Does Perception Matter in Asset Pricing? Modeling Volatility Jumps and Returns Using Twitter-Based Sentiment Indices*

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Abstract

In this paper, I argue that we can use consumer and investor perceptions to forecast short-term fluctuations in asset prices. Using tweets scraped from Twitter between 2009 and 2019, I perform textual analysis to construct daily sentiment indices. While other scholars have relied on third-party companies to complete this task, doing so limits our potential understanding of sentiments' effects on asset pricing. The sentiment indices I constructed are numerical, not dichotomous, scores, which allows to control for sentiment strength. Results indicate that sentiments can forecast daily stock returns and volatility jumps.

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1 Introduction

Over the last several years, a growing number of news articles have claimed that investors use social media to help them guide investment decisions (Huang, 2015; Openshaw, 2013; Kollmeyer, 2016; Borzykowski, 2016). Yet, in general, investors are quick to dismiss disinformation. As such, if more investors are turning to social media to make investment decisions, it must be the case that social media contains some valuable information. This article, focusing on Twitter specifically, asks: do consumer and investor perceptions matter in asset pricing? In his now seminal 1988 presidential address, Roll (1988) argues that news, as defined by the Dow-Jones News Retrieval System, had little to no relationship with stock returns. Although news itself may not impact stock returns directly,[1] the way we feel, react, interpret, and/or perceive new sources of information may affect stock returns (Boudoukh et al., 2013; Hirshleifer, 2001). For instance, Baker and Wurgler (2006) and Stambaugh et al. (2012) (and to some extent, Cen et al. (2013)) find that sentiments affect a cross-section of asset prices. Brown and Cliff (2005) finds evidence that sentiments, constructed from a survey of investor sentiments, explain long run (1-3 years) deviations from the the market's intrinsic value (in their case, the Dow Jones Industrial Average index). In this paper, I show that not only do sentiments (defined broadly to include sentiments from consumers as well as investors) explain variations in individual stock prices even after controlling for known asset pricing factors, but they also predict jumps in volatilities. Other scholars have demonstrated that individual opinions posted on Twitter can predict firm earnings and announcements (Bartov et al., 2015) and that investor sentiments from stock-related message boards can forecast Amazon stock returns (Das and Chen, 2007). This article presents a somewhat different argument: my position is that tweets can actually alter investors' information set and thus provide us with a forecast of a stock's returns and its volatility. As such, this work expands the liter-

[1] But please note that Manela and Moreira (2017) have found that news can in fact predict above average stock returns and periods of economic disasters.

ature mapping linkages between the sentiment consensus of consumers/investors and firm asset returns and volatility (Hribar and McInnis (2012); Da et al. (2013); Shefrin (2008)).

I obtain "perceptions" by converting tweets scraped from Twitter into quantifiable signals about consumer and investor sentiments towards a product or company. Assume, for example, that consumers are deciding whether to buy the most recent smartphone from some company. If the smartphone has potential issues, such as bugs or annoying features, others' perceptions about the product should impact consumers' decision to purchase it. For example, when Apple decided to remove the headphone socket from its phones, consumers were outraged. Yet, as they began adopting the new smartphone, consumers started to report that the change to the phone was not a deal breaker. Sales of Apple's new phone started more slowly than for previous releases, but they picked up and were eventually in line with expectations (Dunn, 2017). Although this is merely one example, it shows how social media can be a source of information when deciding whether or not to adopt a new product or technology. In a more recent example, Bloomberg (Vasquez, 2018) reported that a tweet by Kylie Jenner had caused a 6.1% decline in the stock of Snapchat after she claimed to no longer be using the smartphone application. The company's stock plummeted from a close of $18.64 on the day before Jenner's tweet to a close of $16.32 a few days later (the day of the tweet, the stock closed at $17.51). More than a month later, Snapchat stocks had still not recovered fully from the Kylie Jenner tweet. Although this example is anecdotal, it suggests that Twitter user sentiments (especially from "influential" users) may have a significant effect on asset prices, irrespective of the fundamental valuation of the firm. This phenomenon is precisely what this article explores.

Since Twitter is primarily driven by information that is not necessarily based on fundamentals,[2] asset pricing theory would suggest that consumer sentiments would

[2] I would argue that the majority of tweets made by the general public (not investment professionals) with respect to a specific company are based on spur of the moment feelings, not firm fundamentals.

merely contribute to price noise, if they contribute at all (Roll, 1988).[3] As this paper will show, this should be reflected in our ability to forecast short-term returns fluctuations if we assume that these fluctuations are driven by short-term fears or other human emotions.[4] Currently, very little scholarly work attempts to model short-term return fluctuations using high-frequency financial market data. Most research argues that noise is something that cannot be estimated (Cochrane, 2009; Campbell and Hentschel, 1992). I argue that short-term fluctuations in asset prices can be modeled.

Figure 1 shows our current ability (based on the three best/most used models) to forecast asset prices or returns at various time horizons (Sanford, 2017):

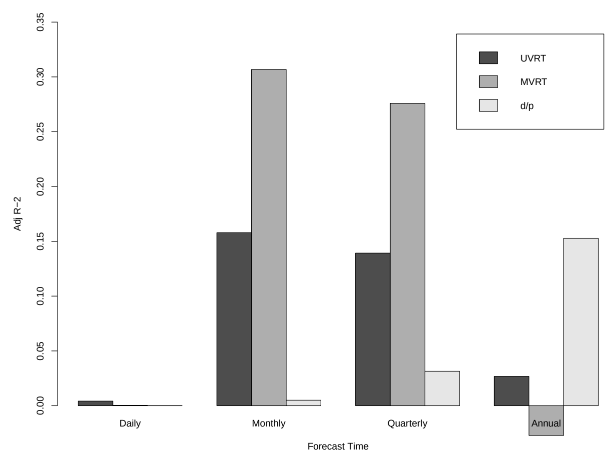

Figure 1: Adjusted R^2 - Forecasting Models

On figure 1, the x-axis represents the forecast horizon while the y-axis represents the adjusted R^2 for the forecast. The darkest bar is the forecast regression using the recently developed Recovery Theorem (Ross, 2015); the middle bar represents the multivariate Recovery Theorem (Sanford, 2017); and the lightest bar uses dividend-price ratio (Cochrane, 2008). Clearly, we do quite well at forecasting asset prices at horizons ranging from one month to a few years. However, very few models are successful at explaining short-term (say, one-day) variations in asset prices or returns.

[3]What is meant by noise is a stock's deviations from the fundamentally valued price.

[4]Throughout this paper, the terms "short-term fluctuations" and "noise" are used interchangeably.

This is where sentiments from social media come into play: they can help explain these short-term variations. More specifically, I explore the proportion of short-term noise that can be explained using sentiments from social media.[5]

My findings indicate that, contrary to the literature's expectations, it is possible to forecast high-frequency stock returns and volatility jumps using consumer and investor sentiment indicators. Using tweets that I scraped from Twitter, I perform textual analysis to construct daily sentiment indices. While other scholars (see, for example, Lee et al. (2002)) have relied on third-party companies like Stocktwits to complete this task, doing so reduces transparency and limits the potential for customization. The sentiment indices I constructed are numerical scores, not dichotomous variables, which allows me to control for sentiment strength (e.g., good vs. great), and not just positive/negative overall feelings. Results show that sentiment indices can not only be used to forecast daily asset returns, but can also forecast volatility jumps. Using a Markov-switching framework, I find that, as overall sentiments shift from positive to negative, volatility jumps occur.

The rest of the paper proceeds as follows: section 2 defines and derives the model of short-term stock returns; section 3 introduces a Markov-switching framework for modeling volatility jumps; section 4 provides an overview of the data; section 5 presents the empirical results; and section 6 concludes.

2 Stock return modeling

This article tests whether stock returns can be attributed, at least in part, to a behavioral component. In the era of social media, other people's perceptions of a company and/or of its products have become important decision drivers for investors. The model presented in this section is akin to the early factor models of Fama and French (1993, 2012).

[5]For the purposes of this paper, short-term noise is is equivalent to short-term returns and therefore, the two are used interchangeably – simply put, daily returns are often viewed as noise.

Stock returns To test whether sentiments can explain short-term asset returns, I employ a simple forecast linear model, as follows:

$$r_t = \alpha + \beta\omega_{t-1} + v_t \tag{1}$$

where r_t is the current period's return and ω_{t-1} is the previous period's sentiment. Note that, in regression 3, the sentiment variable ω appears as a single number. In reality, if we had a sentiment score distribution that ranged from -3 to $+3$, the sentiment variable would reflect the tweet count for each score in that range. Hence, the regression equation would look more like this:

$$\begin{aligned} r_t = \alpha + \beta_1\omega(-3)_{t-1} + \beta_2\omega(-2)_{t-1} + \beta_3\omega(-1)_{t-1} + \beta_4 \\ \omega(+1)_{t-1} + \beta_7\omega(+2)_{t-1} + \beta_6\omega(+3)_{t-1} + v_t \end{aligned} \tag{2}$$

where $\omega(-1)$, for example, represents the number of times words associated with a sentiment score of -1 appeared in the sample.

One would expect that, as the amount of information being fed into the market at any given time increases, so would the volatility of asset prices. This will be formally tested using a forecast volatility regression as follows:

$$\Delta\sigma_t = \alpha + \beta\omega_{t-1} + v_t \tag{3}$$

where $\Delta\sigma_t$ is the change in a stock's volatility at time t and ω_{t-1} is the previous period's sentiment.

3 Volatility jumps

In section 2, I presented a model by which stock returns can be explained using Twitter sentiments. In addition, I suggest that a Markov-switching model will allow us to explain volatility jumps in asset returns (Hamilton, 1989). By definition, as the quantity of short-term fluctuations increases in the market, so does volatility. As such, if a sentiment distribution helps to explain changes in a stock's return fluctuations, it should also explain changes in the stock's volatility. More interesting, however, is whether changes in sentiments can help explain drastic changes in volatility states. I test this proposition by assuming that volatility has two possible states: a low state and a high state.[6] As the noise increases, so should volatility. Ultimately, this will present as volatility jumps. As the general sentiment about a given company or product changes from "positive" to "negative" (or vice versa), we would expect volatility jumps to occur. I assume a Markov-switching model with two possible volatility states described by the following set of equations:

$$\sigma_t = \begin{cases} \alpha_0 + \beta z_{t-1} + \epsilon_t, & s_t = 0 \\ \alpha_0 + \alpha_1 + \beta z_{t-1} + \epsilon_t, & s_t = 1 \end{cases} \tag{4}$$

where σ is the volatility of stock returns, z is the skewness of the sentiment distribution from previous period $t-1$, and ϵ_t and β are i.i.d. random variables with mean zero and variance equal to σ_ϵ^2. This model introduces a system where volatility is a linear model with two different intercepts: α_0 and $\alpha_0 + \alpha_1$. In other words, the "jump" in this system is based on the introduction of an additional intercept in the process (α_1). As a simple example, let us assume that coefficient β is equal to one, that we have a skewness value equal to 0.2, and that, in initial state s_0, α_0 is equal to zero. In other words, we have a system where the volatility is constant and equal to 0.2. In this switching model, when the state switches from state zero to state one, if we assume that the additional intercept term is equal to 0.1, we would now have a new volatility level equal to 0.3. This is the idea behind this Markov-switching model. I will assume

[6]Please see the appendix for a Markov-Switching model with three possible states.

that the transitions are governed by a first-order Markov process defined as follows:

$$\begin{aligned} Prob(s_t = 1|s_{t-1} = 1) &= p_{1,1} \\ Prob(s_t = 0|s_{t-1} = 1) &= p_{0,1} \\ Prob(s_t = 1|s_{t-1} = 0) &= p_{1,0} \\ Prob(s_t = 0|s_{t-1} = 0) &= p_{0,0} \end{aligned} \tag{5}$$

which can be represented in matrix form as:

$$P = \begin{bmatrix} p_{0,0} & p_{0,1} \\ p_{1,0} & p_{1,1} \end{bmatrix}$$

which represent the probabilities of switching between the two states of the model. For example, assuming that we were in state s_0 in the previous period, the probability of transitioning to state s_1 is equal to $p_{0,1}$. The question then is whether we can forecast accurately when the model will switch between states and, perhaps more interestingly, what is the probability of switching between states. As mentioned above, the switch will depend in large part on the skewness of the sentiment distribution derived in this paper. In other words, we should be able to re-write the probabilities as functions of sentiment skewness:

$$\begin{aligned} Prob(s_t = 1|s_{t-1} = 1, z_{t-1}) &= p_{1,1} \\ Prob(s_t = 0|s_{t-1} = 1, z_{t-1}) &= p_{0,1} \\ Prob(s_t = 1|s_{t-1} = 0, z_{t-1}) &= p_{1,0} \\ Prob(s_t = 0|s_{t-1} = 0, z_{t-1}) &= p_{0,0} \end{aligned} \tag{6}$$

These probabilities are precisely what we estimate in section 5.3. This simple example can easily be generalized to an N-State Markov-Switching model. As an example, I extend the two-state model presented here to a three-state model in the appendix.

4 Data

4.1 Sample selection

The sample used in this paper is from June 10, 2009 to February 28, 2019. However, the focus of the paper is on a subsample from June 10, 2009 (when I started scraping Twitter) to December 31, 2009. I selected this particular subsample because, starting in 2010, it became impossible to scrape the entire population of tweets from Twitter. At that time, Twitter placed restrictions on data scraping (more in section 4.2). One option would be to purchase all the tweets between 2009 and 2019, but that would cost billions of dollars and is not feasible. That being said, I still show results using the entire sample of tweets for the decade below. But I must note that important tweets may be missing from the sample as a result of Twitter's restrictions on data scraping. As an illustration, during the subsample period (June–Dec. 2009, for which I have the entire population of tweets), people tweeted about Apple approximately 600,000 times (an average of about 4,600 tweets per day). In the full sample (2009–2019), I have approximately 3.1 million tweets related to Apple, or 1,276 tweets per day. Given the growth trajectory of Twitter between 2009 and 2019, we would expect the number of tweets about Apple to growth during this period. Clearly, we are missing a large number of Apple tweets in the larger sample analyzed in this paper.

Why Apple? Apple is the firm with the largest number of average daily tweets in my sample. This is important because it means that people are posting about Apple whether or not something important is happening to the company. I do not want to focus on companies about which people tweet only when something newsworthy happens. Instead, I want to analyze a steady stream of perceptions about a company irrespective of the news. To be sure that the empirical results are not biased by my use of Apple as a case, I also include results for 11 other firms for the same sample period. The other firms were selected randomly from various industries in the S&P 500 composite index. The analyzed companies (other than Apple) are: Fedex (7,393 tweets), Ford (900,000 tweets), Google (1,000,000 tweets), JP Morgan (62,277 tweets), Lockheed Martin (58,090 tweets), Microsoft (100,000 tweets), Pepsi (232,330 tweets), Pfizer (656,774 tweets), Verizon (195,950 tweets), Wal-Mart (170,238 tweets), and Wells Fargo (5,910 tweets). In total, of the 500 millions tweets in the subsample, I analyze approximately 3.988 million (approximately 0.8%). Despite the use of an extremely powerful server computer (the details of which are discussed below), this small fraction of tweets took several months to analyze.

I obtained return data for Apple stocks from the Wharton Research Data Services (WRDS) database for June–December 2009. Price data were collected from the Center for Research in Security Prices (CRSP) dataset.

4.2 Twitter data

Using Twitter data, I determine the sentiment "value" of tweets by associating certain words with a score. One of the most significant advantages of Twitter is the length of statements. Because of the 140-character limit, users must make precise statements. This means that, in general, we do not need to worry about things like double negatives. For example, we would not expect someone on Twitter to write: "I did not not want to go to the store." The limited length removes a lot of subjectivity based on grammar. It allows me to use the tweets at face value instead of wondering about ulterior meanings.

I scraped Twitter data directly from twitter.com. According to the World Wide Web Foundation (2018), tweets grew from about 2.5 million per day in 2009 to about 35 million per day in 2010. Twitter limits the number of live tweets that can be scraped from its servers. The tweeting levels reached in 2010 made scraping the entire population of tweets impossible beyond the last day of 2009. Why is this important? By 2010, the scraping limits imposed by Twitter meant that one's scraped database might miss influential tweets that had a significant impact on the stock market. In other words, if I was scraping tweets about Snapchat in early 2018, because of Twitter's scraping restrictions, it is not guaranteed that my algorithm would have captured the

Kylie Jenner tweet that single-handedly affected Snapchat's stock price. As such, I have limited the main analysis to the time period in which no tweets were missing (i.e. we could capture the entire tweet population): from June 2009 to December 2009. Each tweet in the database contains the date and time of the tweet, its location, and the text of the tweet. To test the hypothesis that stock prices are affected by investor/consumer sentiments in the short-term, I subset tweets by day.

Up to this point, I have scraped upwards of 500 millions tweets. This might seem like a lot, but my dataset is still missing a large number of datapoints. Nonetheless, scraping in real-time over ten years has provided me with data that I would not have otherwise had access to. Twitter does allow users to download historical tweets for a fee. However, a dataset like the one that I have gathered would cost upwards of $760,000 and would still take 400 months (33.33 years)[7] to collect because of Twitter's restrictions. In other words, because of 1) the computational complexity of the problem, 2) the data limitations of Twitter, and 3) the costs imposed by Twitter, the best Twitter analysis that we can currently do is the one presented in this paper.

To produce the sentiment indices, I use two word dictionaries (see section 4.3). I match words from each tweet to their score in the two dictionaries and aggregate scores for each day. For example, if, on day X, 125 words with a score of +3 are used in tweets about Apple, then the +3 bin for that specific day will have a count of 125. The scores associated with each tweet represents the word with the maximum score in that tweet. In other words, only a single word in each tweet is used to determine that tweet's sentiment score – if a tweet has the words "good" and "great," since "great" has the highest score, that word will be used for that tweet's sentiment score.

The sentiment indices are used to forecast daily fluctuations in asset prices. I aggregate all sentiment scores for a given day and compare them to the next-day stock price

[7]This was calculated by looking at the most generous data download service from Twitter for non-enterprise downloading: the Premier tier. At this tier, Twitter allows users to make 2,500 download requests per month and each request is capped at 500 tweets at a cost of $1,899.99 per month. This information is available directly from Twitter's website here: https://developer.twitter.com/en/pricing.html.

for the asset. Sentiment scores obtained on days where trading does not occur (such as weekends and holidays) are aggregated until trading occurs. For example, weekend tweets about Apple are summed together as a single measure (Friday to Sunday) that is used as the sentiment for the next trading day, Monday. As another example, if trading did not occur on a Tuesday because of a holiday, the tweets would be aggregated with the Monday tweets as the sentiments predicting stock price for Wednesday.

To isolate sentiments about specific companies, some tweets had to be dropped from the sample. For example, if one is constructing a sentiment index for Apple, someone's tweet about the great time they had at the apple orchard on a particular day cannot be included. As such, it is essential to filter the tweets to make sure that only tweets related to the company or its products remain in the sample. To accomplish this, I adopted a two-step triage system. The first step involves listing possible word combinations that should not be part of the final tweet sample. In our example, that would mean removing any tweet with the word *orchard* preceded or followed by the word *apple*. The second step involves examining each flagged tweet to ensure that it was not related to the company or its products. The second step was only possible because the subset of tweets that were rejected by the sorting algorithm was quite small (a few thousand tweets). In a larger sample, this entire process would need to be automated.

A final verification involved creating a subsample of one week and reading all tweets to verify their relevance to Apple, the company. The weekly subsample was selected randomly. All tweets in the subsample were indeed about Apple, which led me to conclude that the subsetting was working properly. To ensure that over-deletion did not occur, the deleted tweets were read individually. A minimal number (less than 0.1%) of tweets were brought back into the sample after being deleted.

4.3 Dictionaries

To associate words with scores, I use two separate word sentiment dictionaries (Loughran and McDonald, 2011; Nielsen, 2011). The two dictionaries 1) provide a robustness check on each other, and 2) attribute scores differently to words. Each dictionary is described in turn below.

Loughran and McDonald (2011) word dictionary The first dictionary (Loughran and McDonald, 2011) is a dictionary of mostly business words. For example, in the world of finance, we often say that we are "going long" when buying a stock. In normal parlance, going long does not mean much (at least not in terms of defining a sentiment). Yet, if a tweet states that investors should go long on Apple, it reflects a positive sentiment toward Apple products. The Loughran and McDonald (2011) dictionary defines words as either positive or negative (binary scores). For example, it would give a score of $+1$ to the word *good* and a score of -1 to the word *bad*. Similarly, the dictionary gives a score of $+1$ to the word *excellent* and a score of -1 to the word *horrible*.

The dictionary combines words from the EDGAR 10-X fillings with base words from the English dictionary. Only those words that appear at least 100 times in the 10-X filings and that can be identified as actual words are added to the dictionary. The dictionary is updated almost every year to incorporate words that are in vogue at that moment in the business world. Words are divided into seven categories: negative, positive, uncertain, litigious, constraining, superfluous, and interesting. In this article, I use only words that fall into the negative or positive categories because these are the words that are clearly associated with sentiments. The rest of the dictionary is somewhat arbitrary. In total, the dictionary contains over $85,000$ words. Once we subset the word list to only include words that are positive or negative, we are left with a dictionary of about $2,700$ words. As an example, the dictionary identifies *boom* as a positive word and *bankrupt* as a negative word. Interested readers should visit the website to obtain more information on the dictionary compilations and the various dictionaries available.[8]

Nielsen (2011) word dictionary Instead of proposing a positive-negative dichotomy, the second dictionary (Nielsen, 2011) distinguishes the relative strength of words. Scores range from negative three to positive three. Using this dictionary, I am able to demonstrate that forecast results are wildly different when we account for the fact that *excellent* is stronger than *good*. For example, I conducted a textual analysis to match the words for every Apple-related tweet on 3 August 2009 (see figure 2). A score is recorded for each tweet containing a word in the Nielsen (2011) dictionary. This information can be aggregated into a distribution such as the one shown in figure 2. The sentiment distribution allows us to: 1) control for the relative strengths of certain words, and 2) determine if certain characteristics of the distribution have a stronger impact on prices than others. More specifically, certain groupings of words or moments of the distribution may have different impacts on asset prices.

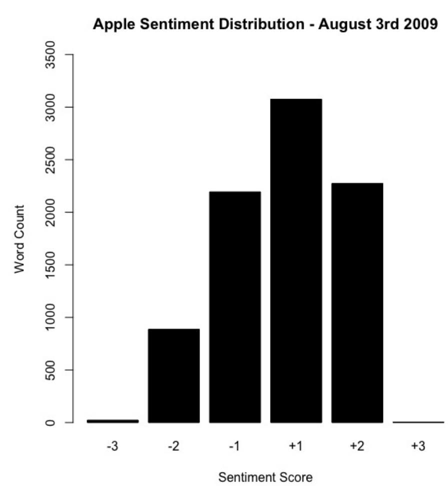

Figure 2: Apple Sentiment Distribution - August 3rd 2009

Figure 2 gives an example of what the sentiment index of Apple looks like on August 3rd, 2009. On this day, the distribution seems to be quite normal, although one could

[8] https://www3.nd.edu/~mcdonald/Word_Lists.html

argue that the distribution does appear to have a slight negative skew (longer tail on the negative side of the distribution).

One shortcoming of the Nielsen (2011) dictionary is that Twitter users may consciously choose to use words with fewer characters. In the example above, *excellent* was stronger than *good*. However, *excellent* has five more characters than *good*. Even if a user truly wanted to use the word *excellent*, they may decide to use the word *good* to ensure that they can say everything they want to say within the 140-character limit imposed by Twitter. Furthermore, the Nielsen (2011) dictionary was not constructed to associate sentiment scores to business terminology. For example, it does not recognize *long* and *short* as words that have any sentimental value. This is why using both the Loughran and McDonald (2011) dictionary (which codes sentiments for finance words) and the Nielsen (2011) dictionary (which codes a range of sentiments) is so important.

One shortcoming of both dictionaries is that they cannot identify "abbreviations/ shortcuts." For example, while *great* would receive a positive sentiment score, *gr8* is not scored. Although it is difficult to know what abbreviations are in vogue at any point in time, it would be worthwhile to consider these devices in future research.

4.4 Computations

Before moving on to the results section, it is important to discuss the computational complexity of the problem examined in this paper. With relatively easy access to powerful computers and powerful supercomputers, it is easy to forget that some operations, such as the textual analysis conducted in this piece, are still incredibly computationally taxing. I used computing resources at the University of Washington. More specifically, the machine used for this paper's analysis is a: Dell PowerEdge M620 Blade server with 16 2.00GHz Intel Xeon processors and 192GB of RAM. Despite the impressive specifications of this supercomputer, the analysis was still quite long to conduct. For example, textual analysis of the subsample of Apple data from June 2009 to December 2009 required approximately a month of computing time (24 hours a day, seven days a week). This is above and beyond real-time scraping of the data (one day of scraped data takes one data to extract because data is scraped as it is posted on Twitter). As such, conducting this same analysis for the entire population of firms and the entire population of tweets would simply be impossible using the computational tools available to me at this time. This is the major reason why the analysis focuses on a subset of time and a subset of firms.

5 Results

5.1 Descriptive statistics

The two samples analyzed for this article are from June 10, 2009 to December 31, 2009 (subsample) and from June 10, 2009 to February 28, 2019 (full sample). The subsample corresponds to 138 trading days, while the full sample corresponds to 2,436 trading days. In this section, I describe Apple data for the larger sample period (prices, returns, etc.) and provide summary statistics for the sentiment indices.

Table 1 shows the number of observations (2,436 days), minimum, first quartile, median, mean, third quartile, maximum, and number of missing observations for each variable. The descriptive statistics are not surprising or out of the ordinary. For example, the average return during the period of interest for Apple was about 0.12% per day while the maximum daily return was about 8.8%.

Variable	**n**	**Min**	$\mathbf{q_1}$	$\widetilde{\mathbf{x}}$	$\bar{\mathbf{x}}$	$\mathbf{q_3}$	**Max**	**#NA**
Prices	2436	12.76547	37.96371	68.99516	85.83516	117.6324	230.2755	0
Log Prices	2436	2.546744	3.636631	4.234036	4.224744	4.767564	5.439276	0
Return	2436	-0.1235581	-0.006889851	0.0009941667	0.001204719	0.01001811	0.08874147	0
SD of Return	2436	0.006405506	0.01270008	0.01489331	0.01583062	0.01842002	0.03126844	0

Table 1: Descriptive Statistics DVs

Table 2 provides summary statistics for the sentiment analysis based on the Nielsen dictionary. The first six rows represent the six categories of sentiments, from “very very negative” (*VV Negative* or -3) to “very very positive” (*VV Positive* or $+3$).

Interestingly, on average, 1.73 words are considered *VV Negative* daily compared to 2.22 *VV Positive* words. Contrary to common perception, there seems to be more people complimenting Apple than complaining about it (or perhaps people use stronger language when promoting companies/products). Thus, we can see a larger number of observations at the *VV Positive* category than at the *VV Negative* category, on average. This fact is consistent across the distribution. On average, Apple receives more positive than negative comments.

Variable	**n**	**Min**	$\mathbf{q_1}$	$\widetilde{\mathbf{x}}$	$\bar{\mathbf{x}}$	$\mathbf{q_3}$	**Max**	**#NA**
VV Negative	2436	0	0	0	1.726601	0	60	0
V Negative	2436	0	20	76	114.8797	140	2280	0
Negative	2436	0	100	220	317.3563	400	3800	0
Positive	2436	0	180	380	545.5439	685	6960	0
V Positive	2436	0	80	160	264.6461	320	3100	0
VV Positive	2436	0	0	0	2.223727	0	480	0
Total	2436	0	420	840	1246.376	1540	14580	0
Mean	2436	0	70	140	207.7294	256.6667	2430	0
SD	2436	0	80.41559	155.349	223.1822	279.9821	2667.096	0
Kurt	2436	-3.333333	-1.728712	-0.5765333	-0.06602994	1.297979	6	0
Skew	2436	-0.9682458	0.3779811	0.8141544	0.8408015	1.260858	2.44949	0

Table 2: Descriptive Statistics IVs (Nielsen dictionary)

In table 2, the seventh row (under the six possible sentiment strengths) is the total count for the sentiment distribution: the number of times words were associated with any sentiment category for each day. The variable ranges from 420 to $14,580$, which indicates that the extent to which people discussed Apple on Twitter varied widely depending on the day. The variables mean, SD, kurt, and skew represent the mean, standard deviation, kurtosis, and skewness of the daily distribution of the sentiment index. The skewness variable will be used later as a summary measure of the overall sentiment about Apple in the economy. When the skew shifts toward the left, it means that the overall sentiment regarding Apple has become more negative, and vice versa.

This is important because it allows us to capture the nuances of word selection when characterizing a company or product on Twitter.

Table 3 presents the same variables as table 2. However, the sentiment categories are presented as proportions of the total number of tweets with flagged sentiment scores on any given day. I use this as a robustness check to ensure that regression results are not simply a function of the level variables.

Variable	**n**	**Min**	$\mathbf{q_1}$	$\widetilde{\mathbf{x}}$	$\bar{\mathbf{x}}$	$\mathbf{q_3}$	**Max**	**#NA**
VV Negative	2436	0	0	0	0.001097463	0	0.5	0
V Negative	2436	0	0.04693627	0.08523612	0.08958894	0.1176471	1	0
Negative	2436	0	0.1971566	0.25	0.2550908	0.3142857	1	0
Positive	2436	0	0.3767929	0.4396552	0.4430029	0.505222	1	0
V Positive	2436	0	0.1428571	0.2	0.2056413	0.2608696	1	0
VV Positive	2436	0	0	0	0.001884014	0	0.3333333	0
Mean	2436	0	0.1666667	0.1666667	0.1660509	0.1666667	0.1666667	0
SD	2436	0	0.1652201	0.1831758	0.1896679	0.2041241	0.4082483	0
Kurtosis	2436	-3.333333	-1.728712	-0.5765333	-0.06602994	1.297979	6	0
Skewness	2436	-0.9682458	0.3779811	0.8141544	0.8408015	1.260858	2.44949	0

Table 3: Descriptive Statistics Ratio IVs

Finally, table 4 provides summary statistics for the sentiment analysis based on the Loughran and McDonald dictionary (applied to the short sample only). This dictionary focuses on words that are regularly used in business. As such, it is used frequently in the textual analysis literature in business (Kuhnen and Niessen, 2012; Garcia, 2013; Loughran and McDonald, 2014; Li et al., 2014). Here, we are including words that may not have been captured by the other (Nielsen) sentiment dictionary, which provides a kind of robustness check. However, I cannot conduct as many in-depth tests as with the Nielsen index because this dictionary does not assess the strength of terms. The first four rows of table 4 present the sentiment measures. The first two are the positive and negative tweet words matching the dictionary, and the second two are proportions of the total number of sentiment words on any given day. The ratio-of-positive-to-negative variable is the number of words that were flagged as positive (numerator) compared to the number of words that were flagged as negative (denominator). Finally, the weighted ratio variable is the ratio of positive to negative multiplied by the total number of tweets expressing a sentiment. This variable captures both the skew from positive to negative (a ratio that is less than one implies more negative tweets that day), and the "importance" of a given day. For example, a day with a thousand tweets might be more important than a day with only ten. The next section discusses the characteristics observed from time series graphs.

Variable	**n**	**Min**	$\mathbf{q_1}$	$\widetilde{\mathbf{x}}$	$\bar{\mathbf{x}}$	$\mathbf{q_3}$	**Max**	**#NA**
Positive Terms	138	19	194	425	474.3188	718.2	1181	0
Negative Terms	138	16	153	352	384.8333	552.5	1331	0
Proportion Good to Total	138	0.1985294	0.4249	0.4475	0.4510679	0.4776	0.7018425	0
Proportion Bad to Total	138	0.2981575	0.5224	0.5525	0.5489321	0.5751	0.8014706	0
Ratio Bad to Good	138	0.424821	1.123	1.237	1.279647	1.361	4.037037	0
Total	138	35	359.5	781	859.1522	1271	2292	0
Weighted Ratio	138	37.6129	452.4	939.1	1082.909	1675	3023.036	0

Table 4: Descriptive Statistics IVs (Loughran and McDonald dictionary)

5.2 Time-series characteristics

This section plots the time-series figures for the dependent variables used in the forecast regressions. Apple stock data is from June 2009 to February 2019. In each group of figures below, the left is the time series plot and the right is the autocorrelation plot. The autocorrelation plot verifies that the series is covariance stationary, which is important in a forecast regression. The first two sets of figures (figures 3–6) are used in the forecast regressions while the last set of figures (figures 7–8) is used for the Markov-switching volatility jump forecasting tests.

Figures 3 and 4 are the daily returns plot and autocorrelation function (ACF) plot for Apple stock, respectively. Visual inspection of the figures suggests the series is at least approximately covariance stationary and ergodic. In a forecasting exercise, a process should be covariance stationary and ergodic because this ensures that our indicators are explaining variations in the returns, and not only explaining the trend of the returns, for example (Hamilton, 1994).

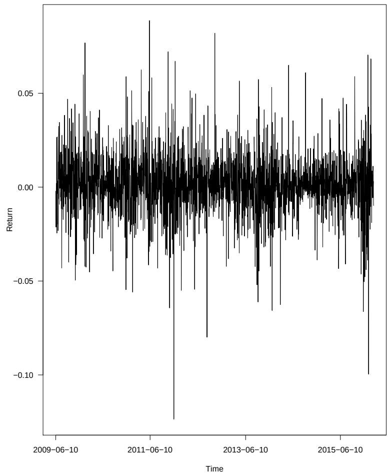

Figure 3: Apple Returns

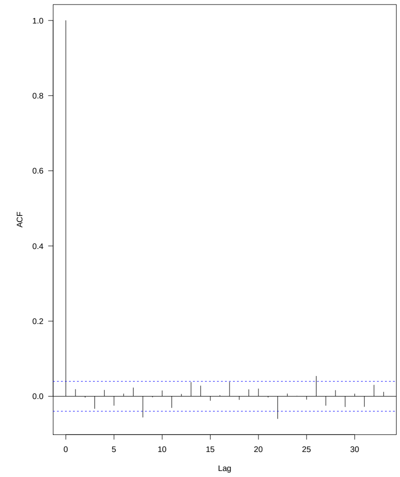

Figure 4: ACF Plot of Returns

Figures 5 and 6 illustrate that the change in daily volatility also appears to be approximately covariance stationary and ergodic. Other than a few spikes in the change in volatility, both the mean and variance are fairly constant.

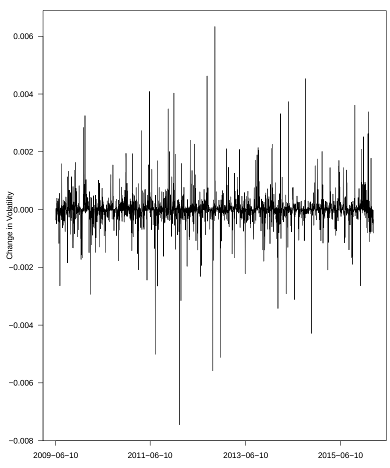

Figure 5: Change in Volatility

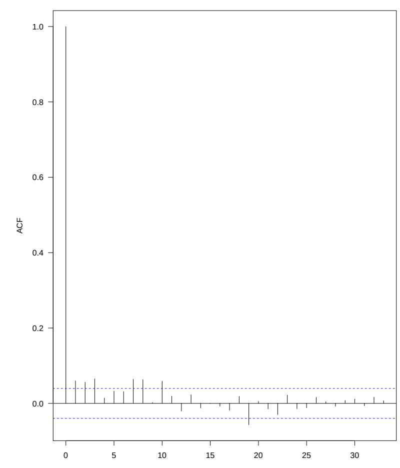

Figure 6: ACF Plot of Change in Volatility

Unlike the previous figures, the volatility time series seen in figures 7 and 8, as expected, does not seem to be covariance stationary and ergodic. The purpose of the volatility analysis is to model the jumps in figure 7 using the skewness of the sentiment distribution. As such, we do not want to transform the series because these jumps are exactly what this article attempts to model. They are the long vertical lines that go up or down significantly. They represent a significant change in volatility from one day to the next. They also appeared in figure 5 as the spikes in the time series figure. The objective below will be to determine if change in skewness of the index can forecast these volatility jumps (for a more in-depth discussion of volatility jumps, see Eraker et al. (2003); Eraker (2004); Kou (2002)).

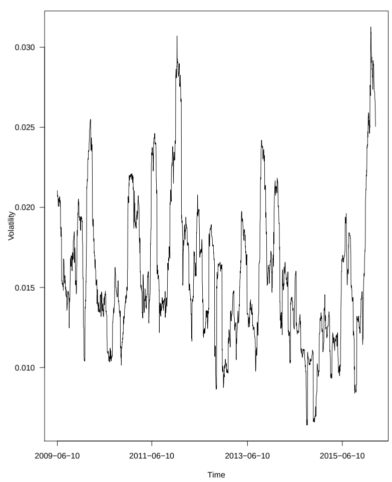

Figure 7: Volatility

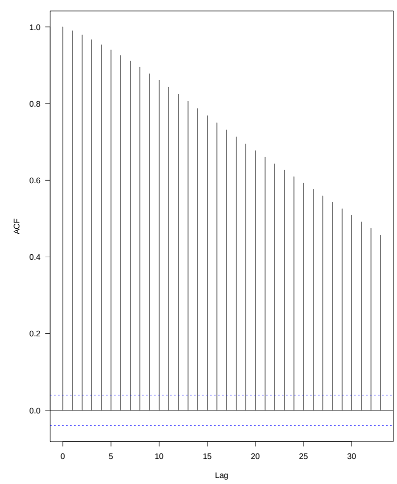

Figure 8: ACF Plot of Volatility

There are theoretical reasons to believe that sentiments indices would impact both returns and volatility jumps. Several articles (including French et al., 1987; Turner et al., 1989; Campbell and Hentschel, 1992; Bekaert and Wu, 2000) have documented "volatility feedback" effects, where periods of low returns are contemporaneously associated with higher volatility. Hence, we should expect that certain indicators, such as sentiments, would be able to forecast both volatility jumps and an asset's returns. The following section presents empirical results.

5.3 Markov-switching results

In this section, I test whether a Markov-Switching model will allow us to explain volatility jumps (or large, instantaneous volatility changes) in asset returns. Let us begin with an ordinary least squares (OLS) regression as follows:

$$\sigma_t = \alpha + \beta skew_{t-1} + \epsilon \tag{7}$$

where σ_t is the daily volatility of Apple stock, α is the regression intercept, β is the regression coefficient, $skew_{t-1}$ is the previous period's skewness value (obtained from the daily skewness of the sentiment index), and ϵ is the error. This ordinary linear regression is used because the relationship between the skewness of the sentiments index (the independent variable) and the volatility is a linear one. Once we have determined this relationship, we can then assume two or three states and the Markov-Switching model should allow us to obtain 1) a different set of parameters for each state and 2) a better fit overall (Goldfeld and Quandt, 1973; Hamilton, 1989; Kim, 1994).

5.3.1 Two-state model – 2009 subsample

As mentioned above, we first assume a linear relationship between the dependent and independent variables. For this setting, the regression produces the following results:

	Model 1
(Intercept)	0.01574^{***}
	(0.00031)
$skew_{t-1}$	0.00375^{***}
	(0.00106)
R^2	0.0390
Num. obs.	138

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table 5: Apple tweets June–December 2009 (≈600,000 tweets)

Now, we can adopt a two-state Markov-switching specification to get the following state-dependent regressions results:

	Regime 1	Regime 2
(Intercept)	0.0181^{***}	0.0147^{***}
	(0.0002)	(0.0002)
$skew_{t-1}$	0.0046^{***}	0.0016^{*}
	(0.0007)	(0.0007)
R^2	0.4435	0.0539
Num. obs.	138	138

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table 6: Apple tweets June–December 2009 (≈600,000 tweets)

Based on the results in table 9, it is clear that the best fit occurs in regime one. The skew variable does not seem to do a very good job at specifying the regime 2 model. This is the first clue that perhaps a three-state model should be used (please see appendix for three-state model results).

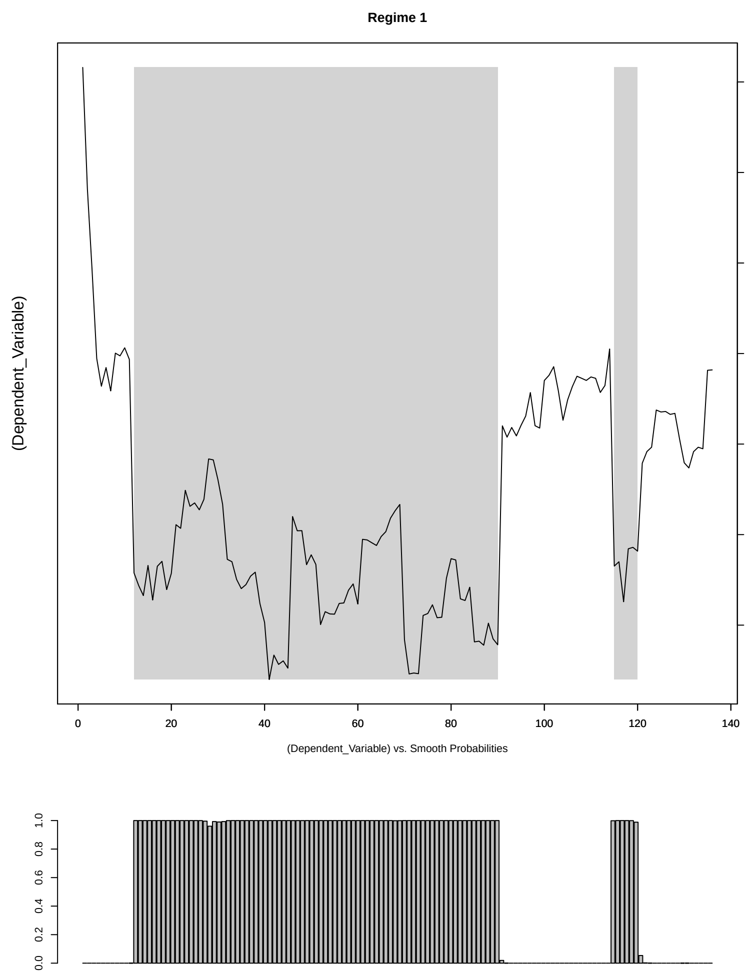

Figure 9: Apple Volatility

Figure 9 shows the fit of the model when we include the one-period lagged skewness of the sentiment distribution. The model captures the two volatility levels quite well (a high- and a low-volatility state). The grayed-out area corresponds to the low-volatility regime. This is the first volatility state in the model.

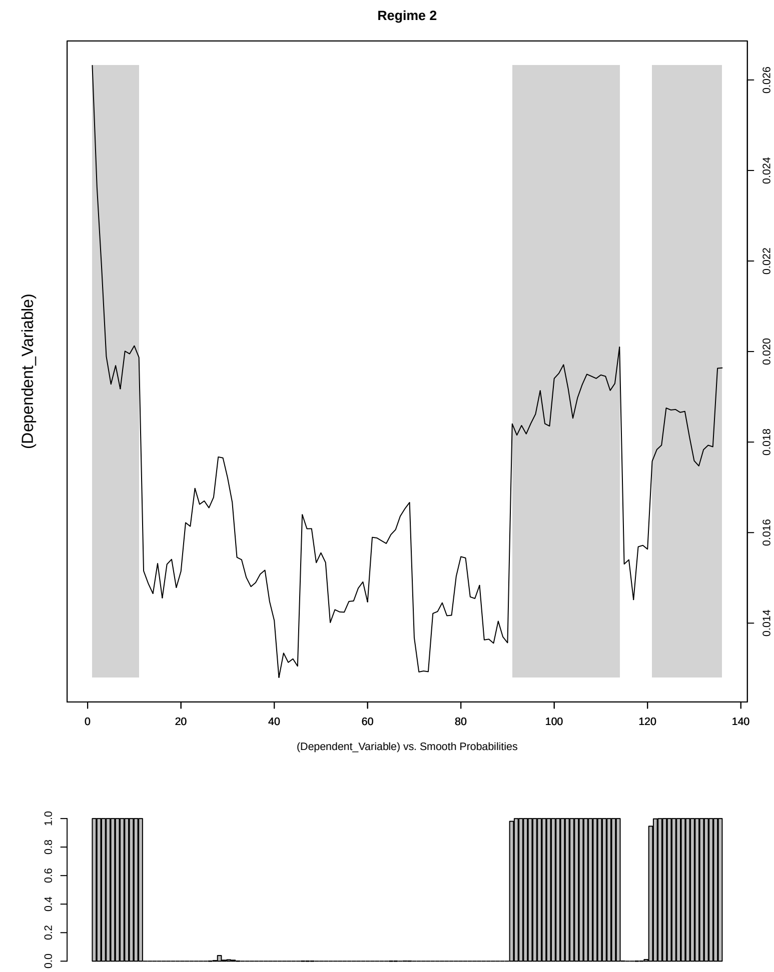

Figure 10: Apple Volatility

The second, high-volatility, state can be seen in figure 10. If we define the high-volatility state as H and the low-volatility state as L, we can rewrite the transition probability matrix as follows:

$$P = \begin{bmatrix} p_{L,L} & p_{L,H} \\ p_{H,L} & p_{H,H} \end{bmatrix}$$

where, for example, $p_{L,L}$ represents the probability that the volatility will transition from a current low-volatility state to a future low-volatility state. In other words, $p_{L,L}$ is the probability that the volatility will remain the same at some point in the future.

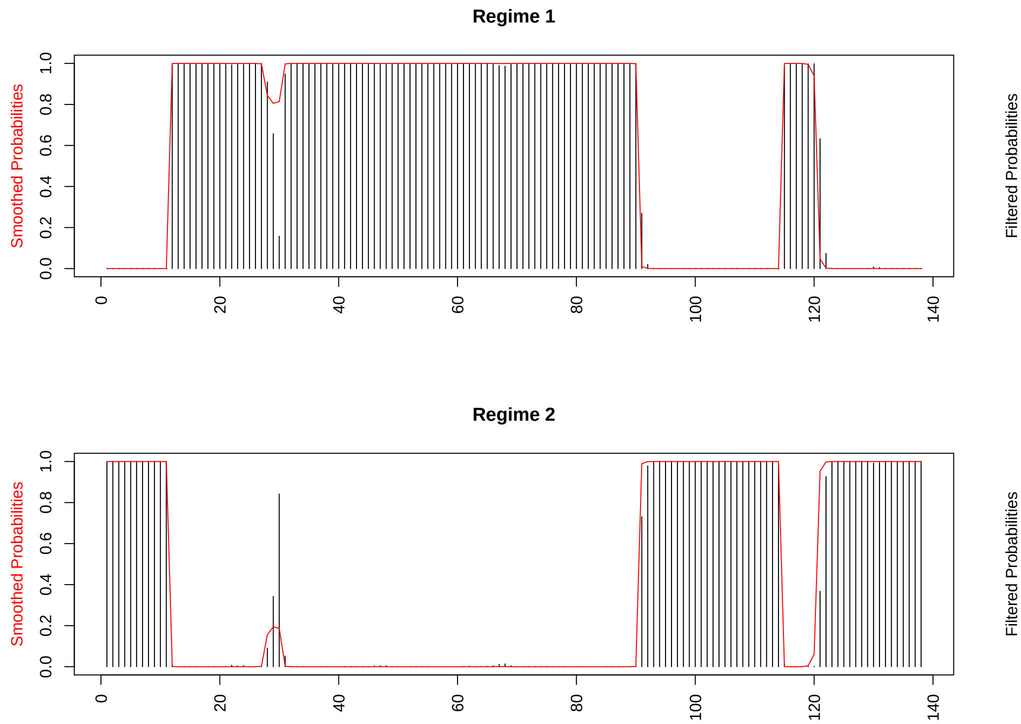

Figure 11: Smoothed and Filtered Probabilities

Figure 11 shows the smoothed and filtered probabilities for regimes one and two based on the Markov-switching specification. The resulting transition probability matrix is:

$$P = \begin{bmatrix} p_{L,L} & p_{L,H} \\ p_{H,L} & p_{H,H} \end{bmatrix} = \begin{bmatrix} 0.9598 & 0.0241 \\ 0.0402 & 0.9759 \end{bmatrix}$$

which illustrates that the initial states are highly persistent. Intuitively, these transition probabilities indicate that there is a very small probability of switching from one state to another in any given period.[9]

[9]The three-state Markov-switching model presented in the appendix provides more interesting transition dynamics.

5.3.2 Two-state model – Other firms, 2009 subsample

This section shows the same sets of Markov-switching results as the previous section (section 5.3.1), but for the 11 firms other than Apple.

Company	n	Regime 1	R_1^2	Regime 2	R_2^2	$p_{L,L}$	$p_{L,H}$	$p_{H,H}$	$p_{H,L}$
Fedex	7,393	0.0034***	0.5855	0.0014***	0.1748	0.9648	0.0352	0.9732	0.0268
		(0.0004)		(0.0004)					
Ford	900,000	0.0094***	0.2967	−0.0037*	0.1052	0.9760	0.0240	0.9606	0.0394
		(0.0022)		(0.0015)					
Google	1,000,000	0.0013**	0.1443	−0.0010*	0.0688	0.9558	0.0442	0.9876	0.0124
		(0.0005)		(0.0004)					
JP Morgan	62,277	0.0006*	0.0388	0.0027*	0.0590	0.9852	0.0148	0.9713	0.0287
		(0.0003)		(0.0011)					
Lockhead Martin	58,090	0.0001	0.0001	0.0005	0.0209	0.9722	0.0228	0.9606	0.0394
		(0.0004)		(0.0005)					
Microsoft	100,000	−0.0009**	0.1128	−0.0031***	0.2208	0.9643	0.0357	0.9757	0.0243
		(0.0003)		(0.0008)					
Pepsi	232,330	0.0025***	0.1468	−0.0002	0.0023	0.9803	0.0197	0.9490	0.0510
		(0.0006)		(0.0007)					
Pfizer	656,774	0.0009**	0.0551	0.0009**	0.0634	0.9761	0.0239	0.9813	0.0187
		(0.0003)		(0.0003)					
Verizon	195,950	0.0010	0.0126	0.0010***	0.0003	0.9480	0.0520	0.9522	0.0479
		(0.0008)		(0.1731)					
Wal–Mart	170,238	−0.0009***	0.2387	−0.0011***	0.3860	0.9656	0.0344	0.9533	0.0467
		(0.0004)		(0.0002)					
Wells Fargo	5,910	0.0024*	0.2704	−0.0014***	0.0268	0.9750	0.0250	0.9565	0.0435
		(0.0010)		(0.0003)					

Table 7: Volatility Regressions (Nielson dictionary)

Table 7 summarizes the results for the Markov-switching model. The first column is the name of the company being analyzed. The second column gives the number of tweets during the sample. The third and fifth columns are the Markov-switching regression coefficient for the first and second volatility regimes respectively (standard errors in parenthesis). The fourth and sixth columns show the R^2 for the first and second regime respectively. Finally, columns seven through ten provide the state-switching probabilities where, for example, $p_{L,L}$ represents the probability of staying in the current low state of volatility. Since the interpretation of the results in this section are the same as for the previous section, I invite readers to refer back to the previous section.

One observation that is worth noting in table 7 is that some of the regime coefficients are positive while others are negative. Since we are using a Markov-switching model, this simply means that the relationship between the level of the volatility is sometimes inversely related to consumer/investor sentiment. As we are mostly interested in modeling the jumps here, the overall fit of the model, which is very high, is more important than the actual coefficient value.

5.3.3 Two-state model – Full sample

Here, the sample period is much larger than in section 5.3.1 (June 10, 2009–February 28, 2019). This sample includes approximately 3.1 million tweets related to Apple.

	Model 1
(Intercept)	0.01654^{***}
	(0.00015)
$skew_{t-1}$	-0.00094^{***}
	(0.00015)
R^2	0.01302
Num. obs.	2436

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table 8: Apple tweets June 2009 to February 2019 (≈3,036,173 tweets)

Table 8 presents the results for the OLS regression without the Markov-switching specification. Although the results are significant (the sentiment skewness does seem to explain some variation in volatility levels), these results are less than convincing. Once we have these benchmark results, we can apply the Markov-switching specification to get the following state-dependent regression results:

	Regime 1	Regime 2
(Intercept)	0.0164^{***}	0.0164^{***}
	(0.0002)	(0.0002)
$skew_{t-1}$	0.0039^{***}	-0.0025^{***}
	(0.0002)	(0.0001)
R^2	0.2103	0.2472
Num. obs.	2436	2436

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table 9: Apple tweets June 2009 to February 2019 (≈3,036,173 tweets)

Clearly, the regime-switching framework does a much better job at capturing the different levels of the volatility (high and low respectively). We obtain a model with a much higher R^2 in both regimes, all while maintaining statistical significance. The negative coefficient means that, during low-volatility periods, there is an inverse relationship between the skew and the volatility. Since the sentiment distribution is fairly constant at both levels, the fact that, on average, volatility is decreasing during low-volatility periods explains this negative sign. Again, though, the major goal here is to model overall volatility switches via sentiment distribution shifts rather than to model micro movements in the daily volatilities of stocks.

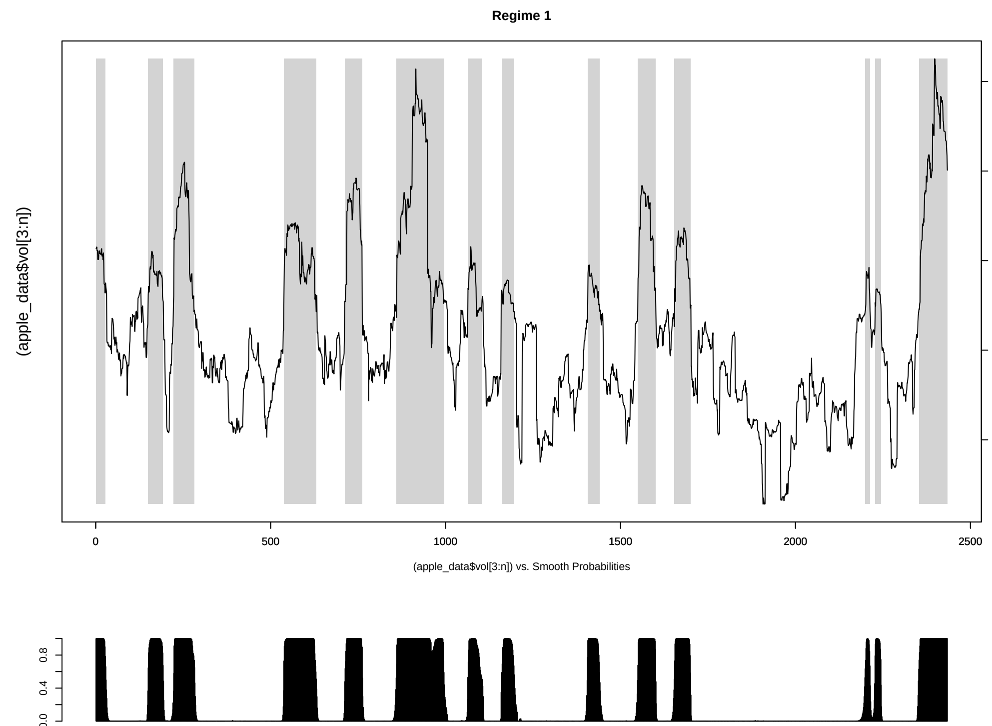

Figure 12: Apple Volatility

Figure 12 shows the overall fit of the model using the full sample. The model includes the one-period lagged skewness of the sentiment distribution. As was the case with the shorter 2009 subsample, the model captures the two volatility levels quite well (note that the grayed-out area corresponds to the high-volatility regime).

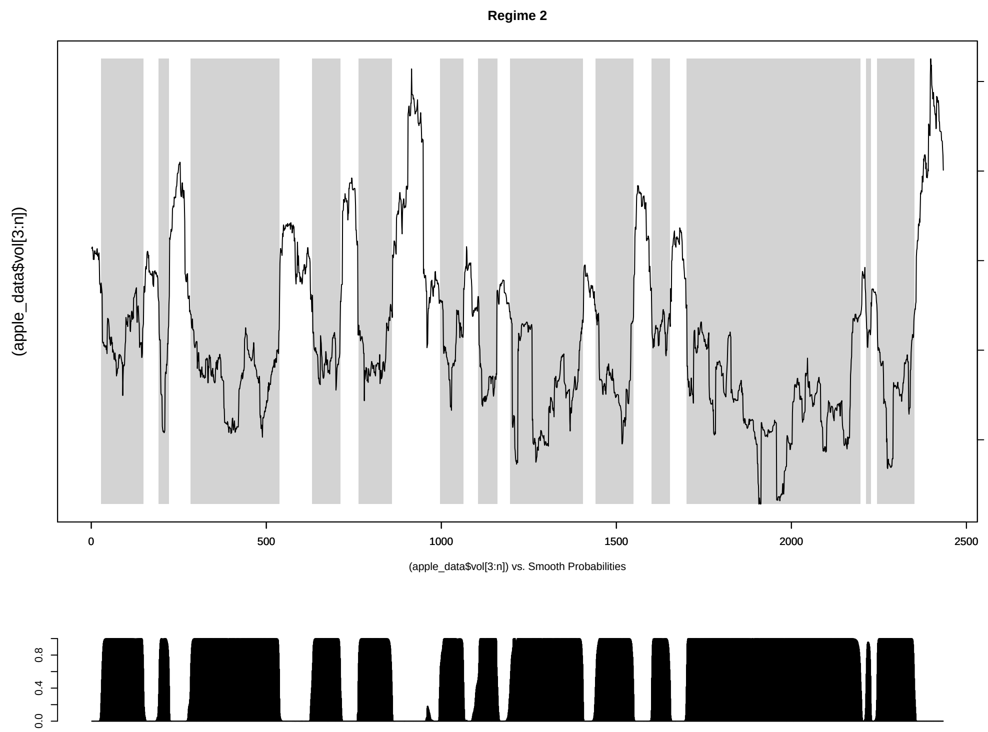

Figure 13: Apple Volatility

Figure 13 shows the overall fit of the model for the second (low-)volatility state. Again, the model does identify and forecast the low-volatility state quite accurately.

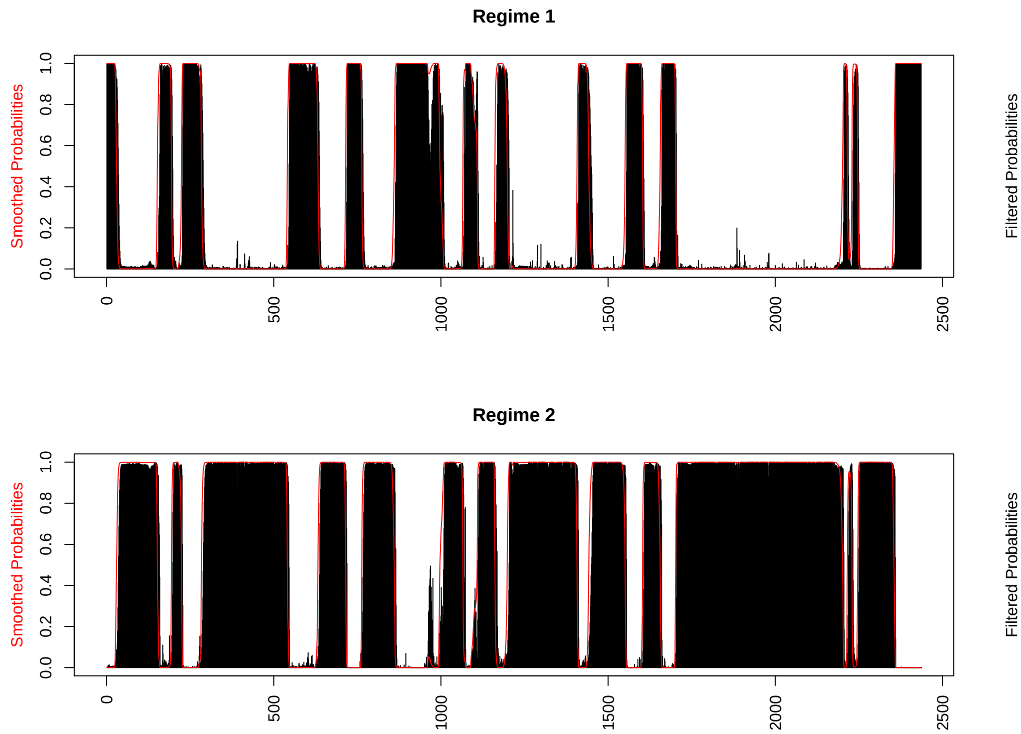

Figure 14: Smoothed and Filtered Probabilities

Figure 14 shows the smoothed and filtered probabilities for regimes one and two based on the Markov-switching specification. The resulting transition probability matrix is:

$$P = \begin{bmatrix} p_{L,L} & p_{L,H} \\ p_{H,L} & p_{H,H} \end{bmatrix} = \begin{bmatrix} 0.9819 & 0.0079 \\ 0.0181 & 0.9921 \end{bmatrix}$$

5.4 Forecast results

In this section, I present the results for the forecast regressions for return and volatility of Apple stock. To be clear, forecast regressions mean that, at time zero, a user of the model would obtain a forecast for time t. These results are compared to the realized return for the same period. All forecast regressions conducted in this section are, unless otherwise noted, for a one-day period.

5.4.1 Results – Nielsen word dictionary

Using the Nielsen (2011) word dictionary, the regression specification (table 11) is the following:

$$r_t = \alpha + \sum_{i=1}^{6} \beta_{t-1,i} z_{t-1,i} + \epsilon_t \tag{8}$$

where r_t is the return at time t, α is the regression intercept, $\beta_{t-1,i}$ is the regression coefficient on the independent variable with a one-day lag, $z_{t-1,i}$ is the previous day's sentiment for the various sentiment scores i, and ϵ_t is the regression error term.

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.00124^{**}	$0.00071^{\dagger}$	0.00185	0.00090
	(0.00047)	(0.0004)	(0.0031)	(0.00292)
VV Negative	$1.24713^{\dagger}$	0.75513	4.22388	4.22545
	(0.65394)	(0.5233)	(2.92898)	(2.72102)
V Negative	-0.16515^{***}	-0.11019^{**}	0.12793	0.03865
	(0.0496)	(0.0399)	(0.1228)	(0.11779)
Negative	-0.04697^{*}	-0.04589^{**}	-0.04697	0.00217
	(0.0206)	(0.0167)	(0.04796)	(0.04494)
Positive	0.02034^{*}	0.02014^{**}	0.14251	0.09524
	(0.0080)	(0.0066)	(0.09408)	(0.08793)
V Positive	0.06916^{**}	0.05152^{**}	-0.27163^{*}	$-0.19593^{\dagger}$
	(0.0216)	(0.0177)	(0.11505)	(0.10801)
VV Positive	0.91876^{**}	0.15239	4.54095	6.61489
	(0.2972)	(0.4280)	(7.65321)	(7.11768)
R^2	0.0219	0.3794	0.0989	0.2484
Num. obs.	2,436	2,436	138	138
Factor Controls	No	Yes	No	Yes

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table 10: Apple Return Regressions

Table 10 shows the regression results. Model 1 is the base model for the full sample without any factor controls. Model 2, still for the full sample, includes factor controls (e.g., momentum, small minus big, high minus low, and market return). Model 3 is the regression results for the 2009 subsample without any factor controls, and model 4 is the 2009 subsample with factor controls. For reference, the R^2s for the factors alone in these regressions are 0.3689 for the full sample and 0.1886 for the 2009 subsample. So the R^2 increases by about 1.1% in the larger sample and by about 6% in the smaller sample. Ultimately, we can conclude that sentiment indices at the very least contribute to explaining asset returns (in other words, sentiments are another worthwhile factor in the sea of already defined factors in asset pricing). The coefficients in the regressions are quite robust to specification (with or without factor controls).

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.00012	0.00011	-0.1576^{***}	$-0.07460^{\dagger}$
	(0.00203)	(0.00164)	(0.0409)	(0.04287)
Proportion VV Negative	0.06110^{*}	0.03676	0.2430	1.69452^{*}
	(0.02986)	(0.02357)	(0.8891)	(0.83095)
Proportion V Negative	-0.01135^{*}	-0.00776^{*}	0.2304^{*}	0.12185
	(0.00480)	(0.00381)	(0.1134)	(0.10673)
Proportion Negative	$-0.00628^{\dagger}$	-0.00873^{**}	0.1699^{**}	0.13875^{*}
	(0.00330)	(0.00265)	(0.0615)	(0.05672)
Proportion Positive	0.00542^{*}	0.00544^{*}	0.1579^{**}	0.08392
	(0.00270)	(0.00218)	(0.0505)	(0.05601)
Proportion V Positive	$0.00605^{\dagger}$	0.00487	0.1316^{*}	-0.01837
	(0.00367)	(0.00297)	(0.0646)	(0.06962)
R^2	0.0106	0.3758	0.1225	0.2704
Num. obs.	2,436	2,436	138	138
Factor Controls	No	Yes	No	Yes

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table 11: Apple Return Regressions – Proportions

In table 11, variables are calculated as the number of observations in a given sentiment category divided by the total number of observations on that day. For example, if there were 1,000 sentiment words on any given day and 100 were in the *V Negative* category, the *V Negative* variable would get an observation of 0.1 on that specific day. The columns are defined in the same way as in table 10. Since the variables in the models are proportion variables, the proportion of *VV Positive* has been omitted and serves as the reference category.

This level of forecasting at the daily interval compares to the forecasting power of models for medium- (say, monthly) and long-term (say, yearly) forecasts (Cochrane, 2009).

The regression specification for table 12 is the following:

$$\Delta\sigma_t = \alpha + \sum_{i=1}^{6} \beta_{t-1,i} z_{t-1,i} + \epsilon_t \tag{9}$$

where $\Delta\sigma_t$ is the change in volatility at time t, α is the regression intercept, $\beta_{t-1,i}$ is the regression coefficient on the independent variable with a one-day lag, $z_{t-1,i}$ is the previous day's sentiment for the various sentiment scores i, and finally ϵ_t is the regression error term.

	Model 1	Model 2
(Intercept)	-0.000047^{**}	-0.0001
	(0.000017)	(0.0002)
VV Negative	-3.516	0.9056
	(2.444)	(1.7128)
V Negative	0.60630^{**}	0.0543
	(0.1844)	(0.1750)
Negative	0.06931	0.1946^{**}
	(0.08731)	(0.0707)
Positive	0.01855	-0.2582^{***}
	(0.05538)	(0.0682)
V Positive	-0.2040^{*}	0.1503^{*}
	(0.8543)	(0.0705)
VV Positive	3.0600^{**}	10.1482^{*}
	(1.0720)	(4.5306)
R^2	0.01625	0.1599
Num. obs.	2435	137

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table 12: Apple Change in Volatility Regressions

In table 12, the key indicators are the raw sentiment word counts. The columns correspond to the full sample and 2009 subsample results, respectively. The forecast for changes in volatility for Apple is particularly good for the 2009 subsample with an R^2 of about 0.16.

The coefficients for the independent variables in table 12 have been scaled by a magnitude of $10,000$ to see the full effect of the sentiments on changes in volatility. In other words, 10,000 *Negative* tweets would be expected to have a 0.069 effect on the daily change in the standard deviation of returns. The coefficients increase significantly along with the “level” of the variable. In other words, as the words become more extreme, their effect on the change in volatility also increases. Sentiment indices do not impact changes in volatility in a clear direction. But one would expect that extreme sentiments should lead to larger swings in volatility, which is exactly what we observe. Whether a slightly positive or slightly negative sentiment should have a positive or negative effect on the change in the volatility is not so clear.

5.4.2 Results – Loughran and McDonald word dictionary

The second set of results is for the forecast regressions using the Loughran and McDonald (2011) word dictionary. Analysis in this section was limited to the 2009 subsample. The regression specification for table 13 is the following:

$$r_t = \alpha + \sum_{i=1}^{k} \beta_i \left(\frac{Good}{Total} \right)_{t-i} + \epsilon_t \tag{10}$$

where r_t is the return at time t, α is the regression intercept, β_i is the regression coefficient on the independent variable at lag k, the ratio $\left(\frac{Good}{Total}\right)_{t-i}$ is the previous period's count of good sentiment words to bad sentiment words, and finally ϵ_t is the regression error term.

	Model 1	Model 2
(Intercept)	-0.0053	-0.0026
	(0.0110)	(0.0158)
$\left(\frac{Good}{Total}\right)_{t-1}$	-0.0194	0.0198
	(0.0241)	(0.0243)
$\left(\frac{Good}{Total}\right)_{t-2}$		-0.0062
		(0.0244)
R^2	0.0390	0.0424
Num. obs.	133	132

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table 13: Apple Return Regressions (scaled independent variable)

One important note about table 13 is that the coefficients are for sentiment scores for every 1,000 tweets. The coefficients remain consistent when we add an additional lag to the model specification (model 2). These results show that the forecasts are dependent on the dictionary specification. Here, clearly, the sentiments obtained using the Loughran and McDonald (2011) word dictionary are unable to capture Apple's returns during the subsample period. In the online appendix, I propose to use a weighted measure of good-to-bad sentiments.[10]

6 Conclusion

I performed a textual analysis of tweets to obtain sentiment indices that explained stock returns and volatility jumps. This paper makes two key contributions. First, I find that, by using sentiment indices rather than sentiments obtained from dichotomous variables, I am able to forecast daily fluctuations in stock returns. Hence, at the very least, this paper adds to the (already rich) literature attempting to estimate asset returns using various factor models (Brennan et al., 1998; Welch and Goyal, 2007; Fama and French, 2015; Kelly et al., 2018). Second, and more importantly, by adopting a very simple Markov-switching model, it is possible to use the skewness of the sentiment index

[10]The ratio of good-to-bad reflects the skewness of the sentiment about Apple in the market.

distribution to better predict volatility jumps. In other words, when overall sentiment towards a company or its products shifts, we can expect a volatility jump to occur. Hence, consumer and investor perceptions (or sentiments) do indeed matter in asset pricing. Firms would benefit from considering carefully what consumers and investors are saying about them on social media.

One important implication of this piece concerns open access of social media data. Without a doubt, such data should be used carefully to preserve the privacy of social media users. However, as I have shown in this paper, more complete data could further our understanding of the linkages between economic systems and their participants. The literature has long argued that stock market noise and volatility jumps could not be explained using traditional datasets. And yet, here we are. Social media information could potentially help us explain phenomena that have yet to be understood in economics more generally, and in financial markets more specifically. But, as of today, if we were to attempt to collect the population of tweets over any significant amount of time, it would cost millions of dollars and take researchers several years because of the artificial barriers imposed by social media companies (limits on requests, for example). Although social media platforms own these data, there should be realistic pathways through which researchers can access data without prohibitive time and cost constraints.

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