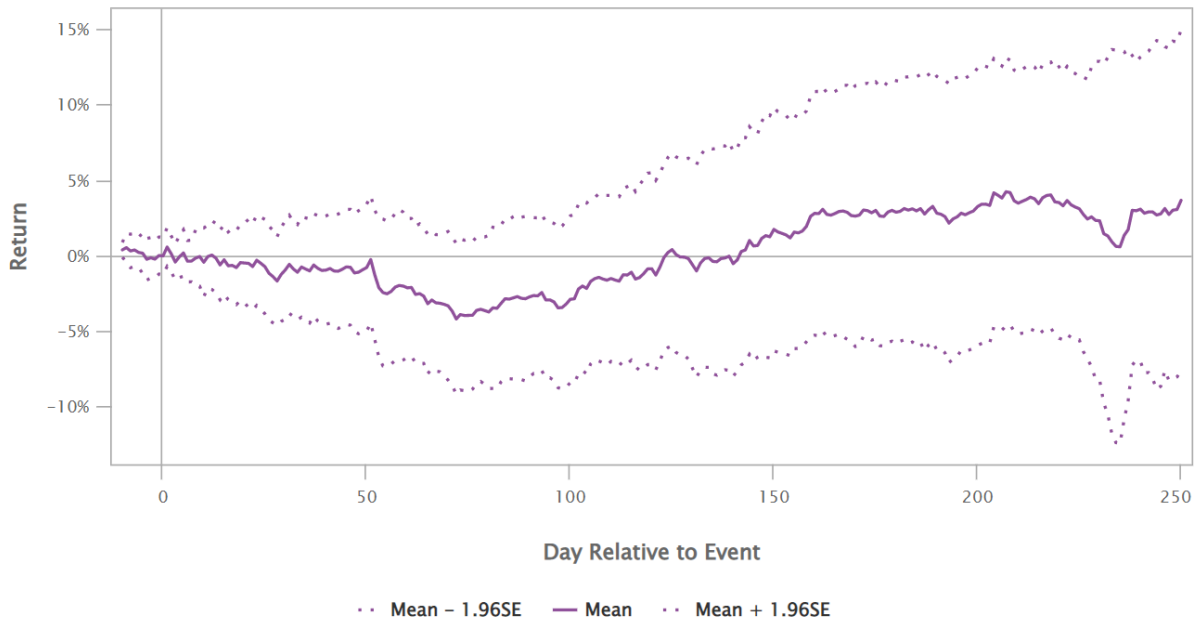
## Appendix B

### Exhibit B-1: Trump-tweets: Negative Information Content: 20 DAY and 250 DAY Estimation

Cumulative Abnormal Return: Mean & 95% Confidence Limits



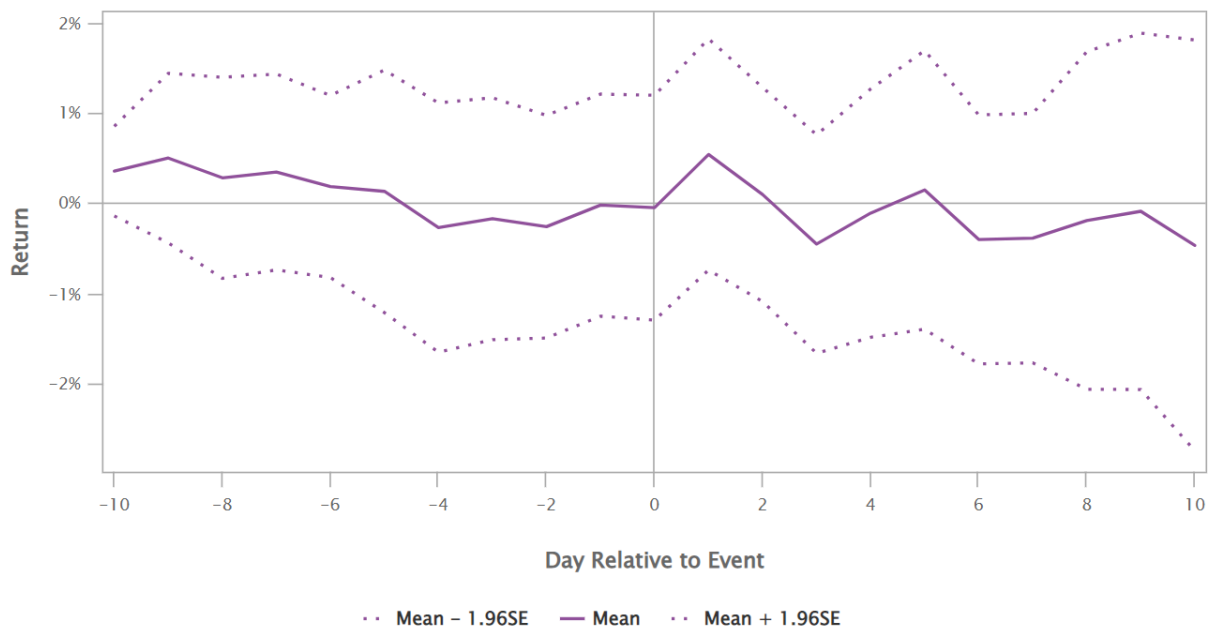
There are 22 events in total with non-missing returns.



Cumulative Abnormal Return: Mean & 95% Confidence Limits

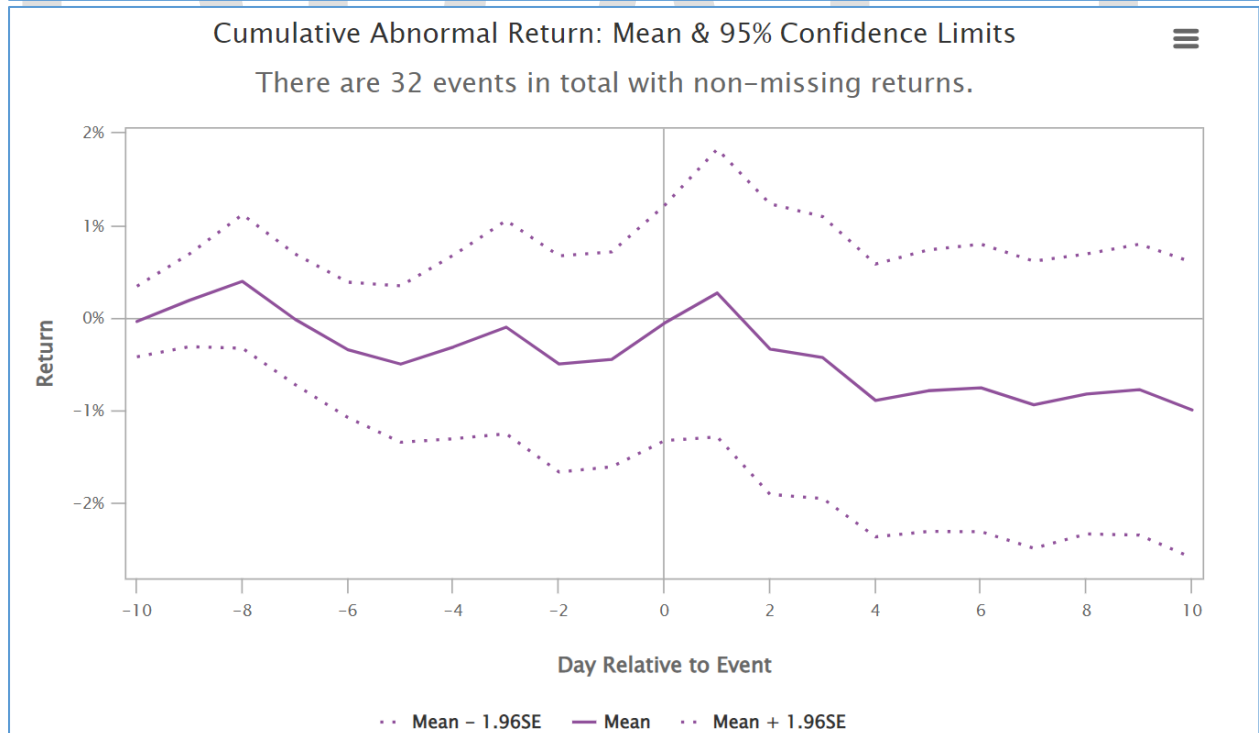
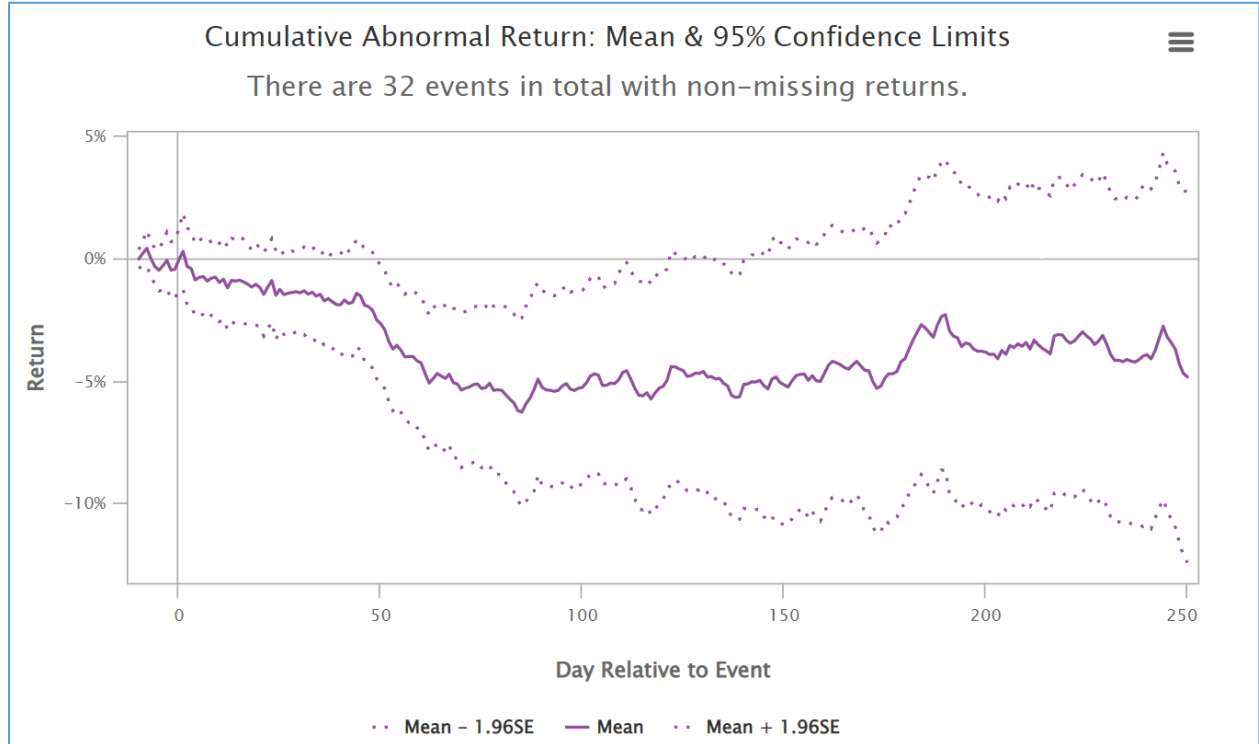


There are 22 events in total with non-missing returns.



\* The long-term positive CARs for negatively themed Trump-tweets seems somewhat counterintuitive, however a look at Exhibit B-6 will show that Trump was mostly positive on industrial stocks (legacy type, which underperformed) and negative on high technology stocks. The weighted CARs are computed as:  $WCAR = \sum_{i=1}^N \sum_{t=T_1+1}^{T_2} \omega_i AR_{i,t}$ . The period from 2016 to 2020 mostly favored growth technology names and Tesla took market share from Ford and GM, which used to be Trumps favorites.

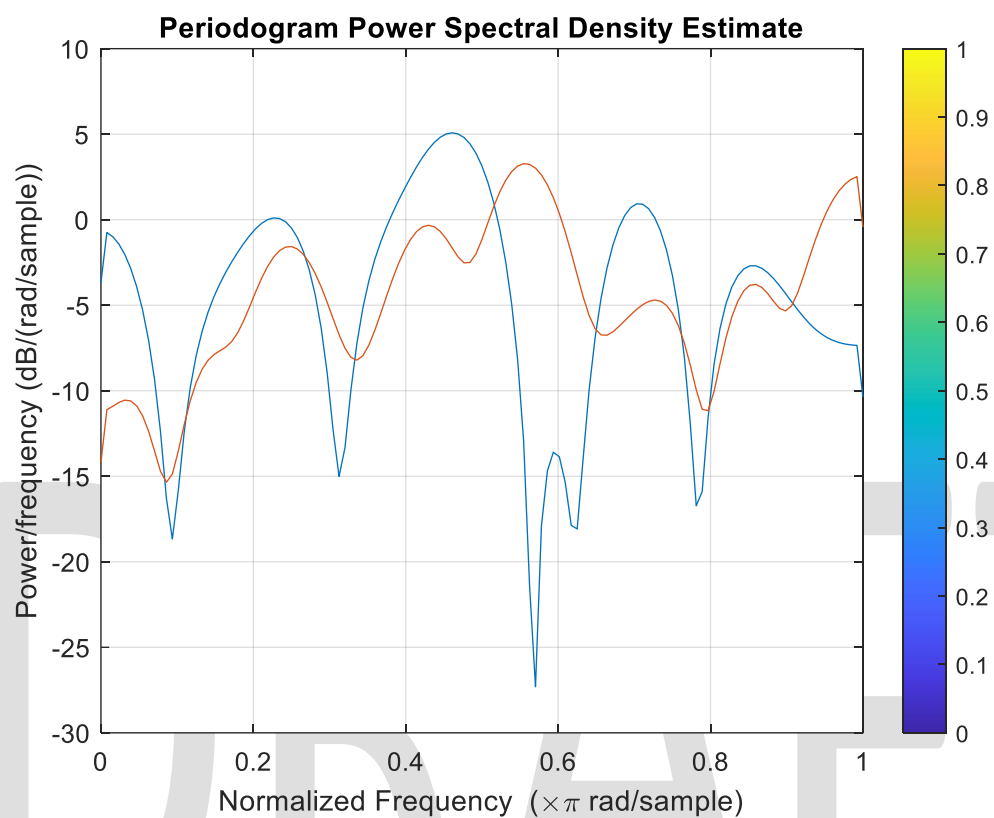
## Exhibit B-2: Trump-tweets: Positive Information Content: 20 DAY and 250 DAY Estimation



\* The long-term negative CARs for positively themed Trump-tweets seems somewhat counterintuitive, however a look at Exhibit B-6 will show that Trump was mostly positive on legacy stocks. The variance of the CARs, captures by the dotted confidence  $2\sigma$  bands and as shown in the paper is:

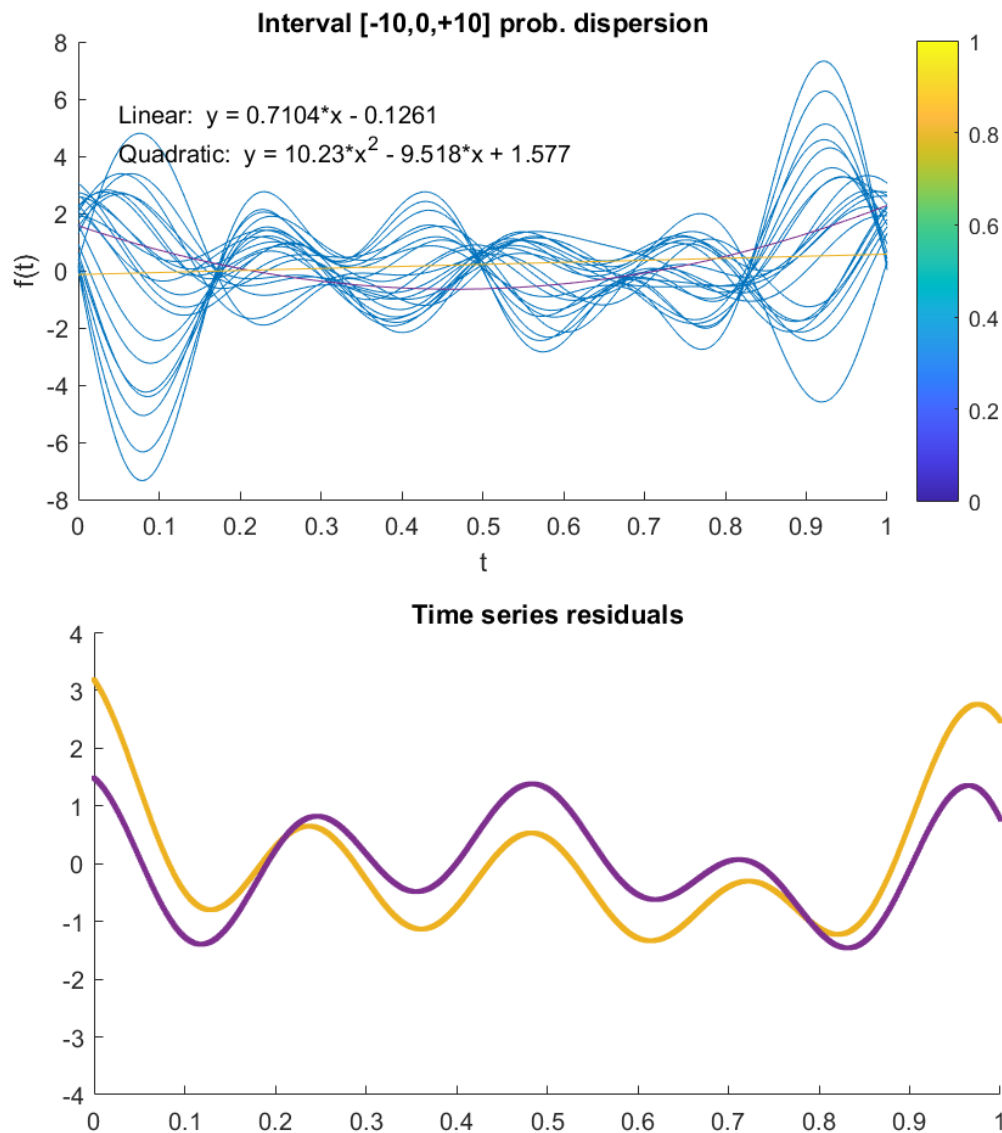
$var(CAR_q) = var(\sum_{t=0}^q u_{it}) = \sum_{t=0}^q var(u_{it}) = q var(u_{it}) = q var(\epsilon_{it})$ . The period from 2016 to 2020 mostly favored growth names while classic industrials used to be Trump favorites.

**Exhibit B-3: Frequency of Return response**



\* The drops and reversals in the t-stats associated with 'good tweets' (blue line) are larger than those with 'bad tweets' (red line), also indicative of investor 'overreaction.' The reversal in returns from the pre-market to the market close results in the returns associated with 'bad tweets' to be positive and they also have reversals that are lesser in magnitude (Ref. Exhibit B-6,7,9). The wavelet transform of a time series signal is  $x(t) = \cos(t * 2\pi/A) + \cos(t * 2\pi/B)$ , for a scalar A, B.

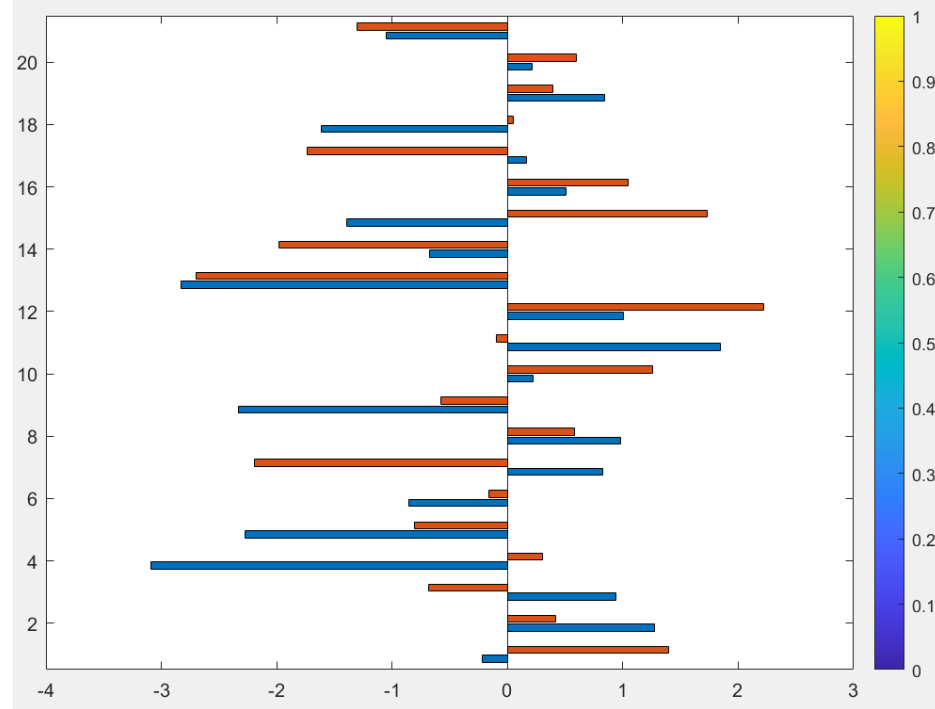
**Exhibit B-4: Magnitude and Frequency of Significance path (ref. Exhibit B-9)**



\* This shows the oscillation of the drops and reversals in the p-values associated with 'good tweets' (blue line) at each of the points on the 20 point event window. The 0 to +2 event period has a higher cluster of the lowest p-values [0 to 0.10], indicative of the disturbance/volatility caused by tweet releases. (Ref. Exhibit B-9). The variance  $\sigma^2$  of the wavelet can be

computed as: 
$$\frac{\int_{-\infty}^{\infty} \left| \frac{dx(t)}{dt} \right|^2 dt}{\int_{-\infty}^{\infty} |x(t)|^2 dt}$$

**Exhibit B-5: *t*-stats for 'good tweets' (orange) versus 'not good tweets' (blue)**



\* This shows the relative magnitude to the t-stats (-4 to +3 on the X-axis) and associated with the AR's at different points on the 20 point event window. The *t*-test to test the significance of the CARs is constructed as:  

$$t\_stat = \frac{CAR_q}{\sqrt{q \, var(\epsilon_{it})}}$$
 The 10 to 14 points on the Y-axis correspond to the -2 to +2 event period and have a higher cluster of higher t-stats occurrences, indicative of the significant effect of the tweets on market based abnormal return performance. (Ref. Exhibit B-9).

## Exhibit B-6: Companies Addressed by Donald Trump's Tweets, Segmented by Type and Release Time

Company Ticker	Tweet Date	Type G	Release Time	Company Ticker	Tweet Date	Type NG	Release Time
AET	2/15/2017	G	1634 ETH	AAPL	2/19/2016	NG	1638 ETH
AET	5/4/2017	G	0828 ETH	AMZN	8/16/2017	NG	0612 ETH
AVGO	11/2/2017	G	1558 RTH	AMZN	12/29/2017	NG	0804 ETH
BA	12/22/2016	G	1726 ETH	BA	12/22/2016	NG	---
BA	2/17/2017	G	0638 ETH	BA	12/6/2016	NG	0852 ETH
CHTR	3/24/2017	G	1359 RTH	BA	4/15/2019	NG	0629 ETH
F	11/17/2016	G	2101 AH	F	3/15/2016	NG	---
F	1/3/2017	G	---	F	2/13/2016	NG	---
F	3/28/2017	G	0636 ETH	F	1/18/2017	NG	---
F	1/24/2017	G	1946 ETH	FB	10/30/2016	NG	---
F	1/9/2017	G	0916 ETH	FB	3/6/2016	NG	---
F	1/4/2017	G	0819 ETH	GM	1/18/2017	NG	---
F	1/3/2017	G	1144 RTH	GM	1/3/2017	NG	0730 ETH
F	11/17/2016	G	---	GOOG	10/30/2016	NG	---
GFF	5/1/2017	G	---	GOOG	7/16/2019	NG	0746 ETH
GLW	7/20/2017	G	2331 AH	GOOG	8/28/2018	NG	1102 RTH
GM	1/3/2017	G	---	JWN	2/8/2017	NG	1051 RTH
GM	1/24/2017	G	1946 ETH	LMT	12/22/2016	NG	1726 ETH
GM	1/17/2017	G	1255 RTH	META	7/11/2019	NG	2015 AH
GM	3/16/2019	G	1701 ETH	MRK	8/14/2017	NG	0854 ETH
HOG	2/3/2017	G	1326 RTH	MRK	8/15/2017	NG	1809 ETH
HOG	2/2/2017	G	1256 RTH	T	6/3/2019	NG	0650 ETH
INTC	2/8/2017	G	1422 RTH	TM	1/5/2017	NG	---
LMT	12/12/2016	G	---	XOM	12/11/2016	NG	---
LMT	1/18/2017	G	---				
LMT	12/22/2016	G	1726 ETH				
MRK	7/21/2017	G	2332 AH				
PFE	7/22/2017	G	2333 AH				
TM	1/5/2017	G	---				
UTX	11/24/2016	G	1011 RTH				
UTX	11/29/2016		2240 AH				
WMT	1/17/2017	G	1255 RTH				
XOM	3/6/2017	G	1619 ETH				
XOM	12/13/2016	G	0643 ETH				

G: Good Tweet

NG: Not Good

ETH/RTH/AH

Tweet released in Extended/Regular/After Trading Hours

\* Former US President Trump was banned from Twitter on Jan 8th, 2021; his account was reinstated on Nov 19th, 2022, however as of March 27<sup>th</sup> 2023 he had not started Tweeting again. The focus of his Tweets changed with the onset of Covid-19 in the year 2020. On balance it seems Trump was more negative on technology names and positive on industrial companies.



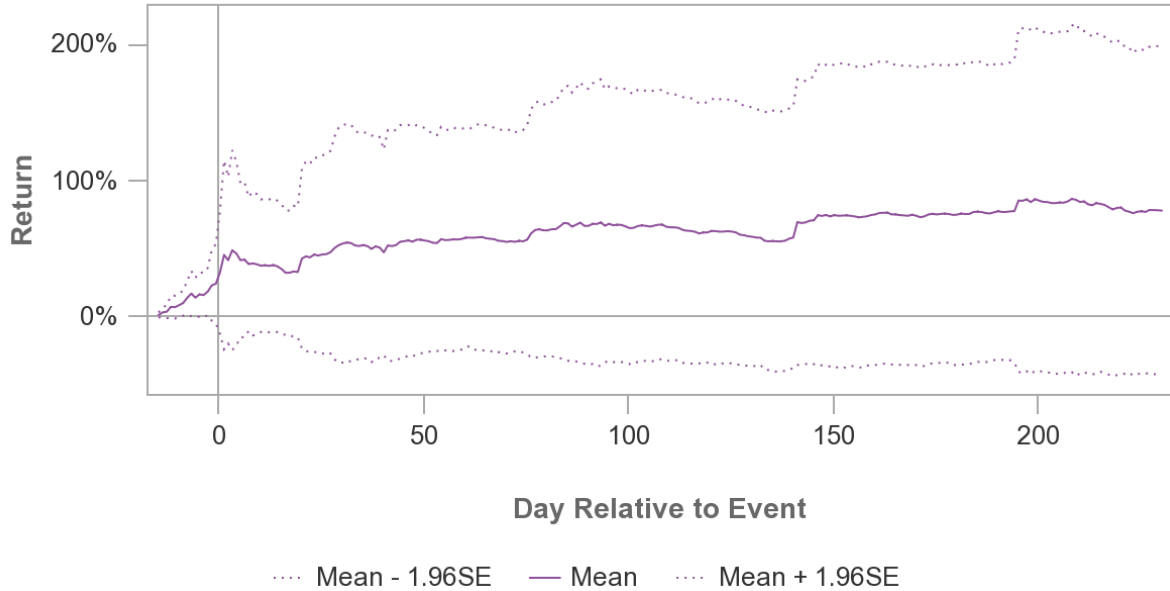
**Exhibit B-7: Companies Addressed by Elon Musk's Tweets, Segmented by Type and Release Time**

Company Ticker	Tweet Date	Release Time	Market Hours	Type G	Tweet
TSLA	8/7/2018	12:48	RTH	G	Am considering taking Tesla private at \$420. Funding secured.
TSLA	5/1/2020	11:11	RTH	NG	Tesla stock is too high IMO.
MSFT	5/3/2020	03:56	AH	G	Minecraft has amazing legs
AMZN	6/4/2020	14:01	RTH	NG	Time to break up Amazon.
Dogecoin (DOGE-USD)	12/20/2020	04:30	AF	G	One word: Doge
ETSY	1/26/2021	06:25	AH	G	I kinda love Etsy.
GME	1/26/2021	16:08	AH	G	Gamestonk!!
Bitcoin (GBTC)	1/29/2021	09:22	AH	G	Added #bitcoin to Twitter bio.
SHOP	1/30/2021	16:31	AH	G	Shopify is great too.
SAND	2/4/2021	04:34	AH	G	Sandstorm is a masterpiece
GOGO	10/14/2021	11:13	RTH	G	Yes...talking to airlines about Starlink ... connectivity in the air.
HTZ	11/1/2021	21:48	AH	G	Hertz deal has zero effect on our economics
TWTR	4/14/2022	06:23	AH	G	I made an offer sec.gov/Archives/edgar...
KO	4/27/2022	20:56	AH	G	Next I'm buying Coca-Cola ...
*material non-repetitive tweets; Hertz did not trade over the 2020-2021 period; TWTR was delisted 11/2022					

**Exhibit B-8: Musk-tweets: Information content: 20 DAY and 250 DAY Estimation**

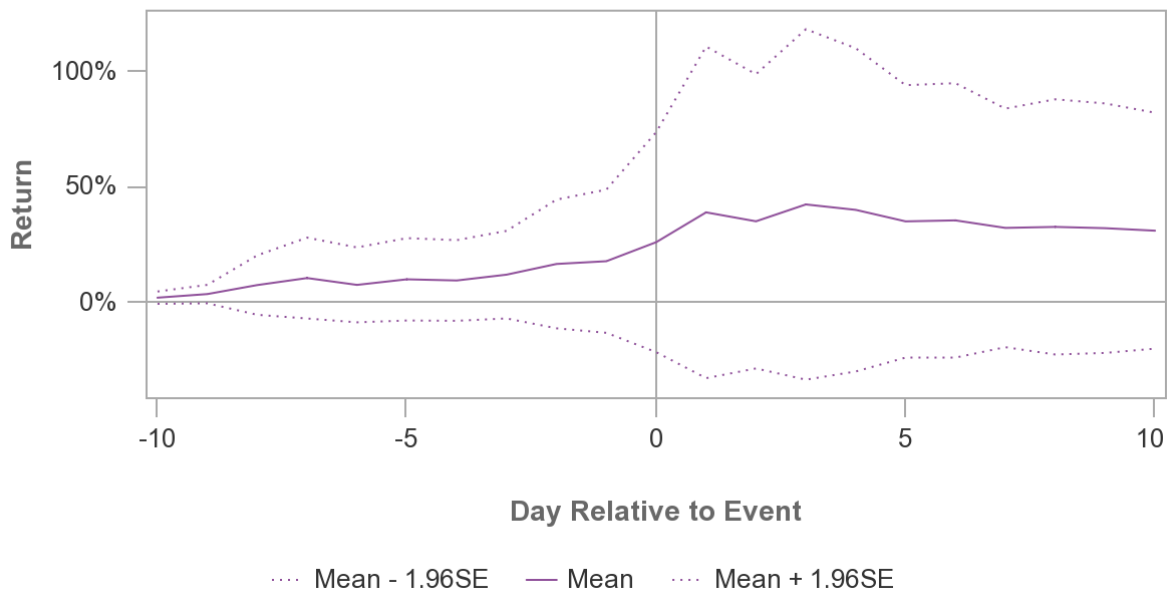
**Cumulative Abnormal Return: Mean & 95% Confidence Limits**

There are 11 events in total with non-missing returns.



**Cumulative Abnormal Return: Mean & 95% Confidence Limits**

There are 11 events in total with non-missing returns.



\* Twitter (TWTR), stopped trading after Elon Musk took it private, it was delisted from the New York Stock Exchange on November 8<sup>th</sup>, 2022, according to a filing with the U.S. Securities and Exchange Commission (incidentally the U.S. midterm elections were being held the same day). The variance of the CARs, captures by the dotted confidence  $2\sigma$  bands and as shown in the paper is:

$var(CAR_q) = var(\sum_{t=0}^q u_{it}) = \sum_{t=0}^q var(u_{it}) = q var(u_{it}) = q var(\epsilon_{it})$ . The weighted CARs are computed as:

$WCAR = \sum_{i=1}^N \sum_{t=T_1+1}^{T_2} \omega_i AR_{i,t}$ . Hertz did not trade for most of 2020-2021. Hence we have  $n=11$  instead of  $n=12$ .

## Exhibit B-9: Aggregated CARs test statistics (includes the Corrado test)

Day Relative to Event	Mean Total Return	Mean Abnormal Return	Mean Cumulative Abnormal Return	Cross-sectional t-statistic for Abnormal Return	Probability, Cross-sectional t-statistic for Abnormal Return	Standardized Cross-sectional t-statistics for Abnormal Return	Probability, Standardized Cross-sectional t-statistics for Abnormal Return	Generalized Sign Test Statistic (Zg)	Probability, Generalized Sign Test	Corrado Signed Rank Test Statistic (Zr)	Probability, Univariate Signed Rank Test Statistic	Univariate Wilcoxon Signed Rank Test Statistic	Probability, Univariate Wilcoxon Signed Rank Test	Univariate Sign Test Statistic	Probability, Corrado Signed Rank Test
-10	0.03%	-0.04%	-0.04%	-0.219	0.828	-0.276	0.784	-0.353	0.362	-0.468	0.860	-30	0.583	-1	0.320
-9	0.45%	0.23%	0.19%	1.278	0.211	1.087	0.286	0.707	0.240	0.534	0.597	35	0.521	2	0.297
-8	0.36%	0.20%	0.39%	0.936	0.356	0.773	0.445	0.353	0.362	0.670	0.860	42	0.441	1	0.251
-7	-0.30%	-0.41%	-0.02%	-3.093	0.004	-3.054	0.005	-2.473	0.007	-2.515	0.020	-150	0.003	-7	0.006
-6	-0.25%	-0.33%	-0.35%	-2.277	0.030	-2.074	0.046	-1.060	0.145	-1.641	0.377	-110	0.038	-3	0.050
-5	-0.03%	-0.15%	-0.50%	-0.852	0.401	-1.136	0.265	-0.707	0.240	-1.058	0.597	-54	0.320	-2	0.145
-4	0.34%	0.19%	-0.32%	0.823	0.417	0.973	0.338	-0.707	0.240	-0.064	0.597	-7	0.898	-2	0.475
-3	0.32%	0.21%	-0.10%	0.981	0.334	1.187	0.244	0.000	0.500	0.614	1.000	27	0.621	0	0.269
-2	-0.25%	-0.40%	-0.50%	-2.333	0.026	-2.020	0.052	-1.767	0.039	-1.779	0.110	-117	0.026	-5	0.038
-1	0.06%	0.05%	-0.45%	0.224	0.824	0.501	0.620	-0.707	0.240	0.115	0.597	-6	0.913	-2	0.454
0	0.58%	0.39%	-0.06%	1.842	0.075	1.798	0.082	1.767	0.039	1.550	0.110	89	0.097	5	0.061
1	0.49%	0.33%	0.26%	1.006	0.322	0.798	0.431	0.707	0.240	0.538	0.597	38	0.486	2	0.295
2	-0.58%	-0.61%	-0.34%	-2.831	0.008	-2.850	0.008	-1.767	0.039	-2.346	0.110	-131	0.012	-5	0.009
3	-0.06%	-0.09%	-0.43%	-0.672	0.506	-0.540	0.593	-0.353	0.362	-0.169	0.860	-19	0.728	-1	0.433
4	-0.48%	-0.46%	-0.90%	-1.392	0.174	-1.458	0.155	-1.060	0.145	-1.157	0.377	-68	0.209	-3	0.124
5	0.21%	0.10%	-0.79%	0.507	0.616	0.283	0.779	1.060	0.145	0.854	0.377	52	0.339	3	0.197
6	0.21%	0.03%	-0.76%	0.163	0.872	0.155	0.878	-1.413	0.079	-0.320	0.215	-21	0.701	-4	0.375
7	-0.03%	-0.18%	-0.94%	-1.610	0.118	-1.804	0.081	-1.767	0.039	-1.227	0.110	-77	0.153	-5	0.110
8	0.18%	0.12%	-0.83%	0.841	0.407	1.197	0.240	1.060	0.145	0.821	0.377	48	0.378	3	0.206
9	-0.03%	0.05%	-0.78%	0.211	0.834	0.309	0.759	-0.707	0.240	0.140	0.597	-8	0.884	-2	0.444
10	-0.13%	-0.22%	-1.00%	-1.054	0.300	-1.112	0.275	0.353	0.362	-0.414	0.860	-17	0.756	1	0.339

\*These are for the 'Good Tweets' sub-panel, the 'Bad Tweets' have similar activity at t+1 and can be supplied by the authors on request.

The Corrado and Zivney (1992) test statistic is given as:

$$z = \sqrt{L_2} \left( \frac{\overline{K}_{T_1+1, T_2} - 0.5}{S_{\overline{K}}} \right) \quad \text{with} \quad \overline{K}_{T_1+1, T_2} = \frac{1}{L_2} \sum_{t=T_1+1}^{T_2} \overline{K}_t$$

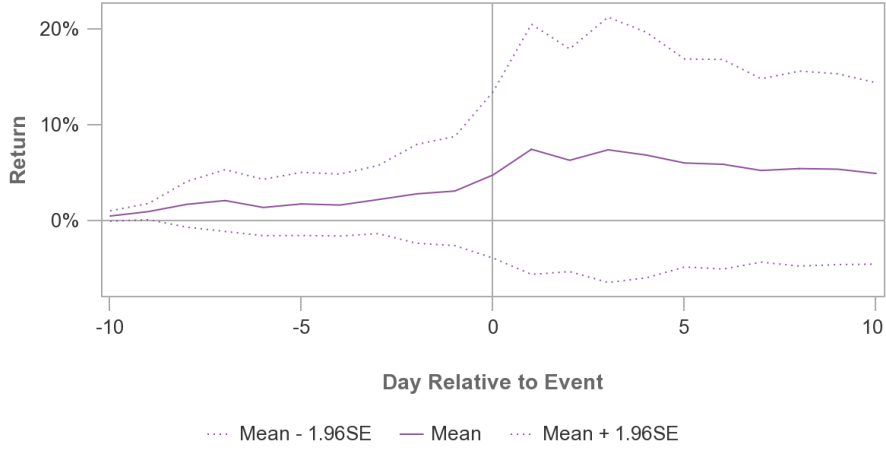
For any  $i$  where  $L_{i,2}$  denotes the number of non-missing  $AR_{i,t}$  during the event window and for any  $t$ , we denote the number of non-missing  $K_{i,t}$  by  $N_t$

The non-parametric Corrado-Zivney ranked test indicated significance during the event window at  $t=+1$  and perhaps interestingly seven trading days prior (Tao, et al. 2023) to the Tweet releases.

## Aggregated Musk/Trump Information Release CARs: 20 DAY and 250 DAY Estimation

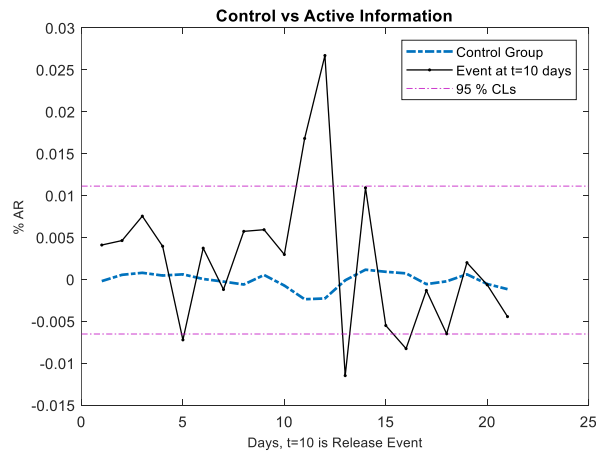
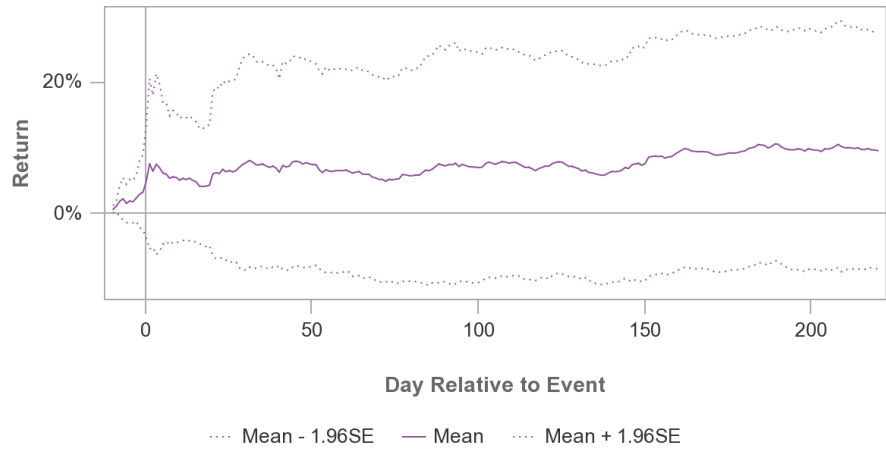
### Cumulative Abnormal Return: Mean & 95% Confidence Limits

There are 61 events in total with non-missing returns.



### Cumulative Abnormal Return: Mean & 95% Confidence Limits

There are 61 events in total with non-missing returns.



\* Tweet information releases of Musk/Trump create large volatility compared to a large control group of Dow Jones index constituents that had Earnings releases on Twitter. Our event driven CARs clearly cannot be modeled as a stationary (AR ( $\rho$ )) process of order  $\rho$  for a prices  $X_t$  with parameter  $|\vartheta| = 1$ , and  $\varepsilon_t$  the error term  $X_t = \sum_{i=1}^p \vartheta_i X_{t-i} + \varepsilon_t$ . Neither does it follow a stochastic process  $X_t$  given as:  $[X]_t = \int_0^t \sigma^2 X_t^2 dt$ . Both violate the Weak form and the Semi-strong form of market efficiency. The control however follows the standard Wiener process:  $dX_t = \mu X_t dt + \sigma X_t dW_t$

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<sup>i</sup> [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

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