

An Inquiry into the Regulation of Social Media Disclosure Policy and its Impacts on Retail Investor Trading Activity

A Thesis presented to the faculty of
the Haslam College of Business and
the Howard Baker Center at the
University of Tennessee - Knoxville

In Partial Fulfillment of the
Requirements for the Degree
Bachelor's of Science in Business
Administration, Global Leadership
Scholars Program, Chancellor's
Honors Program, and the Baker
Scholars Program

by
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June 2018 - March 2019

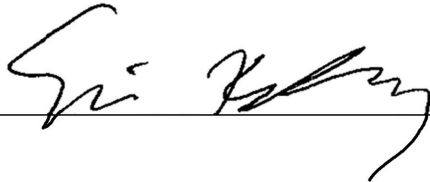
The undersigned, appointed by the dean of the Haslam College of Business School, have examined the thesis entitled:

An Inquiry into the Regulation of Social Media Disclosure Policy and its Impacts on Retail Investor Trading Activity

presented by Sebastian Soldner,

a candidate for the degree of Bachelors of Science in Business Administration

and hereby certify that, in their opinion, it is worthy of acceptance.

A rectangular box containing a handwritten signature in black ink. The signature is cursive and appears to read "Sebastian Soldner".

DEDICATION

This thesis is dedicated to my mother and father, who have given me the privilege of an upbringing and education that has allowed me to explore my passions, pursuits, and curiosities. My father, as long as I can remember, has taught me not to ask what, but to ask why- and in the event of not finding an answer, it was my duty to discover it myself.

Special thanks to colleague and friend Matthew Lamsey, who helped me with coding efficiency, methodology, and general life advice. The rate of progress was significantly aided by his feedback and dedication.

This thesis pays homage to Dr. Laura Cole, who has inspired me, challenged me, and given me incredible opportunity in my undergraduate career. I would not be in the position to write this thesis, or even transition forward in life with the opportunities I have been given, without the consistent guidance, understanding, and passion of faculty like Dr. Cole.

ACKNOWLEDGMENTS

The work in this dissertation is the combined ideas and work carried out at the University of Tennessee - Knoxville, from 2017-2019.

I owe my deepest gratitude to the **Global Leadership Scholars Program**

I am incredibly grateful for the **Masters Investment Learning Center**

I am fortunate to be part of the **Baker Scholars Program**

I am very thankful to have participated in the **EURēCA Presentation Program**

TABLE OF CONTENTS

<u>Acknowledgements</u>	4
<u>Table of Contents</u>	5
<u>List of Figures</u>	8
<u>List of Tables</u>	9
<u>Abstract</u>	10
<u>CHAPTER I: Introduction to Financial Disclosure Policy</u>	12
<u>Why Do Firms Disclose in the First Place?</u>	14
<u>A Brief History of the SEC & EDGAR</u>	15
<u>The SEC</u>	15
<u>EDGAR</u>	15
<u>Regulation Fair Disclosure</u>	15
<u>Recent Overhauls & Changes</u>	16
<u>CHAPTER II: Literature Review</u>	17
<u>The Nature of Information Asymmetry, Disclosure, and Liquidity</u>	17
<u>Motivation: Unrestrained Tweeting appears to have consequences</u>	21
<u>CHAPTER III: Methodology</u>	23
<u>Trading Data Sets and Parsing</u>	24
<u>Twitter Data & Python Tools</u>	24

<u>Python Libraries & Settings</u>	24
<u>Twitter Developer Account</u>	25
<u>Twitter, API's & Python</u>	26
<u>CHAPTER IV: Analysis & Data Findings</u>	28
<u>Twitter Data</u>	28
<u>TAQ Data</u>	29
<u>Twitter & TAQ Data Sets</u>	31
<u>Final Sample of Data - Merging TAQ & Stock Data</u>	32
<u>Logic of Variable Creation</u>	34
<u>Regressions and Visualizations</u>	34
<u>Data Findings</u>	39
<u>Does Tweeting Frequency Increase?</u>	39
<u>Does Earnings Frequency Increase?</u>	40
<u>Retail Investors on Days with Tweets</u>	41
<u>CHAPTER V: Conclusion</u>	45
<u>General Findings</u>	45
<u>Policy Implications</u>	45
<u>Policies for Investors</u>	45
<u>Individual CEO/Executive Policy</u>	46
<u>Implications for Future Work</u>	47
<u>Final Remarks</u>	48

<u>Literature Cited</u>	49
<u>Works Cited</u>	51
<u>Utilities Used</u>	52
<u>VITA</u>	53
<u>Appendix A: List of Top Russell 1000 300 Firms from 2011 with Twitter Accounts</u>	54
<u>Appendix B: Dates used in Sample</u>	57

LIST OF FIGURES

Figure	Page
<u>Figure I: Number of Monthly active Twitter users worldwide 2010-2018 Quarterly</u>	13
<u>Figure II: Twitter Premium Search Documentation (2018)</u>	19
<u>Figure III: Visual Studio Representation of TwitterAPI Python Script Implementation</u>	20
<u>Figure IV: Elon Musk discloses material executive decision on private Twitter</u>	21
<u>Figure V: TSLA share price correlated to Musk Events</u>	22
<u>Figure VI: Virtual Studio code implementation of Python Twitter scripts</u>	25
<u>Figure VII: Twitter Developer Documentation</u>	26
<u>Figure VIII: Example Tweet Containing company disclosure statement</u>	27
<u>Figure IX: Breakdown of volume of tweets for top firm accounts</u>	29
<u>Figure X: Example of TAQ Data file</u>	30
<u>Figure XI: Earnings Tweets per Firm</u>	36

LIST OF TABLES

Table	Page
Table 1: <i>Pre April 3rd, 2013 Statistics (Only Earnings Date)</i>	35
Table 2: <i>Post April 3rd, 2013 Statistics (Only Earnings Date)</i>	35
Table 3: <i>Pre April 3rd, 2013 (Earnings Date + M1 + P1)</i>	37
Table 4: <i>Post April 3rd, 2013 (Earnings Date + M1 + P1)</i>	37
Table 5: <i>Summary Statistics</i>	38
Table 6: <i>Summary Statistics (Earnings Announcement Dates & +/- 1 Day Window)</i>	38
Table 7: <i>Two-sample T-Test - Number of Tweets(Pre & Post April 3rd, 2013 Event)</i>	39
Table 8: <i>Two-sample T-Test - Number of Earnings Tweets(Pre & Post April 3rd, 2013 Event)</i>	40
Table 9: <i>Two-sample T-Test - Number of Earnings Tweets if Earnings Announcement Dates & +/- 1 Day Window (Pre & Post April 3rd, 2013 Event)</i>	40
Table 10: <i>Summary of Fixed Effect Regressions</i>	43

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Eric Kelley, Thesis Supervisor

ABSTRACT

Finance theory has evolved rapidly over recent decades, as the growth of mass electronic data sets have allowed researchers to apply theory and craft it to results seen in the real world. Financial policy has seen intense debate all across the world, but one of the more silent agents of advancement has been online financial disclosure policy. Through the past few decades, we have seen the mutual growth between technology and policy, and how their interplay shapes the modern world we live in. Investor relations policy has never been at a greater point of allowing information dissemination than today, as with the de-regulation of social media disclosure, companies are able to, like never before, access a worldwide audience to deliver news, earnings, and press release statements to any average person (from now on referred to as the retail investor). Although firms now routinely disclose relevant information through media like Twitter, little research has studied how those disclosures affect retail investor trading decisions. Previous literature in social media's impact on investors delves into accounting and psychologically focused material. In this paper, we look at the timeline of a year before and after the deregulation of social media as a hub of investor disclosure, from mid 2012 to mid 2014, and take the top 250 companies in the United States as a source for tweet releases, as well as high frequency TAQ (Trade and Quote) data parsed for data unique to retail investors. Through our research on the window of 2012-2014, we have discovered

that retail investor trading activity is indeed influenced by Twitter company disclosures, especially on earnings days and tweets with earnings information. The implications of this are very exciting, as this effect has likely only multiplied in the 5 years since, and leads twitter and other DAIT's to be a significant factor in retail investor trading decisions.

CHAPTER I:

INTRODUCTION TO FINANCIAL DISCLOSURE POLICY

The retail investor has never been in a better position to make educated and articulate choices about how to best manage their capital than in the digital age. In the infancy of public company regulation, financials and business goals had to be reported in paper form. This led to massive physical storage spaces spread around countries; institutional investors needed subordinates to scour through vaults to derive educated valuations of company prospects. This gave large institutions and banks a huge advantage in estimating the *true price* of an asset, and left the average person in the dark regarding educated decision making. Then came the surge of online databases- from 1993-1996, the SEC's EDGAR system in the US became the flagship of online repositories for these filings. As shown by **Huang and Gao (2018)**, EDGAR expanded the availability of information exponentially; with access to these documents online, more people than ever could conduct investment research, allowing potentially better-informed decisions than ever before. Individual investor trading became much more informed when investors were paired with information and access to the internet. These documents, however, were still based on a *pull* system, meaning that individuals and institutions had to seek out this information. After the explosion of the internet, eventually companies could release press statements and earnings reports on their websites- this led to an even greater availability of information. All of these advancements pale in comparison, however, to the advent of social media.

We have entered the era of a *push* system, where information is immediately accessible to the largest audience in history. Instantly, millions of people can be alerted by Twitter and other outlets regarding company statements and earnings reports. Now retail investors have a leap closer towards

competing with institutional investors, and are potentially able to make more immediate, educated, and strategic choices than ever before. This is potentially great for the economic wealth distribution of society as a whole, as when more people gain the same playing field of information, more people can potentially use of all this information to make more rational and informed decisions.

This research focuses on data from Twitter, with a global user base of [335 million](#) people in September of 2018. As shown by *Exhibit I*, Twitter had averaged 160.25 million users in 2012, 223.5 Million users in 2013, and 274.5 Million users in 2014. Year over year growth saw 39% user growth in 2013, and 23% growth in 2014 (**Statista 2018**). From 2012 to 2014, Twitter had a potential audience of hundreds of millions of people; the greatest breadth of potential information sharing in human history.

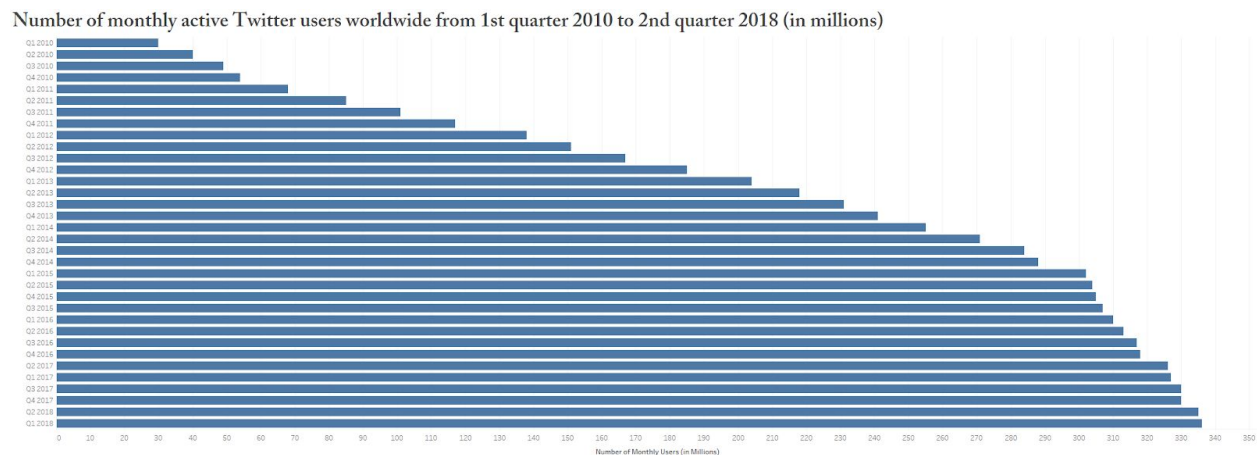


Exhibit I: Number of Monthly active Twitter users worldwide 2010-2018 Quarterly

There has been no tangible financial research published regarding financial social media disclosure policy and its impacts on retail investors, especially regarding an expansion into United States policy implications.

Ever since the inception of public corporation policy, investors have needed information to make decisions. Whether that be financial statements, production quotas, or any variety of general

news, investors demand accurate, up to date information to best make their decisions. The more accurate and widely spread information is, the more accurate markets are, and the more organically the economy can grow with genuine value (**Healy, Hutton, and Palepu 1999; Bushee and Noe 2000**).

Why do Firms disclose in the first place?

As highlighted by **Loewenstein 1996** and **Pellisserry 2012**, corporations disclose financial & firm related information because it is the most effective and efficient method for invoking better firm management. It is arguably common thought that financial disclosure requirements can change behavior just because certain information must be disclosed (**Farrar, Hannigan, 1998**), potentially lowering agency issues. On an obvious legal basis, the *Securities Act of 1933* makes disclosures of all “material information” mandatory to file as a public firm. *Blue Sky Laws* were previous state-regulated policies regarding securities sales pre-1933; these were absolutely superseded by the *1996 National Securities Markets Improvement Act*. Ultimately, as a holistic argument, capital is more easily distributed in a market where investors feel there is safety, honesty, and transparency. As demonstrated by **Skaife, Collins, LaFond 2005**, cost of equity for firms with less transparent earnings is *higher*, while firms with more independent audit committees have a lower cost of equity. It is in the shareholder’s best interest (and by proxy, the best interest of management) to release accurate, transparent, and timely financial disclosures.

A Brief History of the SEC & EDGAR

The SEC

The U.S. Securities and Exchange Commission (SEC) was founded in 1934 with the *Securities Exchange Act*. This independent agency of the United States government enforces the many financial policy doctrines established by the federal government (more recent notable enforcement include *Reg FD* and *the Sarbanes Oxley Act of 2002*).

EDGAR

EDGAR, or the Electronic Data Gathering, Analysis, and Retrieval system, is a locus of all official public firm financial disclosures in the United States (overseen by the SEC). Beginning in 1992-1993, all US firms began to transport their filing process to the electronic repository (official end of transformation was May 6th, 1996). Annual reports are not required to be filed on EDGAR, but are often done so for shareholder ease of use. Since 2002, all foreign companies doing business with the USA must also file on EDGAR. As of March 31, 2018, there are over 12 million filed documents in the EDGAR repository.

Regulation Fair Disclosure

Passed in August 2000, Regulation Fair Disclosure (Reg FD) is a federal doctrine stating that no public companies may disclose previously non-public, material information to certain parties unless information is simultaneously distributed to all shareholders or the general public. Reg FD instantiated that *selective disclosure* to certain investors was not condoned, as oftentimes, institutional investors got a significant advantage in received material information. Barring unique confidentiality

agreements to ‘temporary insiders’ learning material information about a firm, this regulation made prosecuting *insider trading* much easier, and arguably significantly leveled the playing field for all investors in the modern era. On August 1st, 2008, the SEC released guidance stating that public website domains could be used by firms to disclose material information.

Recent Overhauls & Changes

The SEC updated Reg FD on August 2nd, 2013, confirming that social media could be a platform for information dissemination, provided that there are no restrictions placed on individual investors (This was in reaction to a Facebook post made by Reed Hastings, the CEO of Netflix, regarding viewer metrics-- more on this in Chapter II). This is the focus of our work in this thesis-- to see how the most recent guidance of the SEC has shaped the investment decisions of the retail investor. We are still being shaped by the connectivity and power social media brings to our lives every passing day; millions of people use social media such as Facebook, Twitter, etc., as their primary source of information, two-thirds of Americans report getting some of their news from Twitter (**Pew Research 2018**). Prior literature research argues that investors have limited time and resources, leading to only using a limited number of sources for information (**Grossman and Stiglitz 1980; Merton 1987; Hong and Stein 1999; Hirshleifer and Teoh 2003, Blankespoor, Miller, White 2013**). We are looking to observe the potential beginning of a cultural shift, specifically in regard to how individual people get their investment related information from media outlets.

II:

Background and Related Literature

In this subdivision, this research is substantiated by previous work in related literature, and additional context for the state of social media.

The Nature of Information Asymmetry, Disclosure, and Liquidity

As *The Role of Dissemination in Market Liquidity: Evidence from Firms' Use of Twitter* is our most closely related paper, we want to highlight the objective, methodology and results of **Blankespoor, Miller, and White 2013** more closely. **B.M.W.** found, “Firm disclosures often reach only a portion of investors, which results in information asymmetry among investors, and therefore lower market liquidity”. This paper highlights that firm news disclosed through twitter leads to *more efficient markets*, through lower bid-ask spreads, greater depth (arguably, greater liquidity), and lower information asymmetry. This result is especially true for ‘less visible’ companies-- companies that are not in the public eye as commonly as Apple, Tesla, Microsoft, etc. In terms of methodology, the paper takes the top 141 firms of an aggregate of top IT and technology magazines that have Twitter accounts, takes press releases based on wire feeds, and correlate this data to real time history of stock bid-ask spreads and depths. **B.M.W.** have various methodologies from statistical data aggregation of click rates and tweet text that we emulate later in this paper.

Even prior to the advent of social media, we see disclosure affected multivariate aspects of public companies, such as a firm’s cost of capital (**Botosan 1997**), institutional investor following (**Bushee and Noe 2000**), and stock price volume and volatility (**Healy, Hutton, and Palepu 1999; Bushee and Noe 2000**). Our work examines a different aspect of disclosure, namely its influence

on retail investors.

Why would a retail investor manage their own money instead of relying on an institution or a financial management professional? Lack of agency problems, career concerns, and/or liquidity constraints might lead to an edge for the unique portfolio compositions of a retail investor as compared to a mutual fund (**Chevalier, Ellison 2002**). We would lend some credibility to the retail investor, as they potentially have the ability (through geographic proximity to individual firms, relationships to employees, insights into customer tastes, etc.) to contribute to the efficiency of markets (albeit, more unconventionally) (**Kelley, Tetlock 2012**).

We track retail investor trading activity through the methods outlined from **Boehmer, Jones, and Zhang 2017**. Marketable orders of retail investors are distinguished by TRF (Trade Reporting Facility) at prices a round penny above NBBO (National Best Bid or Offer) for retail sellers and just a round penny below NBBO for retail buyers. This is demonstrated by the equation: $Z_{it} \equiv 100 * \text{mod}(P_{it}, 0.01)$, where P_{it} is transaction price in stock i at time t . Z_{it} will represent the fraction of a penny associated with the transaction price used to isolate retail investors. We can correlate transactions as retail initiated due to these specific transactions being slightly below or above a round penny. This isolates retail activity due to institutional trades not receiving this aspect of fractional penny price movement (**Boehmer, Jones, and Zhang 2017**).

Our primary interest in social media disclosure policy and its effects on retail investor sentiment came from a rule decision on [April 2nd, 2013 from the SEC](#) shown in *exhibit III*, spurred by Netflix CEO Reed Hasting's use of Facebook in July of 2012 to announce firm specific news that viewers had consumed 1 billion hours of entertainment in one month, shown in *Exhibit II*. Since this

day, companies have been allowed to tweet various information to the largest audience in history (335 million users in September of 2018). One would argue that most retail investors don't even pour through websites or EDGAR to derive information about a firm, they would expressly use social media push notifications to derive portfolio management decisions. This is a compelling sentiment, as **Loughran, McDonald 2018** show us that EDGAR filings are rarely opened (28.4 average report openings immediately after 10-K releases) to derive fundamentals about a firm. Given all of this information, our work in this paper is twofold-- both to understand if firms as a whole release material information in their twitter disclosures more after April 3rd, 2013 than before, and if retail trader sensitivity to firm tweeting of earnings events increases from before to after. We will discuss more about implications for future work in chapter V.



Exhibit II: Reed Hastings post that drew SEC scrutiny

SEC Says Social Media OK for Company Announcements if Investors Are Alerted

FOR IMMEDIATE RELEASE

2013-51

Washington, D.C., April 2, 2013 — The Securities and Exchange Commission today issued a report that makes clear that companies can use social media outlets like Facebook and Twitter to announce key information in compliance with Regulation Fair Disclosure (Regulation FD) so long as investors have been alerted about which social media will be used to disseminate such information.

The SEC's report of investigation confirms that Regulation FD applies to social media and other emerging means of communication used by public companies the same way it applies to company websites. The SEC issued guidance in 2008 clarifying that websites can serve as an effective means for disseminating information to investors if they've been made aware that's where to look for it. Today's report clarifies that company communications made through social media channels could constitute selective disclosures and, therefore, require careful Regulation FD analysis.

"One set of shareholders should not be able to get a jump on other shareholders just because the company is selectively disclosing important information," said George Canellos, Acting Director of the SEC's Division of Enforcement. "Most social media are perfectly suitable methods for communicating with investors, but not if the access is restricted or if investors don't know that's where they need to turn to get the latest news."

Regulation FD requires companies to distribute material information in a manner reasonably designed to get that information out to the general public broadly and non-exclusively. It is intended to ensure that all investors have the ability to gain access to material information at the same time.

Lona Nallengara, Acting Director of the SEC's Division of Corporation Finance, added, "Companies should review the Commission's existing guidance — it is flexible enough to address questions that arise for companies that choose to communicate through social media, and the guidance does so in a straightforward manner."

The SEC's report of investigation stems from an inquiry the Division of Enforcement launched into a post by Netflix CEO Reed Hastings on his personal Facebook page stating that Netflix's monthly online viewing had exceeded one billion hours for the first time. Netflix did not report this information to investors through a press release or Form 8-K filing, and a subsequent company press release later that day did not include this information. Neither Hastings nor Netflix had previously used his Facebook page to announce company metrics, and they had never before taken steps to alert investors that Hastings' personal Facebook page might be used as a medium for communicating information about Netflix. Netflix's stock price had begun rising before the posting, and increased from \$70.45 at the time of the Facebook post to \$81.72 at the close of the following trading day.

The SEC did not initiate an enforcement action or allege wrongdoing by Hastings or Netflix. Recognizing that there has been market uncertainty about the application of Regulation FD to social media, the SEC issued the report of investigation pursuant to Section 21(a) of the Securities Exchange Act of 1934.

Exhibit III: SEC Disclosure Update for policy question

Motivation: Unrestrained Tweeting appears to have consequences

A final note on motivation: As shown in *Exhibits IV and V*, individual instances of outside action (e.g. Elon Musk's commentary as CEO on Tesla's performance) have potential ramifications on the market en masse, leading to likely impact on the retail investor as well. This research will detail only with official firm twitters statements, and while Musk is indeed one of the most prominent examples of this action, we look to see how firm accounts have impacts such as this in a much more nuanced way all throughout markets.



Exhibit IV: Elon Musk discloses material executive decision on private Twitter account, partly in attempt to destroy

positions of short sellers of TSLA. At the time TSLA was at ~\$340 per share, and shot up to ~\$375 off of this tweet.

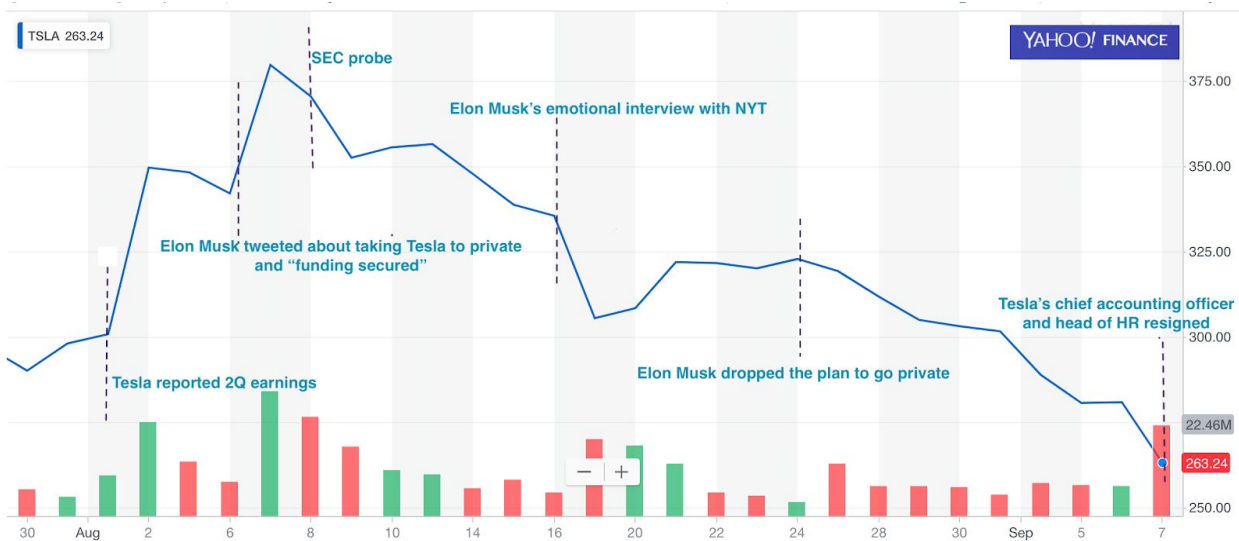


Exhibit V: TSLA share price correlated to TSLA events, including Elon Musk intervention and personal disclosures

III:

Methodology

My directive is to analyze the correlation between firms' social media disclosures and retail investor trading, which is relevant to historical and future policy implications. Due to wanting to isolate the effect of disclosure policy change, we will condense our timeframe, as to analyze the effect of social media deregulation on retail investor trading habits. I focus on the time period of April 3rd, 2012 to April 3rd, 2014, to have a year of distance on either side of April 3rd, 2013, our SEC greenlight event date for officially allowing social media as a platform for disclosure. I have collected records of official company disclosures through Twitter by the 250 largest firms in the Russell 1000 index. I use measures of buying and selling activity of retail investors based on TAQ data. I have built a Twitter bot through Python to collect monthly tweet data, contains any possible disclosures, links, or relevant disclosures from the aforementioned public companies and plan continue to expand upon the capabilities of this program. These data points from Trade and Quote syncopated to official public company Twitter data will allow me to gain insight into the impact social media has on the trading patterns of the average investor. Additionally, by integrating my unique perspective as a U.S. student of finance, international business, and public policy, combined with continued quantitative analysis and qualitative policy review, this research will offer a policy perspective on potential worldwide impacts of wealth distribution that social media has on us all.

Trading Data Sets and Parsing

NYSE TAQ ([Trade and Quote](#)) data measures trade data (actual execution of orders) and quote data (quotes for potential trades) from the NYSE, AMEX, NMS and SmallCap issues. As one can imagine, high frequency trading data can become extremely dense and bureaucratic; with thousands of inputs a second in either category, data for a days worth of data can amount to hundreds of gigabytes. This leads a researcher to try to synthesize and streamline as much data as possible to make sense of the incredible array of information. Since quote data is an order of magnitude more voluminous than trade data, and does not deliver any real insight into retail investor trading strategies, we will not be using it for this research. Instead, we will be looking at trading data, amassing TAQ data through the University of Tennessee's access to the Wharton Research Data Services ([WRDS](#)). I use the proxy for retail trading developed by **Boehmer, E., Jones, C., and Zhang, X**, discussed below. Dr. Kelley, my academic advisor, in line with the methodology from. has parsed TAQ data with a specific algorithm that significantly isolates retail investors buying and selling activity.

Twitter Data and Python Tools

Python Libraries & Settings

To pull and synthesize Twitter data, I have integrated a version of Visual Studio as shown in *Exhibit VI* with Python 3.7.0. Realizing I needed a massive amount of data analysis and collection tools, I am running VS through the [Anaconda](#) Navigator, giving me hundreds of libraries for data science. My script runs from Windows 10, and pulls the data to a comma-delimited text file (CSV). From here, I can import the data into excel, tableau, or any other python script and run analysis on it.

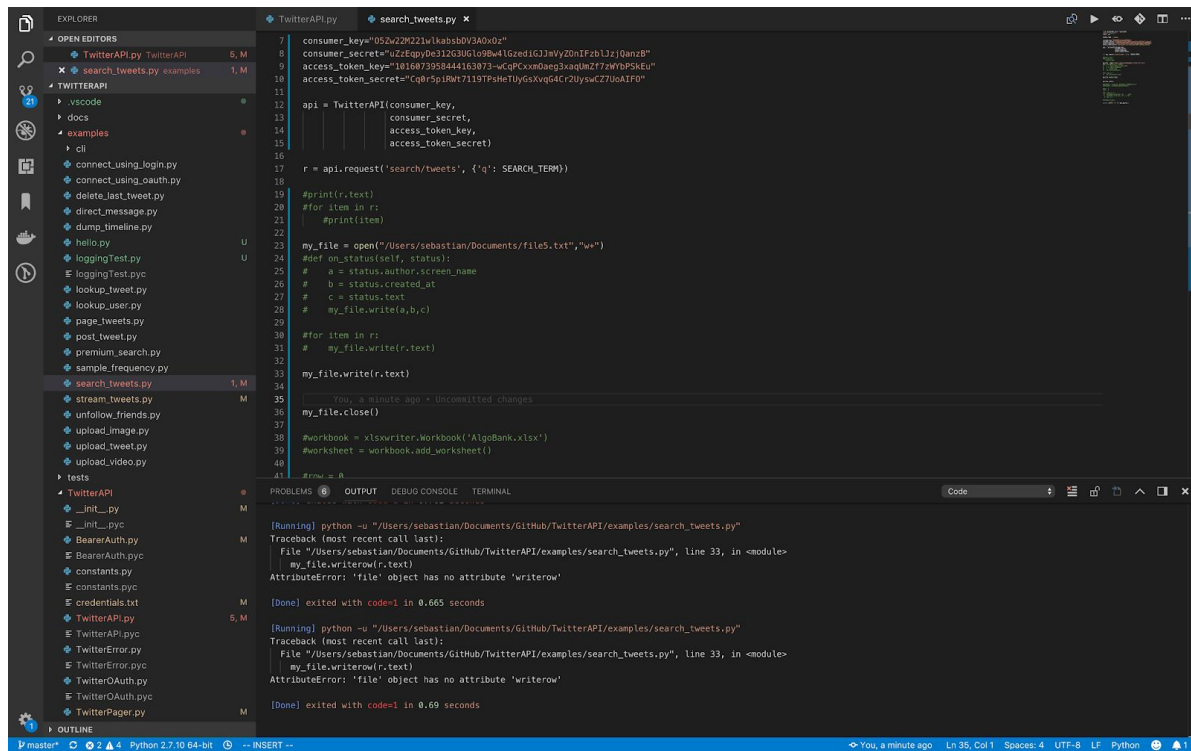


Exhibit VI: Virtual Studio code implementation of Python Twitter scripts

Twitter Developer Account

Due to the nature of academic research, particularly dealing with massive amounts of data from 2012-2014 (official dates of collection for this project are 4-3-2012 until 4-3-2014), Twitter keeps this proprietary data behind many hurdles. My first step was to apply for a Twitter Developer account; I had to write an essay and vouch for the academic intent of the Twitter data. After a few days of waiting, I was approved for a [developer account](#), and set up the necessary dev environment to generate authentication keys that will then be used in a Python platform. My primary usage of the Twitter Developer access is to use the Premium search API with the **Full Archive** access, as shown by *Exhibit VII*, to search for tweets from 2012-2014 (Twitter natively allows a user to search for

tweets up to 7 days back for free, otherwise one needs to use another proprietary search algorithm).

The screenshot shows the Twitter Developer Documentation page for 'Search Tweets'. The left sidebar contains a navigation menu with categories: Basics, Accounts and users, Tweets, Direct Messages, Media, and Trends. The 'Tweets' category is expanded, showing sub-links like 'Post, retrieve and engage with Tweets', 'Get Tweet timelines', 'Curate a collection of Tweets', 'Optimize Tweets with Cards', 'Search Tweets', 'Filter realtime Tweets', 'Sample realtime Tweets', 'Get batch historical Tweets', 'Rules and filtering', 'Data enrichments', 'Tweet objects', 'Tweet compliance', and 'Tweet updates'. The main content area is titled 'Search Tweets' and includes tabs for 'Overview', 'Guides', and 'API Reference'. Under 'Overview', there are links for 'Premium search' and 'Enterprise search'. A 'Premium' badge is visible above the 'Premium search APIs' section. The 'Introduction' section welcomes developers to the premium search API, listing two endpoints: 'Search Tweets: 30-day endpoint' and 'Search Tweets: Full-archive endpoint'. It explains that the API provides low-latency, full-fidelity, query-based access to the Tweet archive. It also mentions that queries are written with premium operators and filter syntax, and that there are two endpoints associated with each premium search product: the 'data endpoint' for full tweet payloads and the 'counts endpoint' for data volume. The page concludes by noting that search queries can match many tweets, with data requests limited to 100 results per page (or 500 for counts), and that pagination is handled using 'next' tokens.

Exhibit VII: Twitter Developer Documentation

Twitter, API's & Python

As the most significantly intensive aspect of this project, my final Twitter bot has gone under many iterations. I have learned Python, Twitter API implementation, and general coding knowledge from coding work by users like [Geduldig](#) on Github (an MIT researcher and proficient builder of tools to access Twitter's REST APIs and Streaming APIs) such as [TwitterAPI](#), and [TEA](#) by user [Sergio LaRosa](#), but found them to be severely obtuse or extremely rate limited. By working with and understanding the work of both users, as well as countless stackoverflow and python documentation, I finally found success with user [Jefferson Henrique](#), using his [GOT](#) tool, hooking into Twitter's Developer portal and record twitter data.

With modification, I am able to pull any firm's data from my desired date range, which is 4-3-2012 until 4-3-2014 (a year before and after the SEC's greenlight of Twitter as a medium for disclosure). This method allows me to run hundreds of queries on every Russell 1000 firm, cataloging every tweet in this range. This is *immensely powerful*, as for weeks, I have been able to log and record the exact tweets of each individual corporation. Having access to any potential tweets allows me to search explicitly for parameters such as "earnings" or "press releases". For the time being, our analysis will filter investor disclosure tweets to tweets containing the phrase "earnings"(as 'earn' pulls derivative information such as tweets with 'learn', etc. in them). Since I am also logging retweets and likes, we can correlate a tweet's "reach" with the potential market movement at a given time. My analysis will use over 1,400,000 tweets for 250 firms. This can be greatly expanded in the future, up to 1000 or 2000 firms if desired. *Exhibit VIII* shows a tweet from one of our covered firms that would fall under our identifier for material disclosure tweeting.

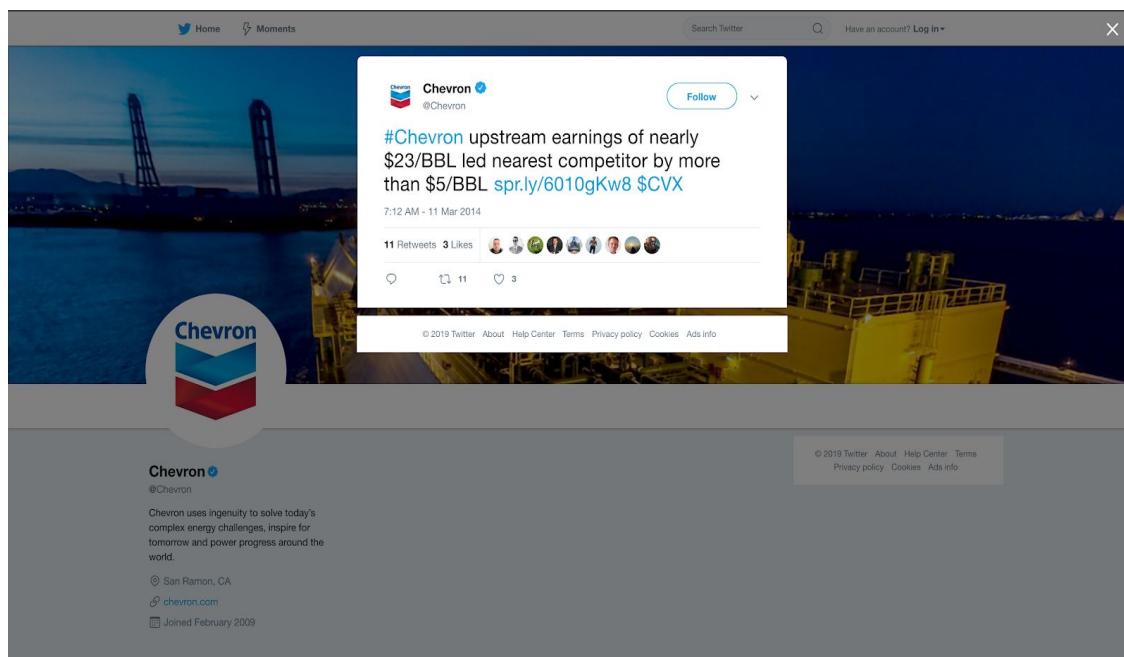


Exhibit VIII: Example Tweet containing company disclosure information

IV:

Analysis & Data Findings

Twitter Data

Our Twitter data is composed of tweets between April 3rd, 2012 and April 3rd, 2014 generated from the top 250 firms on the Russell 1000 index as of July 30th, 2011. This ends up being 1,436,731 tweets and ~300 megabytes of text data. Our twitter data is broken down into 10 variables as follows:

- **Index** (Unique identifier per tweet)
- **Ticker** (Company associated Twitter account. E.g. AAPL is Apple)
- **Date** (YYYY-MM-DD HH-MM-SS Format, essential for correlating to trade timestamps)
- **Text** (Our essential factor in this thesis, we are looking for earnings related content)
- **ID** (Unique ID of a tweet)
- **Permalink** (Link to a tweet, to verify its existence)
- **TAQ_Date** (Time correlated from tweet to stock trading day, defined in detail below)
- **Earn_Count** (Amount of times ‘earn’ appeared in Tweet. In my sample, ranges from 0 to 4)

Our ~1.4 million tweets were parsed and cut down to just tweets pertaining text that contains “**earnings**”, our identifier for investor disclosure information (**IDI**) in potential tweets. This identifier lowered the total tweets related to IDI down to 5,821, meaning that approximately 0.4% of all tweets relate to investor disclosure. *Exhibit IX* shows a breakdown of the distribution of

tweets per firm in our sample (e.g. Walmart leads the pack with ~200,000 tweets, followed by Chipotle,...).

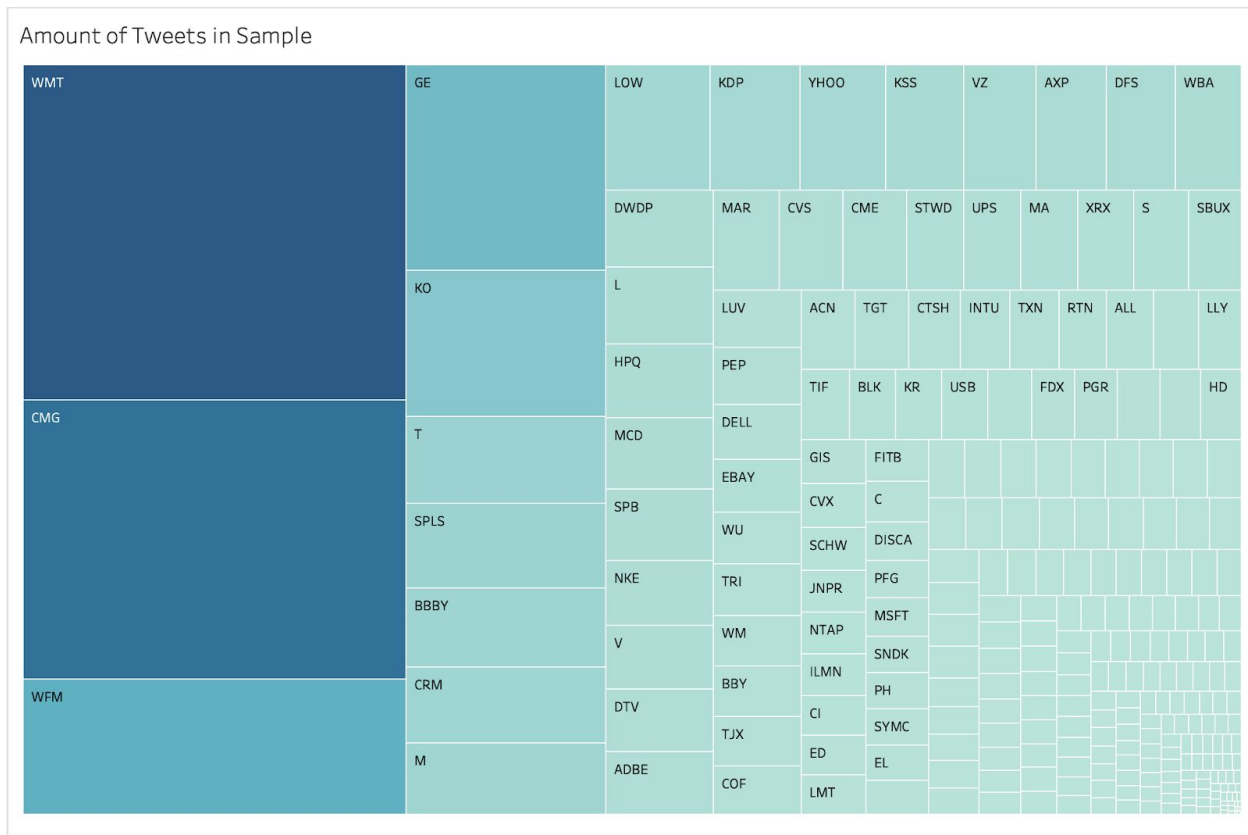


Exhibit IX: Breakdown of volume of Tweets for top firm accounts

TAQ Data

Our trade data came from NYSE TAQ, accessed via WRDS. The Russell 2011 firm dataset was selected to confirm that all the firms that were collected for Twitter data were already in existence prior to the SEC policy change. Our variables for our TAQ data are as follows:

- **Symbol** (Ticker of a firm (E.G. MSFT for Microsoft))
- **Date** (YYYY-MM-DD format)
- **Total_Trades** (Total number of trades per day (all volume, not just retail))

- **SP_Buy_Trades** (Total number of trades executed at prices \$XX.XX90 to \$XX.XX99, which is our proxy for buys by retail investors)
- **SP_Sell_Trades** (Total number of trades executed at prices \$XX.XX01 to \$XX.XX10, which is our proxy for buys by retail investors)
- **Retail_Trades** ((SP_Buy_trades + SP_Sell_trades) This is the value of all retail trades per day per stock)

For the above data, we have values from 2011 to 2014, for every public firm per day, shown in *Exhibit X*. This amounts to over 7.5 million individual entries prior to summarizing to per day variables.

1	symbol,yyyymmdd,total_size,total_trades,SP_Buy_Shares,SP_Sell_Shares,SP_Buy_Trades,SP_Sell_Trades,SUB_PENNY,RETAIL_IMB,RETAIL_TRADES
2	A,20110103,3432697,21675,52483,139325,211,743,0.0888846403578749,0.0964547630485892,6762
3	AA,20110103,39694766,108225,1934286,1593969,3758,3004,0,NaN,0
4	AAPR,20110103,1429,0,0,0,0,0,1,1,0,2
5	AAC,20110103,1160,2,580,580,1,1,0,NaN,0
6	AACC,20110103,16290,114,0,0,0,0,0,NaN,0
7	AADR,20110103,1581,7,0,0,0,0,0.0189780809755905,-0.0818034311133799,166
8	AAT,20110103,5780458,8160,50364,59338,78,88,0,NaN,0
9	AAME,20110103,1400,13,0,0,0,0.0168566093619213,-0.368983957219251,38
10	AAN,20110103,388275,2934,2065,4480,13,25,0.00769657040822609,-0.2,2
11	AADM,20110103,32482,287,100,150,1,1,0.0250651847527413,-0.168099847673333,87
12	AAP,20110103,611923,5376,8465,11566,35,52,0.0430135759412014,-0.107890166281963,4525
13	AAPL,20110103,15017375,87830,288388,357563,2012,2513,0.16452686638136,0.15606936416185,5
14	AAR,20110103,10515,34,1000,730,2,3,0.0415361016763449,0.736217356897916,16
15	AATI,20110103,91270,429,3291,500,15,1,0.214211566038773,0.19961136980296,401
16	AAU,20110103,1181995,2116,151869,101328,269,132,0.0799615112062138,-0.0702463182588297,59
17	AAV,20110103,287876,1694,10701,12318,31,28,0.0125048152428364,-0.0859851049424509,25
18	AAW,20110103,236229,1803,1350,1604,11,14,0.0253417217593639,-0.110095735422106,31
19	AAK,20110103,181361,657,2045,2531,10,21,0.0821259288390288,-0.258605842942054,204
20	AB,20110103,579756,3181,17650,29963,53,151,0.325667172922543,-1,3
21	ABA,20110103,4609,16,0,1501,0,3,0.128986885867069,-0.167874006059767,228
22	ABAT,20110103,1008149,4722,54104,75934,98,130,0.0194550947690724,-0.0250696378830084,10
23	ABAX,20110103,73811,530,700,736,5,5,0.0879578810164272,-0.491324161109578,811
24	ABB,20110103,2347635,9653,52519,153974,143,668,0.0379916043244764,0.0123456790123457,11
25	ABBC,20110103,42641,328,820,800,3,8,0.0365605127118384,-0.519695891872666,337
26	ABC,20110103,2460797,13562,21606,68362,101,236,0.00576950814943026,0.5,2
27	ABCB,20110103,69330,461,300,100,1,1,0.0386724659606657,-1,1
28	ABCD,20110103,10576,77,0,409,0,1,0.00364193328795099,1,1
29	ABCO,20110103,29380,244,107,0,1,0.147707095086708,0.539303196084077,12
30	ABCW,20110103,94051,98,10692,3200,9,3,0.0199987508100216,0.210228381807535,14
31	ABD,20110103,256166,1449,3100,2023,7,7,0.0166487047053561,-0.511450381679389,18
32	ABFS,20110103,196712,1542,800,2475,8,10,0.011177867821713,-0.621527777777778,22
33	ABG,20110103,257652,1601,545,2235,4,18,0.010812597895445,0.750156412930136,21
34	ABH,20110103,475635,998,4106,589,1,4,0,NaN,0
35	ABT,20110103,100,1,0,0,0,0.201750397817686,-0.126760563380282,8
36	ABTO,20110103,35192,117,3100,4000,4,4,0.289902280130293,1,2
37	ABL,20110103,1535,7,445,0,2,0.0085023391969715,-0.166291122127084,15
38	ABM,20110103,260987,1778,925,1294,6,9,0.0741420330841019,-0.0751532581548475,28
39	ABMD,20110103,178212,1034,6110,7103,16,12,0.0810070043650391,0.37593984962406,23
40	ABR,20110103,76808,419,4292,1992,9,14,0.0684877252290188,0.353173758589125,2100
41	ABT,20110103,8438169,35383,391807,186994,1491,609,0.0961290267347483,0.690375,4
42	ABTL,20110103,83537,102,412,100,3,1,0.0306133627110917,0.240257294352853,305
43	ABV,20110103,2254767,12364,42805,26221,217,88,0.184711565785735,1,4
44	ABVC,20110103,7038,41,1300,0,4,0.0998349834983498,-1,1
45	ABVA,20110103,1212,3,0,121,0,1,0.046252557657817,-0.319497542326597,22
46	ABVT,20110103,118761,790,1869,3624,11,11,0.156704723528095,-1,2
47	ABWRA,20110103,4467,19,0,709,0,2,0.0504884405398515,0.00923768336585415,910
48	ABX,20110103,5958453,34266,151806,149027,472,438,0.109625121207024,-0.0272908489645452,197
49	ACAD,20110103,924832,1659,90128,94332,116,81,0.119006351751125,-0.0663573564876281,488
50	ACAS,20110103,2930373,11178,162796,185937,242,246,0.0247670983867303,-0.571855443425077,17
51	ACAT,20110103,132030,855,700,2570,1,16,0.0409078751511769,0.258190604789994,51
52	ACC,20110103,343968,2216,8852,5219,41,10,0.0179926904694968,-0.25,14
53	ACCL,20110103,88925,567,600,1000,4,10,0.018827148184338,-0.166688732953793,171
54	ACE,20110103,1604704,10999,12588,17624,81,90,0.10987598187548,0.383942161339422,60
55	ACET,20110103,101343,961458,6476,41,10,0.230769207692311,1
56	ACFC,20110103,650,6,0,150,0,1,0.0842031629336003,-0.00961068577944291,13
57	ACFN,20110103,72907,148,3040,3099,5,8,0.231563810497769,-0.361956439822142,251
58	ACC,20110103,573017,1040,42331,90359,66,185,0.0406625571309052,-0.115574821417669,120
59	ACGL,20110103,402803,3542,7243,9136,52,68,0.0695605328457621,-0.624501290776813,48
60	ACGY,20110103,183768,909,2400,10383,13,35,0.0582968728784879,0.114123822435429,94
61	ACH,20110103,493457,2361,16025,12742,61,33,0.168677304363811,0.481815462190239,106

Exhibit X: Example of TAQ Data file

Merging the Twitter and TAQ Data Sets

To link and analyze twitter data, we created a new variable called **TAQ_Date**. Since TAQ data strictly draws from regular trading hours (RTH), which is from 9:30AM-4:00PM on trading days, and since tweets can occur at any time, we want to link previous day after-market tweets to the next day of trading. Our rules for this variable are as follows:

- If it's a trading day and tweet time is prior to 4:00PM EST, TAQ_Date is the tweet date.
- If it's a trading day and tweet time is after 4:00PM EST, TAQ_Date is the date of the next trading day.
- If it's not a trading day, TAQ_Date is the date of the next trading day.

With regard to the last bullet, a formula for trading is as follows: “The NYSE and NASDAQ average about 253 trading days a year. This is from $365.25(\text{days on average per year}) * 5/7(\text{proportion work days per week}) = 260.89 - 6(\text{weekday holidays}) - 3*5/7(\text{fixed date holidays}) = 252.75 \sim 253$. The holidays are New Year's Day, Martin Luther King Jr. Day, Washington's Birthday, Good Friday, Memorial Day, Independence Day, Labor Day, Thanksgiving Day, Christmas Day. Up to three trading days (the days surrounding Independence Day, Thanksgiving, and Christmas Day) are shortened, i.e. the exchanges are open from 9:30AM–1:00PM, depending on where they fall in the calendar year.” (Wikipedia 2019) The total amount of trading days over our time span (April 3rd, 2012-April 3rd, 2014) was 503 days. Broken down by year that is:

2012: 187 days in our sample

2013: 252 days in our sample, full year of trading

2014: 64 days in our sample.

For more details, see date catalog at the end of thesis

Additional Data: We have gathered daily stock returns for our entire period from Chicago Booth's Center for Research in Security Prices (CRSP), as well as earnings announcement dates from 2012-2014 for Russell 1000 firms from the Compustat database.

Hurdles in Organizing & Cleaning Data

My knowledge in data collection and analysis has advanced much over the course of this thesis, however while I originally recorded my Twitter Data, I ran into major hiccups with delimitation. In short, delimiters are 'cutoffs' in data, that allow one to associate text into columns in data analysis programs such as Excel, Tableau, Access, Python, etc. My data was recorded with ';' as a delimiter, which became a major problem, as when importing my findings into data analysis programs, text would break my columns, as users obviously could tweet a semicolon at any point. I had to work very carefully to write a script to find and delete semicolons in text, which ended up deleting this data from my dataset, since semicolons offer no relevant data to our final findings. I have since changed all of our data files to '|', or pipe delimitation, to avoid future conflicts.

Working with large data sets also is a huge hurdle-- I have a very powerful computer and ran into immense load times and calculation times. Appending data, creating variables, and running visualizations all take a huge amount of time (E.G., creating my TAQ date variable in the Twitter file took 72 hours to finish compiling). Excel does not allow more than 1 million rows for data analysis, so Python and Matlab were used for data reconstruction.

Final Sample of Data - Merging TAQ & Stock Data:

Our final set of variables is a hybrid of both of our Twitter and TAQ data. The main values of importance were the data correlation (as described above), and the earnings counter, both run as scripts and spread across the whole data set through coding in Matlab. The merging of our data sets had additional requirements to get into a workable format. At first, the top 300 firms *with* Twitter accounts were selected. This means that our list went to the 341st firm, since 41 firms did not have a twitter, or had a private account with inaccessible tweets. Due to firm mergers, potential delistings, and associating tweets with the correct TAQ tickers, and having data over the full two year period, our final list of firms was composed of 251 companies. Afterwards, we collected synthesized our data to a per firm, per day summary of activities for all 251 firms over the 503 days in our sample (more on this below). Our final dataset is composed of 123,504 records, with these variables:

- **IndexDT** (Unique identifier for the trading day ‘t’)
- **Num_Tweets** (Number of tweets from that firm mapping to that particular day (e.g., weekend tweets all map to Monday))
- **Num_Earn_Tweets** (Number of the above that mention ‘Earning’)
- **Num_Earnings_Mentioned** (Number of times the word earning is mentioned in the above tweets)
- **Earn_Date** (Binary value, 1 if day t earning announcement date for firm)
- **Earn_Date_P1** (Binary value, 1 if day t is earning announcement date)
- **Earn_Date_M1** (Binary value, 1 if day t-1 is earning announcement date)
- **PERMNO** (Firm Identifier from CRSP)
- **RET** (Return of firm per day t)
- **ABS_RET** (Absolute value of return per firm per day t)

- **RET_P1** (Return of firm per day, $t + 1$)
- **ABS_RET_P1** (Absolute value of return per firm per day, $t + 1$)
- **RET_M1** (Return of firm per day, $t - 1$)
- **ABS_RET_M1** (Absolute value of return per firm per day, $t - 1$)
- **Post** (Binary Value, 1 if date is post April 3rd, 2013)
- **Post_Earn_Date** (Interaction of Post and Earn-Date)
- **Post_Earn_Date_P1** (Interaction of Post and Earn-Date, $t + 1$)
- **Tweet_Day** (Binary Value, 1 if a firm tweets on day t)
- **Post_Tweet_Day** (Interaction of Post and Tweet_Day)
- **Earn_Tweet_Day** (Binary Value, 1 if a firm day has at least one “earnings” tweet)
- **Post_Earn_Tweet_Day** (Interaction of Post and Earn_Tweet_Day)
- **Log_Retail_Trades** (Natural Log of $1 + \text{Retail Trades}$)

Logic of Variable Creation

To align twitter data with TAQ data, *TAQ_Date* was created and appended to the Twitter file to correlate tweets to active trading days. *Earn_Counter* is used to parse for tweets with our keyword (“earnings”), but could be used for any variable text. Next a summary log for each day of trading in the twitter file was created, logging the total amount of tweets and earning mentions per day.

Regressions & Visualizations

Our first step in this process was to create *Table 1* and *Table 2*, a before and after test of dates to analyze tweet metrics and earnings announcement metrics. *Table 1* is from April 3rd, 2012 to April 2nd, 2013, and *Table 2* is from April 4th, 2013, to April 3rd, 2014. April 3rd 2013 is excluded as

to not influence data in either set. Our findings are below:

Table 1: *Pre April 3rd, 2013 Statistics (All Dates)*

<i>Total Number of Firm-Days</i>	<i>Total Number of Tweet Days</i>	<i>Total Number of Tweets</i>	<i>Total Number of Earnings Tweet Days</i>	<i>Total Number of Earnings Tweets</i>
61,883	39,876	580,397	429	560

There are 61,883 total firm days (firms*days in sample) pre April 2013, composed of 39,876 days that are actually tweeting days, with 580,397 total tweets by our 251 firms. The total number of earnings tweet days is 429. There are 560 separate instances of earnings tweets.

Table 2: *Post April 3rd, 2013 Statistics (All Dates)*

<i>Total Number of Firm-Days</i>	<i>Total Number of Tweet Days</i>	<i>Total Number of Tweets</i>	<i>Total Number of Earnings Tweet Days</i>	<i>Total Number of Earnings Tweets</i>
61,621	44,629	776,340	435	696

There are 61,621 total firm days post April 2013, composed of 44,629 days that are actually tweeting days, with 776,340 total tweets by our 251 firms. The total number of earnings tweet days is 435. There are 696 separate instances of earnings tweets. Tweeting increased 34% between the two years of our data set; number of tweeting days increased 11.2% and total earning tweets increased 24.3%. *Exhibit XI* shows a distribution all firm earning tweet ranges.

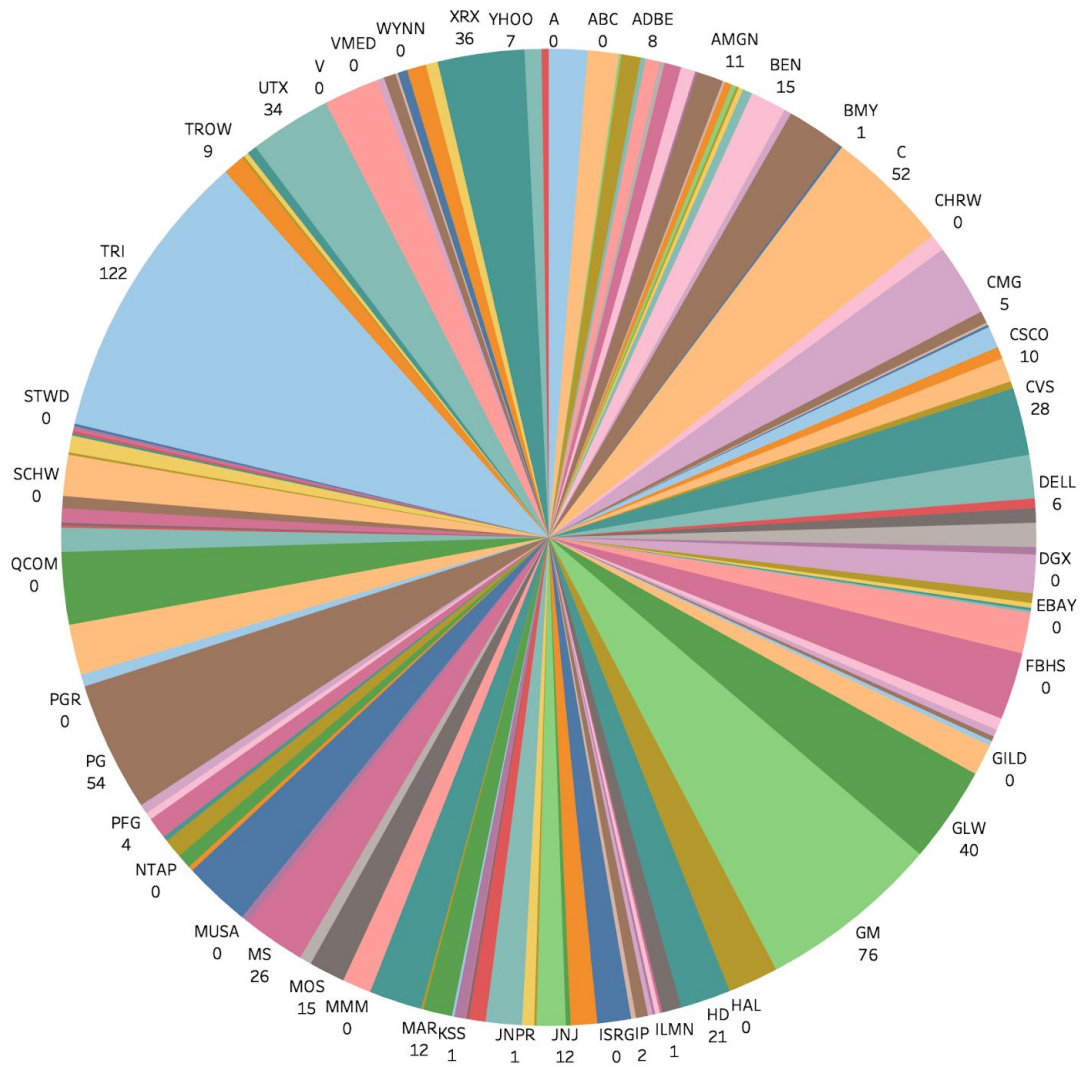


Exhibit XI: Earnings Tweets per Firm

Re-Run Variables around Earnings Dates

With our second table set, we run the same scenario, but treat the day before earnings days (our dummy variable is `earn_date_m1`) and post earnings days (our dummy variable is `earn_date_p1`) as earnings days as well.

Table 3: Pre April 3rd, 2013 (Earnings Date + M1 + P1)

<i>Total Number of Firm-Days</i>	<i>Total Number of Tweet Days</i>	<i>Total Number of Tweets</i>	<i>Total Number of Earnings Tweet Days</i>	<i>Total Number of Earnings Tweets</i>
2,916	2,005	30,892	167	262

There are 2,916 firm-days in our pre dataset around earnings events dates, with a total of 2,005 tweet days in our sample. There are 30,892 tweets, meaning that 5.3% of tweeting in our pre-sample occurs around earnings windows. With 167 earnings tweet days, there are 262 earnings tweets total.

Table 4: Post April 3rd, 2013 (Earnings Date + M1 + P1)

<i>Total Number of Firm-Days</i>	<i>Total Number of Tweet Days</i>	<i>Total Number of Tweets</i>	<i>Total Number of Earnings Tweet Days</i>	<i>Total Number of Earnings Tweets</i>
2,905	2,208	36,036	206	426

There are 2,905 firm-days in our post dataset around earnings events dates, with a total of 2,208 tweet days in our sample. In total, there are 426 earnings related tweets. There are 36,036 tweets, meaning that 4.6% of tweeting in our post-sample occurs around earnings windows. With 206 earnings tweet days, there are 426 earnings tweets total. Across the board, there is a pickup in tweeting, and earnings related tweets as a whole; M1 and P1 invert for the highs of earnings tweet related activity, potentially signaling a potential shift to discussing earnings more after the event date.

Table 5: Summary Statistics

<i>Variable</i>	<i>Mean</i>	<i>Median</i>	<i>N</i>	<i>STDDEV</i>	<i>25th Percentile</i>	<i>75th Percentile</i>
<i>Retail_Trades</i>	88.4182	17	123,504	274.73	3	65
<i>Num_Tweets</i>	10.9854	2	123,504	48.94	0	7
<i>RET(%)</i>	0.00783	0.0652	123,504	1.512	-0.67	0.82
<i>ABS_RET(%)</i>	1.027	0.745	123,504	1.118	0.336	1.369

For our general data, here are summary statistics for key variables. Per day, any given firm tweets roughly 11 times a day. There are around 88 trades per day by retail investors.

Table 6: Summary Statistics (Earnings Announcement Dates & +/- 1 Day Window)

<i>Variable</i>	<i>Mean</i>	<i>Median</i>	<i>N</i>	<i>STDDEV</i>	<i>25th Percentile</i>	<i>75th Percentile</i>
<i>Retail_Trades</i>	84.6557	16	5,821	218.2506	3	65
<i>Num_Tweets</i>	11.4977	2	5,821	53.82043	0	8
<i>RET (%)</i>	.06508	.03902	5,821	3.0351	-1.0568	1.18883
<i>ABS_RET (%)</i>	1.85621	1.12084	5,821	2.40208	4.948	2.25666

On earnings announcement window days, it's interesting to note that there are less given retail investor trades per day, but marginally more tweets.

Data Findings

To concretely run regressions and analysis, Twitter data was synthesized down to per day variables for each firm, leading to roughly 126,000 records. Using STATA, a statistical analysis software, the tables below were generated.

Does Tweeting Frequency Increase after SEC Guidance?

Table 7: Two-sample T-Test - Number of Tweets(Pre & Post April 3rd, 2013 Event)

<i>Pre/Post</i>	<i>Observations</i>	<i>Mean</i>
<i>Post - Period</i>	61,883	12.55
<i>Pre - Period</i>	61,621	9.42
<i>Combined</i>	123,504	10.99
<i>Difference</i>	---	3.126
<i>T-Statistic</i>	---	(11.2315 ^{***})

Our variable **post** is a dummy variable that equals one for observations on or after April 3rd, 2013, and zero otherwise. It identifies our windows before and after the SEC greenlight event. We begin by comparing how firms' tweets per day changed around the SEC event. As shown in the table above, tweeting frequency increases by about 33% between the years; this is in part to do with a growing Twitter userbase, but mainly due to a pickup from firms to get more involved on social media. We can handily say that the 250 top firms are more engaged post-event. The increase is

highly statistically significant with a T-Statistic of 11.2315.

Does Earnings tweet frequency increase after SEC Guidance?

Table 8: Two-sample T-Test - Number of Earnings Tweets(Pre & Post April 3rd, 2013 Event)

<i>Pre/Post</i>	<i>Observations</i>	<i>Mean</i>
<i>Post - Period</i>	61,883	.011247
<i>Pre - Period</i>	61,621	.0090878
<i>Combined</i>	123,504	.0101697
<i>Difference</i>	---	.0021592
<i>T-Statistic</i>	---	(2.1207***)

While tweeting frequency increased, we are more interested in firms' propensity to tweet about their earnings. We therefore restrict the Twitter sample to tweets containing the word "earnings" and repeat the above t-tests for changes in tweeting frequency. Earnings tweet frequency increases 23% post event, which confirms that earnings tweet frequency is increased post event. Our T-Statistic is significant at 2.1207.

Table 9: Two-sample T-Test - Number of Earnings Tweets(Pre & Post April 3rd, 2013 Event)

<i>Pre/Post</i>	<i>Observations</i>	<i>Mean</i>
<i>Post - Period</i>	2,905	0.1466437
<i>Pre - Period</i>	2,916	0.0898491
<i>Combined</i>	5,821	0.1181928
<i>Difference</i>	---	0.0567946

T-Statistic --- (2.9674^{***})

In a similar spirit, we isolate tweets that occur in the 3-day window around firms' quarterly earnings announcements. Doing so filters the sample to include just under 3,000 firm-day observations in each period. The results are similar. The post period mean is 63% larger than the pre period, meaning that firms tweet significantly more about earnings around an earnings window than prior to the SEC greenlight event. Our T-Statistic is 2.9674, which is highly significant.

Do Retail Investors trade more on days with tweets? Does this change after guidance?

After establishing that firms tweet more about earnings following the SEC greenlight event, we analyze retail investors' trading activities around these tweets. I analyze our data in a multivariate setting to relate retail trading and tweeting. Specifically, I run a series of fixed effect regressions with the retail trading as the dependent variable and tweeting variables and controls as the independent variables. Since Tables 5 and 6 reveal the retail trading variable is right-skewed, I use the natural log transformation of (1 plus) retail trading in the regressions. The models include firm fixed effects to account for unobserved firm-level determinants of retail trading. The models also include day fixed effects to account for day-to-day variation in market-wide retail trading.

I present the results from these models in table 10 below. Since retail trading may occur alongside tweeting more generally (regardless of whether the tweet references earnings), I include the tweet day dummy in the first model to establish a base-case. I interact the tweet day dummy with the post dummy to test for changes in the relationship between retail trading and tweets. Other models include the post dummy and its interactions with various independent variables to analyze how relationships have changed after the SEC greenlight. The next model also include control variables

for absolute returns to capture attention-grabbing events that may drive both tweeting and retail trading. The third model also contains controls for earnings announcement days to capture earnings-related trading that may occur irrespective to tweeting activity.

Table 10 contains the results. In each of the first three models, the coefficient for Tweet Day is positive and significant, reflecting greater retail trading activities on days that firms also tweet. The interaction with the Post dummy is negative but only marginally significant. Thus, in general, retail trading is slightly less sensitive to firm tweeting activity in the Post period. The control variables included in Models II and III do not alter the relationship between retail trading and firm tweets.

Table 10: Summary of Fixed Effect Regressions

<i>Independent Variable</i>	<i>Model I</i>	<i>Model II</i>	<i>Model III</i>	<i>Model IV</i>	<i>Model V</i>	<i>Model VI</i>
<i>Tweet Day</i>	.0390788 3.73***	.0388098 3.71***	.0386604 3.69***	.0404229 3.86***	.0401769 3.83***	.0400369 3.82***
<i>Post * Tweet Day</i>	-.0225149 -1.78	-.0225149 -1.78	-.0225283 -1.78	-.0250078 -1.97*	-.0249874 -1.97*	-.0249908 -1.97*
<i>Earn Tweet Day</i>	---	---	---	-.1171577 -2.38	-.1186518 02.41*	-.1168989 -2.36*
<i>Post * Earn Tweet Day</i>	---	---	---	.2380224 3.48	.2373576 3.47***	.2352968 3.44***
<i>ABS_RET</i>	---	.4090074 1.44	.3910291 1.36	---	.4022375 1.41	.3885044 1.35
<i>ABS_RET_M1</i>	---	.1505885 0.53	.1447068 0.51	---	.1485778 0.53	.1433226 0.50
<i>Earn_Date</i>	---	---	.0078824 0.33	---	---	.0053659 0.22
<i>Earn_Date_M1</i>	---	---	-0.041908 -1.80	---	---	-.0409916 -1.76
<i>R-Square (Overall)</i>	0.0134	0.0134	0.0135	0.0135	0.0135	0.0135
<i>Number of Observations</i>	123,504	123,504	123,498	123,504	123,498	123,498

Firm Fixed Effect: Yes

Day Fixed Effect: Yes -- Coefficient is top variable, T is bottom variable

The final three columns contain the main results. There, I include the Earn Tweet Day dummy variable, which equals one if the firm tweets specifically about earnings on that day and zero otherwise. The key variable of interest is this Earn Tweet Day dummy interacted with the Post dummy. In all three models, the coefficient on this interaction is significantly positive, which suggests retail trading activity is more sensitive to earnings tweets in the post period. Moreover, the magnitude of this coefficient is more than twice that of the negative coefficient on the Earn Tweet Day dummy. Together, these coefficient estimates suggest retail trading decreases on Earn Tweet Days during the Pre period, but it increases on Earn Tweet Days during the Post period.

Importantly, these relationships hold after controlling for general tweeting activity, attention-grabbing events proxied by absolute return, and earnings announcement days. Broadly, these findings are consistent with earnings disclosures via social media playing a meaningful role in retail investors' information sets once firms were given the social media greenlight by the SEC.

V:

Conclusion

General Findings

Our analysis, juxtaposing a regression of high frequency trading data parsed for retail investor trading activity, as well as a collection of all tweets from April 3rd, 2012- April 3rd, 2014 by the top 250 firms on the NYSE, and analysis thereof, has concluded that there is indeed an impact between tweet disclosures by firms, and the trading and decision making of the average investor. This result is particularly magnified around earnings announcement dates (+1 and -1 day from the event). Through the growth and globalization of Twitter, the amount of twitter disclosures and user acknowledgement thereof has likely only increased since 2013, leading to even higher levels of retail investor decision making based off of DAIT usage. This finding potentially has great ramifications for financial policy implementation of the future, as it becomes more apparent that many people consider social media their primary source of knowledge. Regular people have more access than ever to more information in a quicker fashion-- this does indeed impact the market, and as a result, the overall investment portfolios and wealth of all those involved.

Policy Implications

Policies for Investors

As stated above, more people than ever glean knowledge from DAITs, and make decisions or incorporate a world-view from this set of information. Other than the April 2nd guidance by the SEC on 2013, social media rules are woven into the existing structure of RegFD in terms of

reasonably making information available to the public. This is a potentially pretty unregulated environment for DAITs, as disclosures by firms can have nearly instantaneous and long-term impacts on the share price of an organization; with loose rules, there is potential for an accidentally error-filled tweet coming from an official channel to alter the market in a way that damages the investor's wealth, particularly still since some investors do not use DAITs as an information source. With the increasing prevalence of social media as an official news channel, it may perhaps be a good idea to probe into a potential official rule set specifically engineered for DAIT information releases.

Individual CEO/Executive Policy

Given no official governmental ruleset on DAIT disclosures, most companies have lended themselves to internal policing, some creating various accounts for different functions (hiring, news, general information, etc.), while obviously maintaining to Reg FD as closely as possible-- most firms operate in a very restricted, hand off approach to releasing information, leading them to post tweets slightly past earnings calls or document releases through official channels. There are of course, fantastic gray areas that have come up-- infamously Elon Musk and his tweeting habits. When Elon Musk [tweets about production quotas](#), we can directly see stock price movement- how much of that is retail investor activity? Regarding continuously updating repercussions (and subpoenas) from the power of [public disclosures](#) on Twitter, will there be a firm specific or governmental policy issued to more closely regulate the manner in which a firm executive can comment on potential firm issues? As an executive of a firm, where does policy align in terms of a social media account as an official channel of disclosure? Should account handles, which can change with relative ease (or not even be easily discoverable with a search), be tied to a serial ID of sorts to verify official disclosures? When

Elon tweets about TSLA's production numbers (or has various other stunts in the media), TSLA swings wildly, causing a variety of complications for investors. One incredibly illegal outward objective of Elon was to destroy the position of short sellers of TSLA-- leading him to tweet on 'private funding', causing TSLA share price to soar in a short period of time. This caused substantial losses due to a tweet, not through the official company channel, with misleading and incorrect information (as the funding was never secured and the claim was incorrect). Mr. Musk was greatly punished by the SEC, who has fined him, the firm, and decreed that his tweets must be pre-approved by an official governmental channel. Usually, one would think a company executive to work in the best interest of the firm, but perhaps there are rules the government should implement regarding executive/employee disclosures on social media, as these can fundamentally have impacts on the market, even if not delivered through official sources.

Implications for Future Work

As Twitter data is notoriously hard to get in massive quantities, there is much room for future analysis of firm disclosure and how it interrelates to retail trading. I believe that future areas to explore include expanding the data set and firm count, and perhaps taking a look at "less visible firms", outside of the Russell 3000. Another avenue might include looking at the impact of retweets and likes, and perhaps tying it to a metric for "engagement", showing how much retail trading could be impacted by a particular tweet's reach. Incorporating geographic data is also an interesting avenue for exploration-- perhaps firms in different locations of the world draw more interest from retail investors. Earnings was the only keyword used here to analyze retail trading behavior-- future work could look at expanding this list of keywords to a more all encompassing set of Twitter keyword identifiers. Another avenue of exploration is to perhaps run a similar test not on firm specific

accounts, but on notorious individual CEO and top executive accounts of these firms, and see how they might impact trading (even juxtaposed to firm account disclosures). This field is really starting to be explored, and will posit very interesting questions for the future of the impact of DAIT's on the lives of investors.

Final Remarks

Finance theory has evolved rapidly over recent decades, as the growth of mass data sets have allowed researchers to apply theory and craft it to results seen in the real world. As we continue to push the limits of globalization and data dissemination, we will see a continued growth of instantaneous data changing our decisions and thought processes. As evidenced by our findings, these new mediums of information travel already have an impact on subjects as important as our wealth and investment decisions; this impact will only get stronger and more pronounced as time goes on. This body of work has been incredibly exciting, challenging, and rewarding. I would love to continue to this work in the future with expanded data sets, methodologies, and theory.

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Utilities Used

- Python 3.7
- Anacondas Navigator
- JMP Pro 13
- Stata 15
- Tableau
- Bloomberg
- Excel
- Matlab
- WRDS
- Twitter

VITA

Education

The University of Tennessee, Knoxville

Bachelor of Science in Business Administration, Dual Major: Finance & Supply Chain Management; Advanced Coursework (Concentration) in International Business

Academic Employment

Research assistant to Dr. Laura Cole, Department of Finance, University of Tennessee - Knoxville, June-July 2016 & June-July 2017.

Publications

N/A

Presentations at Professional Meetings

An Inquiry into the Regulation of Social Media Disclosure Policy and its impacts on Retail Investor Trading Activity, Forthcoming, UTK 2019 EURECA Conference

Academic Awards

Global Leadership Scholars Program, Haslam College of Business, University of Tennessee, May 2016-May 2019

Chancellor's Honors Program, University of Tennessee, August 2015-May 2019

Baker Scholars Program, University of Tennessee, August 2017-May 2019

Professional Membership

N/A

Appendix A: List of Top Russell 1000 300 Firms from 2011 with Twitter Accounts:

EXXON MOBIL CORP	EQUITY RESIDENTIAL
APPLE INC	WASTE MGMT INC
INTL BUSINESS MACHINES	BLACKROCK INC
CHEVRON CORP	EATON CORP
GENERAL ELECTRIC CO	VORNADO REALTY TRUST
MICROSOFT CORP	APPLIED MATLS INC
AT&T INC	HEINZ H J CO
JOHNSON & JOHNSON	MARSH & MCLENNAN COS
PROCTER & GAMBLE CO	AON CORP
PFIZER INC	ALCOA INC
JPMORGAN CHASE & CO	JUNIPER NETWORKS INC
WELLS FARGO & CO	AETNA INC
COCA COLA CO	PG&E CORP
GOOGLE INC	LAS VEGAS SANDS CORP
ORACLE CORP	SCHWAB CHARLES CORP
CITIGROUP INC	PUBLIC SVC ENTERPRISE
PHILIP MORRIS INTL	SPRINT NEXTEL CORP
INTEL CORP	PPL CORP
PEPSICO INC	CARNIVAL CORP
BANK OF AMERICA CORP	PUBLIC STORAGE INC
MERCK & CO INC	ALLSTATE CORP
CONOCOPHILLIPS	PEABODY ENERGY CORP
VERIZON COMMUNICATIONS	CARDINAL HEALTH INC
QUALCOMM INC	ADOBE SYSTEMS INC
WAL MART STORES INC	NOBLE ENERGY INC
MCDONALDS CORP	INTUIT
CISCO SYSTEMS INC	ST JUDE MEDICAL INC
OCCIDENTAL PETE CORP	PRICE T ROWE GROUP INC
ABBOTT LABORATORIES	LORILLARD INC
UNITED TECHNOLOGIES	CONSOLIDATED EDISON INC
HEWLETT PACKARD CO	PROLOGIS INC
AMAZON COM INC	INGERSOLL-RAND PLC
DISNEY WALT CO	KROGER CO
COMCAST CORP	CITRIX SYSTEMS INC
GOLDMAN SACHS GROUP INC	ALTERA CORP
CATERPILLAR INC	SOUTHWESTERN ENERGY CO
3M CO	SYMANTEC CORP
KRAFT FOODS INC	HCP INC
HOME DEPOT INC	INTUITIVE SURGICAL INC
E M C CORP	DISCOVER FINANCIAL SRVC
UNITEDHEALTH GROUP INC	XEROX CORP
ALTRIA GROUP INC	VALERO ENERGY CORP
BOEING CO	PARKER HANNIFIN CORP

AMERICAN EXPRESS CO	BED BATH & BEYOND INC
AMGEN INC	KOHL'S CORP
UNITED PARCEL SERVICE	PPG INDUSTRIES INC
FORD MOTOR CO	PROGRESS ENERGY INC
UNION PACIFIC CORP	THOMSON REUTERS CORP
CVS/CAREMARK CORP	PROGRESSIVE CORP
DU PONT E I DE NEMOURS	AMERIPRISE FINANCIAL INC
BRISTOL MYERS SQUIBB	CIGNA CORP
US BANCORP	SUNTRUST BANKS INC
APACHE CORP	MOTOROLA SOLUTIONS INC
HONEYWELL INTERNATIONAL	NETFLIX INC
HALLIBURTON CO	KELLOGG CO
VISA INC	HUMANA INC
COLGATE PALMOLIVE CO	OMNICOM GROUP INC
DOW CHEMICAL CO	LOEWS CORP
EMERSON ELECTRIC CO	ECOLAB INC
MEDTRONIC INC	C H ROBINSON WORLDWIDE
NEWS CORP	INTERNATIONAL PAPER CO
DIRECTV GROUP INC	NUCOR CORP
ACCENTURE PLC IRELAND	AMERICAN INTL GROUP
TIME WARNER INC	MCGRAW HILL COS INC
MONSANTO CO	MURPHY OIL CORP
WALGREEN CO	WESTERN UNION CO
LILLY ELI & CO	SEMPRA ENERGY
TEXAS INSTRUMENTS INC	DOVER CORP
MARATHON OIL CORP	EDISON INTERNATIONAL
EBAY INC	CLIFFS NATURAL RESOURCES
METLIFE INC	ROCKWELL AUTOMATION INC
MORGAN STANLEY	MACYS INC
COSTCO WHOLESALE CORP	CAMERON INTL CORP
DEERE & CO	ENTERGY CORP
SOUTHERN CO	ZIMMER HOLDINGS INC
SIMON PROPERTY GROUP INC	STANLEY BLACK & DECKER
BAXTER INTERNATIONAL INC	LYONDELLBASELL INDS
DEVON ENERGY CORP	AVON PRODUCTS INC
NATIONAL OILWELL VARCO	GOODRICH CORP
PRAXAIR INC	ESTEE LAUDER COMPANIES
GILEAD SCIENCES INC	CROWN CASTLE INTL CORP
TARGET CORP	WEYERHAEUSER CO
MASTERCARD INC	XCEL ENERGY INC
NIKE INC	HARTFORD FINL SVCS GRP
BANK OF NEW YORK MELLON	ANALOG DEVICES INC
BAKER HUGHES INC	FIFTH THIRD BANCORP
PNC FINANCIAL SVCS GROUP	DISCOVERY COMMUNICATNS
PRUDENTIAL FINANCIAL INC	WYNN RESORTS LTD
LOWES COS INC	AMERISOURCEBERGEN CORP
FEDEX CORP	FLUOR CORP

VIACOM INC	STAPLES INC
STARBUCKS CORP	AVALONBAY CMNTYS INC
WELLPOINT INC	SARA LEE CORP
CSX CORP	LIBERTY GLOBAL INC
EXPRESS SCRIPTS INC	M & T BANK CORP
CORNING INC	CONSOL ENERGY INC
EXELON CORP	GREEN MTN COFFEE ROASTER
JOHNSON CONTROLS INC	STARWOOD HOTELS & RESRTS
EOG RESOURCES INC	EXPEDITORS INTL OF WASH
CELGENE CORP	ITT CORPORATION
DOMINION RESOURCES INC	MYLAN INC
DELL INC	INVESCO LTD
NORFOLK SOUTHERN CORP	FMC TECHNOLOGIES INC
AUTOMATIC DATA PROCESS	VERTEX PHARMACEUTICALS
NEWMONT MINING CORP	FASTENAL CO
KIMBERLY CLARK CORP	BOSTON SCIENTIFIC CO
BIOGEN IDEC INC	CONAGRA FOODS INC
YUM! BRANDS INC	PIONEER NAT RESOURCES CO
PRICELINE COM INC	ALPHA NATURAL RESOURCES
ALLERGAN INC	LIMITED BRANDS INC
DUKE ENERGY CORP	CF INDUSTRIES HOLDINGS
GENERAL DYNAMICS CORP	LIBERTY INTERACTIVE
JOHNSON CONTROLS INC	TIFFANY & CO
TRAVELERS COS INC	EDWARDS LIFESCIENCES
CENTURYLINK INC	JOY GLOBAL INC
NEXTERA ENERGY INC	NORTHERN TRUST CORP
GENERAL MILLS INC	BEST BUY INC
CAPITAL ONE FINANCIAL	PAYCHEX INC
PRECISION CASTPARTS	REPUBLIC SERVICES INC
TYCO INTERNATIONAL LTD	SANDISK CORP
LOCKHEED MARTIN CORP	MARRIOTT INTL INC
GENERAL MTRS CO	COOPER INDUSTRIES PLC
STATE STREET CORP	FORTUNE BRANDS INC
HESS CORP	WHOLE FOODS MARKET INC
COGNIZANT TECH SOLUTIONS	PRINCIPAL FINANCIAL GRP
ACE LTD	XILINX INC
AFLAC INC	HARLEY DAVIDSON INC
MCKESSON CORP	BMC SOFTWARE INC
CUMMINS INC	CHIPOTLE MEXICAN GRILL
NORTHROP GRUMMAN CORP	NVIDIA CORP
TJX COMPANIES INC	MATTEL INC
AIR PRODS & CHEMS INC	AMPHENOL CORP
SALESFORCE COM INC	VIRGIN MEDIA INC
YAHOO INC	COCA COLA ENTERPRISE
CME GROUP INC	V F CORP
CHESAPEAKE ENERGY CORP	LIFE TECHNOLOGIES CORP
NETAPP INC	QUEST DIAGNOSTICS INC

ARCHER DANIELS MIDLAND CBS CORPORATION FRANKLIN RESOURCES INC BECTON DICKINSON & CO COACH INC BB&T CORP PACCAR INC MOSAIC COMPANY FIRSTENERGY CORP STRYKER CORP CHUBB CORP SYSCO CORP AMERICAN ELECTRIC POWER BROADCOM CORP SPECTRA ENERGY CORP WILLIAMS COMPANIES INC AGILENT TECH NOLOGIES INC RAYTHEON CO	DR PEPPER SNAPPLE GROUP HEALTH CARE REIT INC ILLUMINA INC INTERCONTINENTALEXCHANGE NEWFIELD EXPLORATION CO SOUTHWEST AIRLINES CO O REILLY AUTOMOTIVE INC FISERV INC CLOROX CO F5 NETWORKS INC SIGMA ALDRICH CORP LINCOLN NATIONAL CORP RANGE RESOURCES CORP CIT GROUP INC AUTODESK INC SMUCKER J M CO RED HAT INC BORG WARNER INC WATERS CORP
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Appendix B: Dates used in Sample:

YYYYMMDD				
20120403	20120827	20130124	20130619	20131111
20120404	20120828	20130125	20130620	20131112
20120405	20120829	20130128	20130621	20131113
20120409	20120830	20130129	20130624	20131114
20120410	20120831	20130130	20130625	20131115
20120411	20120904	20130131	20130626	20131118
20120412	20120905	20130201	20130627	20131119
20120413	20120906	20130204	20130628	20131120
20120416	20120907	20130205	20130701	20131121
20120417	20120910	20130206	20130702	20131122
20120418	20120911	20130207	20130703	20131125

20120419	20120912	20130208	20130705	20131126
20120420	20120913	20130211	20130708	20131127
20120423	20120914	20130212	20130709	20131129
20120424	20120917	20130213	20130710	20131202
20120425	20120918	20130214	20130711	20131203
20120426	20120919	20130215	20130712	20131204
20120427	20120920	20130219	20130715	20131205
20120430	20120921	20130220	20130716	20131206
20120501	20120924	20130221	20130717	20131209
20120502	20120925	20130222	20130718	20131210
20120503	20120926	20130225	20130719	20131211
20120504	20120927	20130226	20130722	20131212
20120507	20120928	20130227	20130723	20131213
20120508	20121001	20130228	20130724	20131216
20120509	20121002	20130301	20130725	20131217
20120510	20121003	20130304	20130726	20131218
20120511	20121004	20130305	20130729	20131219
20120514	20121005	20130306	20130730	20131220
20120515	20121008	20130307	20130731	20131223
20120516	20121009	20130308	20130801	20131224
20120517	20121010	20130311	20130802	20131226
20120518	20121011	20130312	20130805	20131227
20120521	20121012	20130313	20130806	20131230
20120522	20121015	20130314	20130807	20131231
20120523	20121016	20130315	20130808	20140102
20120524	20121017	20130318	20130809	20140103

20120525	20121018	20130319	20130812	20140106
20120529	20121019	20130320	20130813	20140107
20120530	20121022	20130321	20130814	20140108
20120531	20121023	20130322	20130815	20140109
20120601	20121024	20130325	20130816	20140110
20120604	20121025	20130326	20130819	20140113
20120605	20121026	20130327	20130820	20140114
20120606	20121031	20130328	20130821	20140115
20120607	20121101	20130401	20130822	20140116
20120608	20121102	20130402	20130823	20140117
20120611	20121105	20130403	20130826	20140121
20120612	20121106	20130404	20130827	20140122
20120613	20121107	20130405	20130828	20140123
20120614	20121108	20130408	20130829	20140124
20120615	20121109	20130409	20130830	20140127
20120618	20121112	20130410	20130903	20140128
20120619	20121113	20130411	20130904	20140129
20120620	20121114	20130412	20130905	20140130
20120621	20121115	20130415	20130906	20140131
20120622	20121116	20130416	20130909	20140203
20120625	20121119	20130417	20130910	20140204
20120626	20121120	20130418	20130911	20140205
20120627	20121121	20130419	20130912	20140206
20120628	20121123	20130422	20130913	20140207
20120629	20121126	20130423	20130916	20140210
20120702	20121127	20130424	20130917	20140211

20120703	20121128	20130425	20130918	20140212
20120705	20121129	20130426	20130919	20140213
20120706	20121130	20130429	20130920	20140214
20120709	20121203	20130430	20130923	20140218
20120710	20121204	20130501	20130924	20140219
20120711	20121205	20130502	20130925	20140220
20120712	20121206	20130503	20130926	20140221
20120713	20121207	20130506	20130927	20140224
20120716	20121210	20130507	20130930	20140225
20120717	20121211	20130508	20131001	20140226
20120718	20121212	20130509	20131002	20140227
20120719	20121213	20130510	20131003	20140228
20120720	20121214	20130513	20131004	20140303
20120723	20121217	20130514	20131007	20140304
20120724	20121218	20130515	20131008	20140305
20120725	20121219	20130516	20131009	20140306
20120726	20121220	20130517	20131010	20140307
20120727	20121221	20130520	20131011	20140310
20120730	20121224	20130521	20131014	20140311
20120731	20121226	20130522	20131015	20140312
20120801	20121227	20130523	20131016	20140313
20120802	20121228	20130524	20131017	20140314
20120803	20121231	20130528	20131018	20140317
20120806	20130102	20130529	20131021	20140318
20120807	20130103	20130530	20131022	20140319
20120808	20130104	20130531	20131023	20140320

20120809	20130107	20130603	20131024	20140321
20120810	20130108	20130604	20131025	20140324
20120813	20130109	20130605	20131028	20140325
20120814	20130110	20130606	20131029	20140326
20120815	20130111	20130607	20131030	20140327
20120816	20130114	20130610	20131031	20140328
20120817	20130115	20130611	20131101	20140331
20120820	20130116	20130612	20131104	20140401
20120821	20130117	20130613	20131105	20140402
20120822	20130118	20130614	20131106	20140403
20120823	20130122	20130617	20131107	
20120824	20130123	20130618	20131108	