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Twitter and the US stock market: The influence of micro-bloggers on share prices[1]

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Abstract: With the increased interest in social media over recent years, the role of information disseminated through avenues such as Twitter has become more widely perceived. This paper examines the mention of stocks on the US markets (NYSE and NASDAQ) by a number of financial micro-bloggers to establish whether their posts are reflected in price movements. The Twitter feeds are selected from syndicated and non-syndicated authors. A substantial number of tweets were linked to the price movements of the mentioned assets and an event study methodology was used to ascertain whether these mentions carry any significant information or whether they are merely noise.

Keywords: Twitter, social network, social media, financial markets, event studies, information.

JEL code: G14.

Introduction

In contrast to traditional, static websites, whereby users are limited to passive viewing of content, the term Web 2.0 refers to those sites that allow interaction between users. Indeed the most well-known examples of the Web 2.0 generation include social media websites such as Twitter and Facebook. These social media sites act as platforms through which individuals can create, discuss and modify shared user content typically centred around a common interest or individual, such as investing or Justin Bieber. This field of research is still in its infancy; however, unlike more traditional lab-based methodologies studies utilizing data from Web 2.0 platforms are more likely to reflect the real-time, real-life behaviour of individuals and groups. Though to date there have been a few studies that concentrate on the effect of social media on political, finan-

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cial and commercial issues such work predominantly focuses on the more static weblogs or message boards rather than dynamic 'microblogs' generated by individuals through sites such as Twitter. Indeed we believe that this is the first study to provide empirical evidence relating to the impact of Twitter use by financial micro-bloggers on corporate share prices.

Twitter was launched in July 2006 and quickly attracted millions of users who share information with a network of followers on a wide range of topics through the use of microblogs or *tweets*. As described in Milstein and Lorica [2008] tweets are short comments of up to 140 characters, which is approximately the same length as a newspaper headline and sub-heading. Twitter users range from ordinary individuals and celebrities to businesses and news agencies with use being divided into three categories: information sharing, information seeking and friendship-like relationships [Java et al. 2007]. By the end of 2015 Twitter had over 320 million monthly active users worldwide with approximately 67 million users in the United States alone (about.twitter.com).

By default tweets are public which means that users can follow others and read their posts without mutual permission. The substantial flexibility of Twitter's application program interface (API) makes it easy to integrate it with other online services and applications. This, combined with a large base audience, means that Twitter is increasingly used by news organizations such as CNN, BBC World and The Wall Street Journal to distribute updates on current events as well as financial commentators as a means to disseminate information to investors. Indeed Twitter feeds are embedded in traders' Bloomberg terminals and NASDAQ's mobile application and incorporate posts from StockTwits, a communications platform for investors and the wider financial community. From the investor's point of view micro-blogging addresses the need for a real-time means of communication. Since tweets can be posted from nearly anywhere and at any time they are likely to contain an immediate reaction to events or information. As such Twitter constitutes a rich source of data for quantitative and qualitative analysis with a longitudinal character which allows for analysis of the dynamic processes. This, coupled with its high frequency, makes for information that is potentially highly responsive to dynamic stock market developments. The rate at which posts are retweeted can be considered to be a simple measure of whether information is perceived interesting and the overall impact on share prices can measure the perceived usefulness of the information.

We use the existence of a tweet as an indicator of some (potentially new) information rather than attempting to evaluate its causality on stock prices. The tweet is seen as a signal of information appearing in the market. We employ an event study approach to identify the impact of selected tweets on the share prices of companies listed on the NYSE and NASDAQ. Tweets associated with abnormal returns are identified and then analyzed with respect to their popularity, content and company size, i.e. how many tweets are linked to earnings. Finally we consider whether Twitter is used as a tool for trading suggestions.

Our results show that nearly a third of the tweets considered is associated with abnormal price movements as evidenced by our event-study approach. Although the 'chatter' is dominated by Google and Apple our research shows that it is not only high-tech firms that are seen as tweet-worthy. In fact the activity is widespread across stocks and markets. The discussion is not limited to traditional financial information and there is a distinct lack of concrete trading recommendations. For example, tweets related to earnings constitute less than 10% of all relevant tweets. This suggests that Twitter is not a replacement for traditional sources which tend to be based on the fundamental information availability.

The remainder of this paper is organized as follows: after reviewing the literature (Section 1), the data collection and methodology are discussed (Section 2 and 3). Subsequently we present our results in Section 4 and conclude in the final section.

1. Literature review

Although stock markets have received a considerable amount of attention, for example Będowska-Sójka [2014] and Folfas [2016], the research on the links between financial markets and digital media is still in its infancy. To date there have been few studies which use Twitter to investigate public opinion most of which are published in conference proceedings rather than academic journals. Typically they attempt to apply analysis of the public mood to either political or economic developments rather than the impact of tweets as news events on markets. Studies to date have largely concentrated on various social issues. For example, Tumasjan et al. [2010] and Wang et al. [2012] perform political sentiment analysis of Twitter posts and attempt to predict results of elections in Germany and the United States, respectively. In a related study O'Connor et al. [2010] compare surveys on consumer confidence and presidential job approval to the mood on Twitter.

Another broad area of research of Web 2.0 is related to the commercial and business sector. Here researchers have been using mostly information contained in weblogs (online blogs). In a relatively early study Gruhl et al. [2005] use blog posts to predict sales of books on Amazon. Although they manage to show reasonable correlation between posts and sales their prediction exercise should be read with caution as the method of analysis is somewhat simplistic. In a similar study Mishne and Glance [2006] show that a positive weblog sentiment is highly correlated with film success. Mei et al. [2007] and Liu et al. [2007] construct more advanced models of sentiment analysis which are quite flexible and can be used for monitoring public opinion, predicting behaviour and making business decisions. Liu et al. [2007] claim that their autoregressive sentiment-aware model (ARSA) predicts box office sales at American cinemas. They show that the sentiment contained in blogs has more predictive power than just a simple number of mentions. Choi and Varian [2012] demonstrate that Google queries can be used as indicators of subsequent consumer purchases and in effect can predict, amongst others, car sales, unemployment claims, travel destinations and consumer confidence. They call it "contemporaneous forecasting" or "nowcasting" [Choi and Varian 2012].

1.1. Web 2.0 and the financial markets

Previous studies that have examined the relationship between online content and stock markets have used information obtained from several sources including news articles, weblogs, message boards (Internet forums) and microblogs. Nardo et al. [2015] offer a concise review of studies analysing the usefulness of online media in predicting movements in financial markets. However these studies have traditionally focused on individual and social sentiment or predictive behaviour, for example Ranco et al. [2015] and Santos, Laender, and Pereira [2015], with only few being published in academic journals.

One of the first sources of information that attracted attention of researchers is message boards. An early study by Wysocki [1998] showed that overnight posting volume on Yahoo message boards could predict changes in the following day's trading volume and returns. Tumarkin and Whitelaw [2001] looked at the Internet service sector and concluded that changes in investor sentiment expressed in message boards correlated with abnormal industry-adjusted returns only on days with unusually high forum activity. Such days were also associated with abnormally high trading volumes which persisted on a following day. Das and Chen [2007] proposed a small investor sentiment index based on Amazon's and Yahoo's message boards and investigated its relationship to the values of 24 tech-sector stocks listed in the Morgan Stanley High-Tech Index. They did not find strong links between sentiment and prices of average stocks but did note a weak relationship between their sentiment index and aggregated tech-stock index.

Preis, Moat, and Stanley [2013] turned to Google searches for terms related to finance in order to find patterns that could be considered as early warnings of stock market moves. They record closing prices of the Dow Jones Industrial Average (DJIA) on the first day of a week then determine how many queries for a specific term were run in a preceding week and by employing a hypothetical investment strategy evaluate whether variation in online queries can capture later changes in stock prices. Their results are promising and show that information gathering behaviour may offer indications of future trends in the behaviour of market participants. They also point out that when predicting movements of the U.S. market models using worldwide search data perform worse than those based only on the U.S. data.

1.2. Twitter

There have been few studies that examine the relationship between Twitter posts and stock market changes and they tend to focus on measuring collective mood. Bollen, Mao, and Zeng [2011] performed a text content analysis of tweets to construct a mood metric. The predictive strength of public mood on the Dow Jones Industrial Average (DJIA) was analyzed through Granger causality (linear approach) and Self-Organizing Fuzzy Neural Network (SOFNN, non-linear approach) methods. They studied nearly ten million tweets posted by 2.7 million users between February and December 2008. Although they showed that changes in public mood matched changes in DJIA closing values three to four days later with up to 87.6% accuracy their results may be difficult to generalize as the analyzed period was marked by a major credit crunch and recession. In another study Zhang, Fuehres, and Gloor [2011] used a randomized sample of tweets covering a period of six months to predict changes in Dow Jones, NASDAQ and S&P500 indices. They found significant and negative correlation between the stock market indices and sentiments of both hope and fear on a daily basis. They proposed three measures of the collective mood: (1) number of tweets that contain either positive or negative mood words, (2) number of followers of such tweets and (3) number of retweets of emotional posts; all of them expressed as a percentage of all tweets in a day. They used only seven mood words: hope, happy, fear, worry, nervous, anxious and upset. Such an approach is unlikely to perform well in mood analysis as inevitably it disregards a large number of posts expressing the same sentiments but using different words. Furthermore it is particularly badly suited to detect irony or sarcasm.

More recently Ranco et al. [2015], Porshnev, Redkin, and Shevchenko [2013], Si et al. [2013] and Sprenger et al. [2013], have agreed that sentiment contained in Twitter posts carries information useful in improving the accuracy of stock predictions. Sprenger, et al. [2013] show that sentiment is associated with abnormal stock returns whilst the volume of tweets predicts the next day trading volume. They also look at the quality of advice given by bloggers and conclude that those whose investment advice is above average tend to have more followers and be retweeted more frequently.

Sul, Dennis, and Yuan [2014] performed a sentiment analysis of tweets on firms traded on the S&P500. Their results show that both positive and negative sentiment expressed through the micro-blogging website is significantly related to firms' stock returns. In particular, tweets by users with a large follower base have a stronger impact on same day returns because the information spreads quickly. On the other hand the information contained in tweets by users with fewer followers takes longer to be disseminated and has a stronger impact on 10-day returns.

In contrast to those studies, whose primary objective is the measurement of sentiment, our study looks at posts by financial commentators and tweets that specifically mention listed companies. Such an approach appears particularly important because, as Yang, Mo, and Lin [2015] show, a community has formed on Twitter which uses the platform primarily to exchange information about financial markets. Consequently our sample is likely to contain less noise compared to studies based on tweets by a wider blogger population and more information for predicting stock movements.

2. Data collection

The data were downloaded using the API available from Twitter for the period September 2011 through June 2013 for fourteen authors, though not all the authors were recorded over the entire period.[4] The authors are a combination of syndicated and non-syndicated financial commentators.

The number of followers for each micro-blogger as of July 2013 is shown in Table 1. In order to put the number of followers in context, Justin Bieber

Table 1. Number of Twitter followers for selected micro-bloggers (July 2013)

Micro-blogger	Followers	Affiliation	Number of Tweets Recorded	Percentage of Justin Bieber	Percentage of CNN Money
@abnormalreturns	31 458	None	3 120	0.081	6.131
@carney	30 852	CNBC	875	0.079	6.013
@cgasparino	30 169	Fox	3 278	0.078	5.880
@cnbcfastmoney	46 372	CNBC	2 824	0.119	9.038
@cnnmoney	513 064	CNN	988	1.321	100
@cnnmoneyinvest	24 062	CNN	3 273	0.062	4.690
@dougkass	60 507	None	3 025	0.156	11.793
@guyadami	30 433	CNBC	568	0.078	5.932
@karenfinerman	18 457	CNBC	562	0.048	3.597
@marketfolly	26 193	None	2 038	0.067	5.105
@Philipetienne	8 321	None	3 205	0.021	1.622
@scaramucci	18 035	CNBC	301	0.046	3.515
@stocktwits	282 484	None	4 345	0.727	55.058
@tradefast	16 643	None	3 378	0.043	3.244
Total	1 137 050		31 780		

[4] This is due to the API restrictions. Though CNN were tweeting in 2011 their high volume of traffic meant that it was not possible to go back this far into their records.

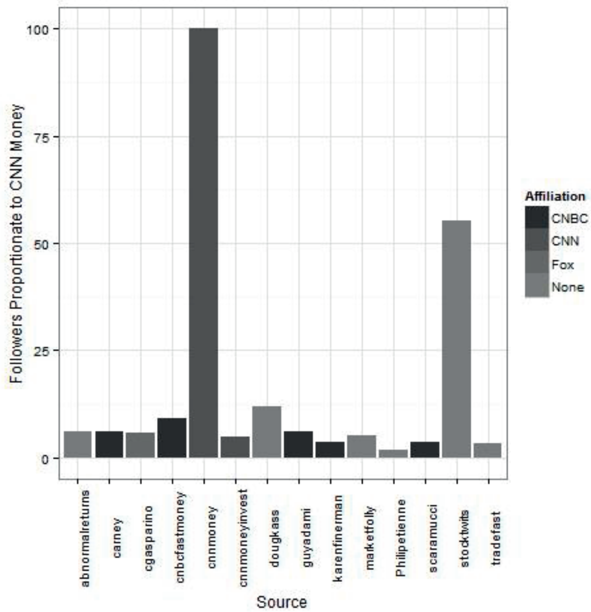

Figure 1. Followers as a proportion of CNN Money

has 38.8 million followers and was considered the most followed person at the time. As one can see the number of financial Twitter followers is small relative to the more / most popular Twitter users. Many of the followings are also small relative to CNNMoney, the largest of the sample considered here. This is shown in Figure 1.

Over the majority of the period there were less than 50 picks, or comments, on a stock per day as shown in Figure 2. However it is noticeable that the number of posts by StockTwits is considerably higher than by other commentators (see Figure 1). Table 1 shows that a total of 31,780 distinct tweets were downloaded using the Twitter API and they had a potential to be considered by over 1.1 million followers. Each tweet was scanned for a stock symbol, i.e. a number of characters following $, and there were approximately 9,600 tweets containing these symbols. These were then split by stock so that each stock pick was associated with an author and date as well as the text. This implies that if a source named more than one stock in a tweet this would be counted as one pick for each asset. This generated approximately 17,000 raw picks from the tweets. The individual picks were filtered to include only business days and to remove tweets that occurred before the stock's IPO etc. Tweets from the individual sources were grouped by date to give event points to use.

In total Figure 2 shows 8,549 individual events each identified by a stock pick and the date upon which the tweet was written. Though the relatively large loss levels appear to be concerning it is inevitable with such a medium

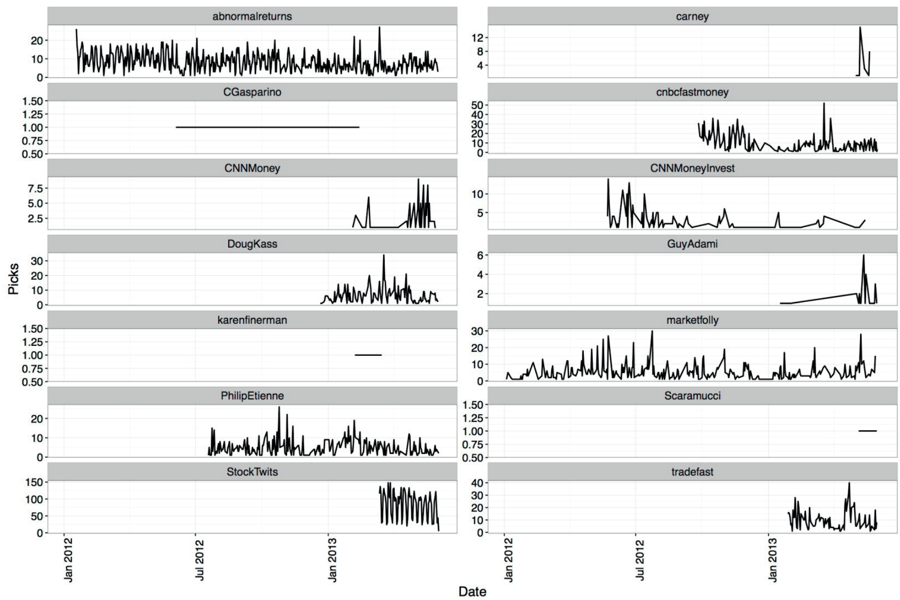

Figure 2. Number of picks in Tweets for 2012–2013

where there is considerable noise, albeit news or other information. It suggests that about 1 in 4 tweets has some sort of stock information in it. This might be higher than one might have expected from the twittersphere. The returns data for the stock and relevant indices were acquired from Yahoo Finance with the underlying index being determined by the exchange on which that the stock was traded. This gave a number of possible indices, the NASDAQ composite, NASDAQ 100 and the S&P 500.

3. Method

Before the data was used for analysis the following data cleaning procedure was implemented:

1. Observations with incorrect share codes, commodities, stock market indices and currencies were removed.
2. Only shares traded on NYSE or NASDAQ (e.g. BRK-B and not BRK-A) were used.[5]
3. Tweets on public holidays and weekends or before their IPO were removed.

To analyze the relationship between a tweet about a company and its share price an event study, as outlined by Campbell, Lo, and Mackinlay [1997], based

[5] The Stata ado-file “Stockquote” by Nikos Askitas was used to download stock data from Yahoo Finance.

on daily data was conducted. A similar approached was used by Rani, Yadav, and Jain [2015], Yang, Zheng, and Zaheer [2015] and Aizenman et al. [2016].

The event window consists of a single day upon which the tweet appeared. The pre-event window is the time period twenty days before and the post-event window is the time period twenty days after the event. Our final sample is presented in Table 2.

Table 2. Sample of NYSE and NASDAQ listed shares

Unit	NYSE	NASDAQ
Unique Shares	742	378
Unique Events	3758	2587
Most Popular Shares	GS, JPM, C	APPL, GOOG, AMZN

As Table 2 shows there are clear bloggers' favourites in each market. In particular Apple and Google dominate the NASDAQ market with over 200 and 100 tweets respectively.

The event study contains three stages: estimating normal returns, calculating the abnormal returns and testing if the accumulated abnormal returns are statistically significantly different from zero. Normal returns, defined as the price change that would be expected if the event (i.e. the tweet) did not take place, are derived by regressing each log share price change on the change of the relevant market indices of the pre-event window (see Equation 1). The market index S&P500 is used for the share listed on the NYSE and the Nasdaq-100 for shares listed on NASDAQ. Before the event t is less than 0, at the event t is equal to zero, and t greater than 0 is after the event.

$$\Delta p_{it} = \alpha_i + \beta_i \Delta p_{mt} + \varepsilon_{it} \text{ for } t < 0, \text{ i.e. before the event,} \tag{1}$$

where Δp_{it} represents the change of the logarithmic share price of share i at time t and Δp_{mt} the change of the logarithmic index value of market m, i.e. the returns on the asset.

In Equation 2 we use the estimated coefficients to predict the normal returns of the shares based on the market index for the post-event window ($t > 0$):

$$\Delta \hat{p}_{it} = \hat{\alpha} + \hat{\beta} \Delta p_{mt} \text{ for } t > 0. \tag{2}$$

Secondly, abnormal returns are calculated by taking the difference between the actual and predicted return. Finally, the cumulative abnormal returns are calculated and a t-test at a 5% significance level conducted to test whether the abnormal returns are statistically significantly different from zero.

4. Results

This section considers the results of the event study and specifically the significant tweets, i.e. those which were found to be associated with significantly abnormal returns following a relevant tweet. Using the methodology above, 1,885 tweets, or 29.7%, were seen to be significant. Examining the results it is clear that the financial twittersphere, as represented by the sample of bloggers, is dominated by discussion of a number of firms, Apple, Google and, to a lesser extent, Facebook. This is somewhat inevitable given the iconic nature of these firms. We can see in Figure 3 that both Apple and Google outstrip the raw number of significant quotes discussed. For clarity Figure 4 removes the visual distortion caused by Apple and Google.

The dominance of the two technology companies in Figure 3 means that it is difficult to put the results into context. Removing these gives a clearer picture of the results which are presented in Figure 4. For the clarity of presentation we also remove stocks with two or fewer significant tweet events (these firms are included in Appendix). Even after removing Google and Apple the most popular companies are still part of NASDAQ (Amazon, Dell, Facebook and Tesla). There is a significant gap between these four and the rest of the companies listed on NASDAQ. The tweet popularity of companies listed on the NYSE is less dispersed with only one company having more than 40 significant tweets (Hewlett Packard).

Table 3 provides a good illustration of this disparity between the two stock exchanges. The table splits stocks into three categories: firms with 50 or more tweets are considered as of high popularity, those with three to 49 tweets as medium and those with two or fewer as of low popularity.

Table 3. Distribution of significant tweets by exchange

Exchange	Firm Tweet Popularity			Total
	High (≥ 50)	Medium	Low (≤ 2)	
NASDAQ	3	52	123	178
NYSE	0	79	251	330
Total	3	131	374	508

According to Table 3 the most tweet-popular stocks are listed on NASDAQ whilst the least tweeted assets dominate on the NYSE. At the same time it appears that the medium level targets are split more evenly across the exchanges. This suggests that rather than being based solely on their status as popular firms, such as Apple, Google or Facebook, these significant tweets are based on information or expectations about a firm or group of firms.

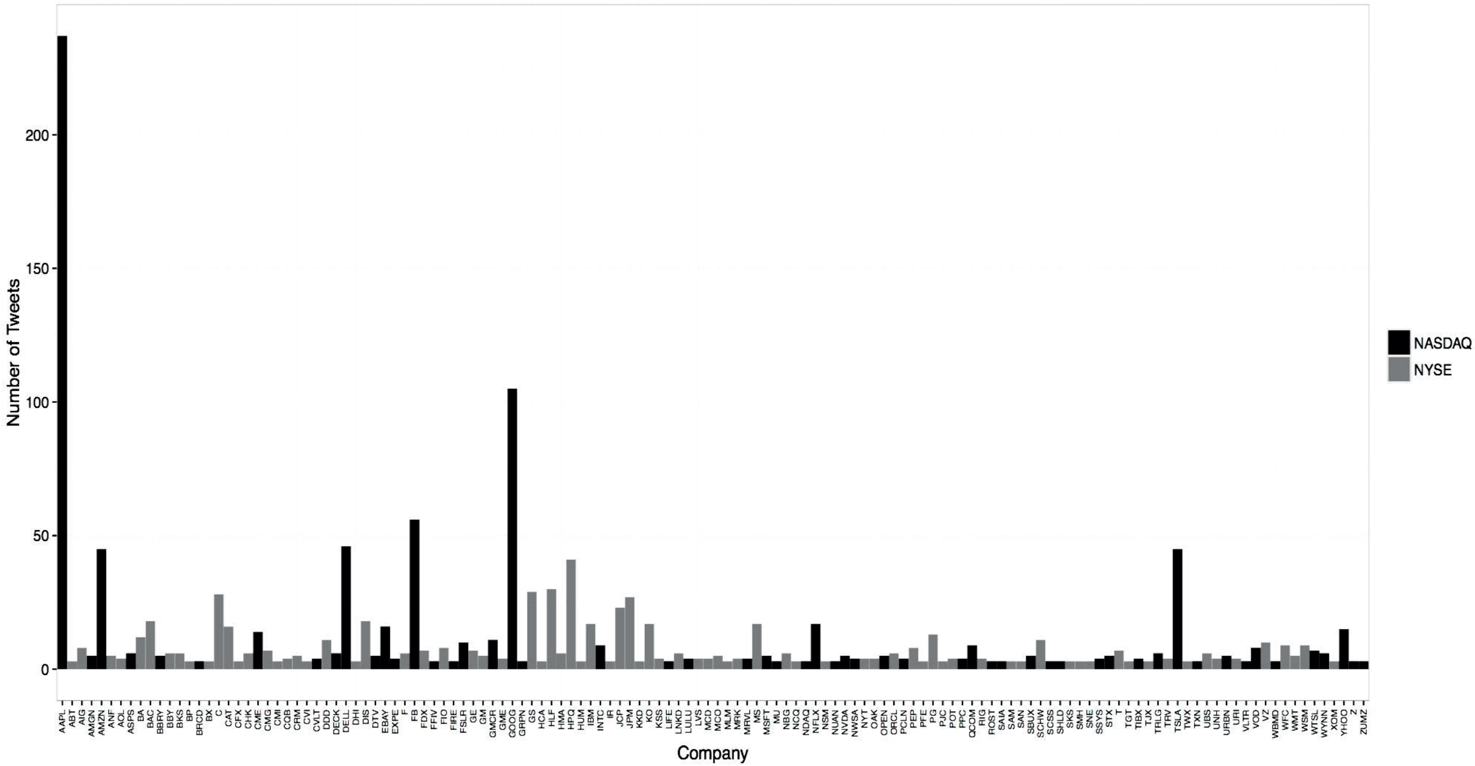

Figure 3. Significant tweets by firm

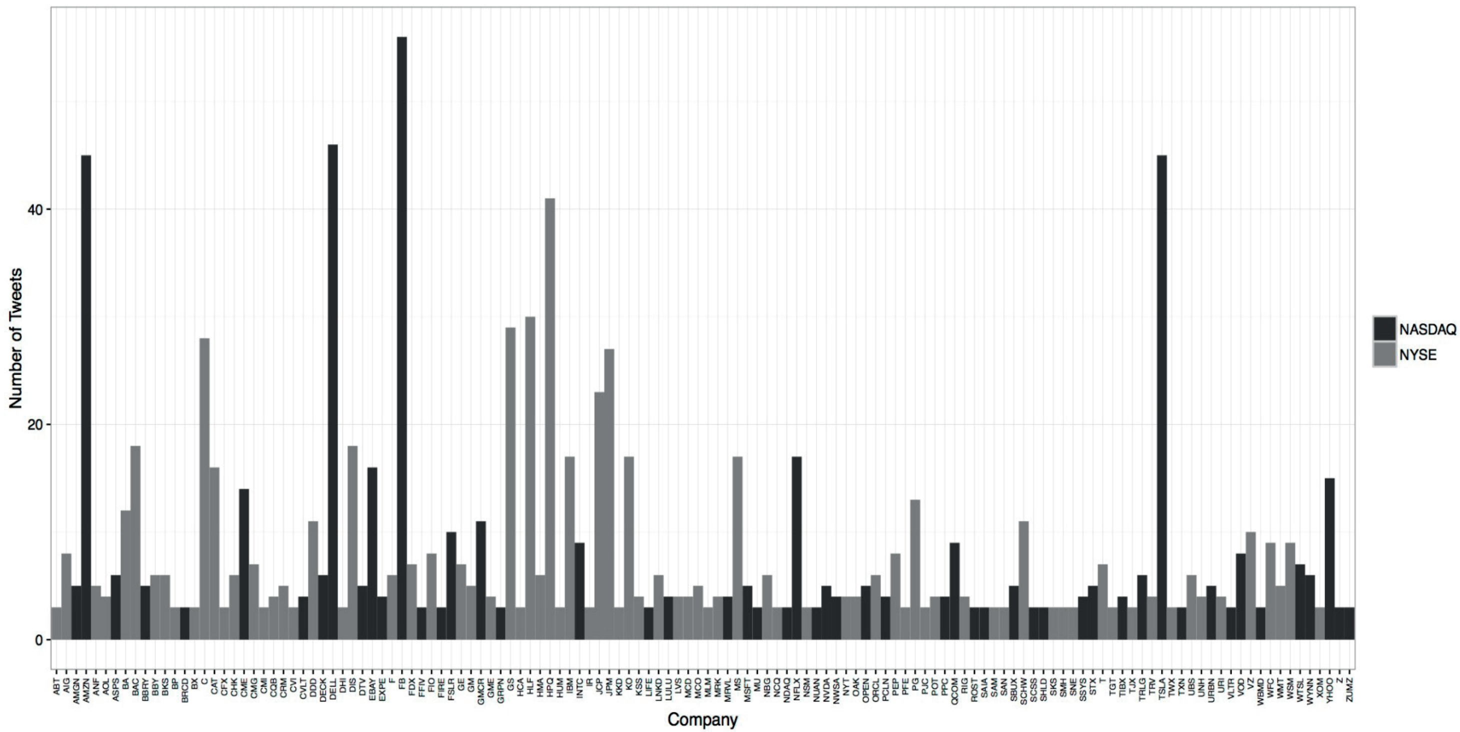

Figure 4. Significant tweets with Apple and Google removed

It might be hypothesized that the pundits might select certain stocks based on the size of the firm. As a measure of this the market capitalization was used[6] and firms were split into quartiles. A positive relationship between Tweet popularity and market capitalization can be observed in Table 4.

Table 4. Tweet popularity by market capitalization

Popularity		Market Capitalization mill USD [2014]				Total
		Lower Quartile	Second Quartile	Third Quartile	Upper Quartile	
		[58.3,2437.5)	[2437.5,7540.0)	[7540,27895.0)	[27895.0,474860]	
High	NASDAQ	0	0	0	3	3
	NYSE	0	0	0	0	0
Medium	NASDAQ	7	15	13	13	48
	NYSE	7	13	16	40	76
Low	NASDAQ	54	31	29	7	121
	NYSE	53	62	63	58	236
Total		121	121	121	121	484

Rather than looking at market capitalization as in Table 4 we can identify keywords within a Tweet information about the nature of the Tweet can be extracted. In the following we will analyse Tweets concerned with earnings and buying / selling recommendations.

4.1. Tweets related to earnings

It is often the case that earnings announcements will be associated with significant events. If this is the case one would expect to see a high proportion of the

Table 5. Proportion of earnings related tweets

Earnings Related	Tweet Popularity			Total (%)
	High (≥ 50)	Medium	Low (≤ 2)	
Yes	9.799	8.577	9.865	9.171
No	90.201	91.423	90.135	90.83

[6] The market capitalisation for March 2014 was used except in the case of Dell where the capitalisation from 10th February 2013 was used as Dell ceased trading on the exchange in 2012. A number of market capitalisations were also missing from Yahoo Finance. These are removed from this table, hence the discrepancies in the totals counts.

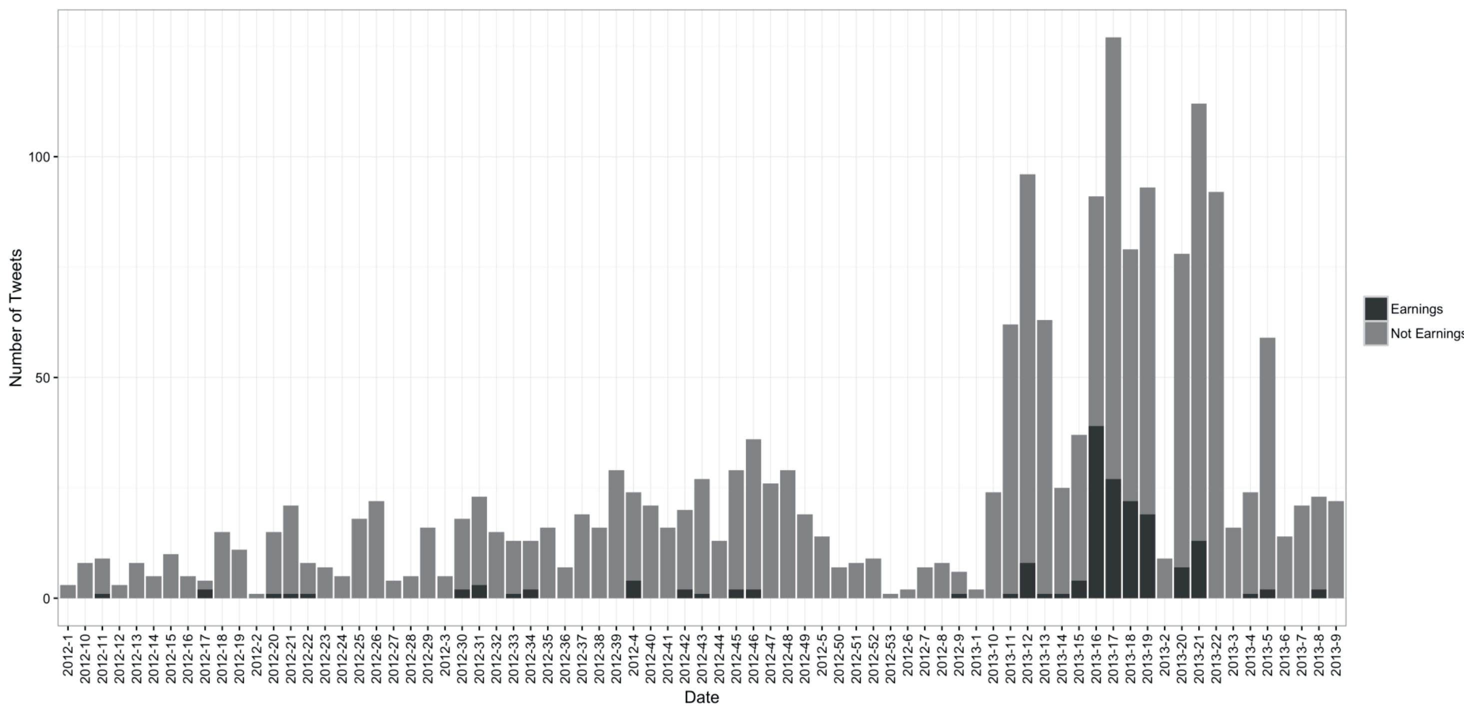

Figure 5. Earnings based tweets by week since January 2012

significant tweets to contain the root 'earn' or 'EPS'. This was sought in the text of the tweets and the proportion of the tweets referring to earnings considered. If these were high then one would suggest that Twitter was acting as another avenue to relay information about the company's official results to the market. The earnings related tweets are reported below. As is seen in Table 5 only approximately 9% of the tweets are earnings or EPS related and these events are clustered at reporting events as seen in Figure 5.

Table 5 suggests that it is not traditional information that is being disseminated across the twittersphere but other news and opinion. These results are rather clustered around the main quarterly result periods as can be seen in Figure 5. The period of the middle of April (weeks 16–18) saw Apple, Coca-Cola, Ebay, Facebook and Google have earnings based tweets hence the large spike. Even taking this into account these three weeks saw 88 tweets about the companies' earnings compared with 297 in total. Thus a higher proportion than usual occurs in this reporting period but these tweets still constitute less than 30% of the traffic about the relevant companies.

4.2. Buy – sell recommendations

It is also possible to consider the buy-sell recommendations by the tweeters. Running a search for either the root 'buy' or 'sell' we notice that the buy recommendations are twice as likely as the sell ones, though both are dwarfed by the 'no signal' chatter. This information, presented in Table 6, combined with the data on dividends and earnings suggest that very little actual concrete trading suggestions are given. Furthermore a more ambiguous signal of bullish or bearish nature is also very limited in their use. This would suggest that the content for these tweets is more amorphous and general rather than an explicit set of suggestions for positions.

Table 6. Bullish / bearish and buy/ sell signals

Trade	Buy	Sell	Both	No Signal
Total	86	40	5	1,754
NASDAQ	33	21	3	905
NYSE	53	19	2	849

Bullish/ Bearish	Bull	Bear	Both	No Signal
Total	16	11	4	1,854
NASDAQ	9	8	1	944
NYSE	7	3	3	910

Using the information in Table 6 buy and sell information is approximately 7% overall. The NASDAQ proportion is lower than that of the NYSE (5.9% compared to 8% respectively) suggesting a buy/ sell focus on the NYSE. Less than 2% of the tweets contain a bullish or bearish signal and these are evenly distributed between exchanges (1.4% and 1.9% respectively).

A simple hypothesis is that pundits will tend to focus on one exchange or another. There is some truth in this as can be seen below in Table 7. It is clear that the most tweeted about firms dominate in posts by a number of authors. This is particularly the case for the non-affiliated authors where much of the traffic is based on the high popularity stocks (Apple, Google and Facebook).

Table 7. Counts by author by exchange

	NASDAQ	NYSE
Abnormalreturns[a]	171 (62)	73
Carney	0	1
Cnbcfastmoney	55 (31)	43
CNNMoney	11 (2)	7
CNNMoneyInvest	2 (1)	15
DougKass[a]	18 (5)	15
GuyAdami	0	2
Marketfolly[a]	35 (14)	27
PhilipEtienne[a]	8 (2)	25
StockTwits[a]	181 (92)	106
Tradefast[a]	136 (10)	24

Numbers in parentheses represent the stocks with fewer than 50 Tweets.
[a] Non-affiliated authors.

Table 7 reinforces the expectation that the NASDAQ is more frequently mentioned than the firms on the NYSE, with the most active micro-bloggers being *abnormalreturns*, *StockTwits* and *tradefast*. Further it is noticeable that these authors are not affiliated with major media outlets.

The results show that there is a great deal of information bouncing around the twittersphere much of which contains little price information. There are, however, kernels of useful information that do appear and much like the traditional media, have to be extracted from the sources. The useful information is not simple to classify- not being a simple buy-sell type signal, but is more ambiguous than that. The twittersphere appears to cluster around the 'popular' firms with 3 stocks accounting for nearly 40% of the significant tweets. These might be considered as the easy wins by pundits whereas the remaining stocks are more evenly spread between the exchanges.

Conclusions

This study has examined whether mentions of listed firms by financial micro-bloggers have any significant impact on the prices and whether this is related to particular periods or phrases, specifically those with links to earnings or profits. There is a substantial number of tweets that are associated with price movements as evidenced by our event-study method. The research shows that it is not only the NASDAQ stocks that are seen as tweet-worthy, the NYSE is also tweeted about, although these appear to be focused on more specific advice rather than being a consistent and persistent chatter about the most popular firms such as Apple and Google. The traffic seems to be widespread and not limited to traditional financial discussions on the concepts related to the art of fundamental stock valuation. This proportion is quite stable across the popularity of the firms amongst the financial bloggers.

In contrast to the fundamental information that can be acquired from more traditional sources there is a distinct lack of concrete trading recommendations on Twitter. This would suggest that Twitter is not a replacement for the traditional sources which tend to be based on the fundamental information availability; instead, tweets are based on the less concrete information.

The tweeters, especially the non-affiliated ones, cluster around a number of stocks; the obvious tech stocks are very popular but neither exchange is dominant once Google and Apple are removed from the analysis. The tweets tend to contain a number of firms' names rather than just one. This in addition to a 140 character maximum tweet length suggests that posts are unlikely to carry significant firm specific information or trading information but rather present a 'scatter gun' approach.

These findings suggest that Twitter is much like the coffee houses of Georgian London or a school playground; places where gossip is batted around, some of which has merit, but where much is merely the passing of time. The talk is often focused in a couple of areas and rarely based on actual fundamentals or news of note. This is in spite of the study's focus purely on micro-bloggers with a large following within the online financial community.

Future research is required to fully understand the value and nature of market related information on Twitter. Using intra-day data and textual analysis would allow researchers to analyze real time responses of commentators and investors to relevant events. Specifically the focus ought to be on the impact of the content of tweets on financial market indicators.

Appendix

Firms with Less than Three Significant Tweets

Name	Exchange	Name	Exchange	Name	Exchange	Name	Exchange	Name	Exchange	Name	Exchange	Name	Exchange	Name	Exchange	Name	Exchange
ABC	NYSE	BONT	NASDAQ	CXW	NYSE	FE	NYSE	INVN	NYSE	MDAS	NASDAQ	PACD	NYSE	SODA	NASDAQ	WAG	NYSE
ACAS	NASDAQ	BPOP	NASDAQ	CYH	NYSE	FEIC	NASDAQ	IPHS	NASDAQ	MDLZ	NASDAQ	PBR	NYSE	SPLS	NASDAQ	WCRX	NASDAQ
ACI	NYSE	BTU	NYSE	CZR	NASDAQ	FIG	NYSE	ISIS	NASDAQ	MDT	NYSE	PCL	NYSE	SPRT	NASDAQ	WDC	NASDAQ
ACM	NYSE	BUD	NYSE	DE	NYSE	FIVE	NASDAQ	ITC	NYSE	MELI	NASDAQ	PCP	NYSE	SPWR	NASDAQ	WERN	NASDAQ
ACT	NYSE	BWLD	NASDAQ	DFS	NYSE	FST	NYSE	ITT	NYSE	MGM	NYSE	PCS	NYSE	SQNM	NASDAQ	WEX	NYSE
ACTG	NASDAQ	CAB	NYSE	DISH	NASDAQ	FXCM	NYSE	ITW	NYSE	MIC	NYSE	PETM	NASDAQ	ST	NYSE	WHR	NYSE
AEGR	NASDAQ	CACI	NYSE	DMD	NYSE	GILD	NASDAQ	JACK	NASDAQ	MJN	NYSE	PLCM	NASDAQ	STI	NYSE	WPO	NYSE
AET	NYSE	CBG	NYSE	DOW	NYSE	GIS	NYSE	JASO	NASDAQ	MKL	NYSE	PNRA	NASDAQ	STMP	NASDAQ	WWD	NASDAQ
AGNC	NASDAQ	CBI	NYSE	DPZ	NYSE	GLO	NYSE	JBHT	NASDAQ	MLNX	NASDAQ	PRU	NYSE	STT	NYSE	WY	NYSE
AKAM	NASDAQ	CBK	NYSE	DRIV	NASDAQ	GLQ	NYSE	JBLU	NASDAQ	MM	NYSE	PTNR	NASDAQ	SVU	NYSE	X	NYSE
AKS	NYSE	CBRL	NASDAQ	DSX	NYSE	GLW	NYSE	JKS	NYSE	MNST	NASDAQ	PXD	NYSE	SWFT	NYSE	XXIA	NASDAQ
ALEX	NYSE	CBS	NYSE	DUF	NYSE	GNC	NYSE	JOE	NYSE	MO	NYSE	QCOR	NASDAQ	SWY	NYSE	YNDX	NASDAQ
ALOG	NASDAQ	CFI	NYSE	DUK	NYSE	GNRC	NYSE	JOSB	NASDAQ	MORN	NASDAQ	QIHU	NYSE	SYY	NYSE	YUM	NYSE
ALU	NYSE	CFN	NYSE	DXLG	NASDAQ	GOLD	NASDAQ	KKR	NYSE	MOS	NYSE	QLIK	NASDAQ	TA	NYSE	ZLC	NYSE
AMTD	NYSE	CG	NASDAQ	ECBE	NYSE	GRMN	NASDAQ	KLAC	NASDAQ	MOV	NYSE	R	NYSE	TCK	NYSE	ZNGA	NASDAQ
ANR	NYSE	CHKP	NASDAQ	ECHO	NASDAQ	GSIT	NASDAQ	KMB	NYSE	MPEL	NASDAQ	RATE	NYSE	TEF	NYSE	ZTS	NYSE

APP	NYSE	CHRW	NASDAQ	EDU	NYSE	GSK	NYSE	KMP	NYSE	MSCI	NYSE	REGN	NASDAQ	TK	NYSE		
ARMH	NASDAQ	CHTR	NASDAQ	EGN	NYSE	HAIN	NASDAQ	LAZ	NYSE	MSN	NYSE	REX	NYSE	TM	NYSE		
ARNA	NASDAQ	CI	NYSE	EGOV	NASDAQ	HAL	NYSE	LGF	NYSE	MTG	NYSE	RF	NYSE	TOL	NYSE		
ARO	NYSE	CLF	NYSE	ELLI	NYSE	HAR	NYSE	LLL	NYSE	MW	NYSE	RHP	NYSE	TPX	NYSE		
ASA	NYSE	CLGX	NYSE	EMC	NYSE	HBAN	NASDAQ	LM	NYSE	NEE	NYSE	RIO	NYSE	TR	NYSE		
ASH	NYSE	CNC	NYSE	EMN	NYSE	HCN	NYSE	LNCO	NASDAQ	NOK	NYSE	RL	NYSE	TRGT	NASDAQ		
BAX	NYSE	CNW	NYSE	EMR	NYSE	HD	NYSE	LO	NYSE	NSC	NYSE	RTN	NYSE	TROX	NYSE		
BBVA	NYSE	COH	NYSE	EQIX	NASDAQ	HGG	NYSE	LOW	NYSE	NVO	NYSE	RYN	NYSE	TSN	NYSE		
BC	NYSE	CONN	NASDAQ	ERJ	NYSE	HOG	NYSE	LPS	NYSE	NWLI	NASDAQ	S	NYSE	TSO	NYSE		
BDBD	NASDAQ	COP	NYSE	ETFC	NASDAQ	HOV	NYSE	LTD	NYSE	NYX	NYSE	SAFM	NASDAQ	TWI	NYSE		
BEAM	NYSE	COST	NASDAQ	EVR	NYSE	HRB	NYSE	LVLT	NYSE	OCLR	NASDAQ	SBAC	NASDAQ	UPS	NYSE		
BEN	NYSE	COT	NYSE	EXLP	NASDAQ	HRS	NYSE	M	NYSE	ODP	NYSE	SBH	NYSE	VALE	NYSE		
BID	NYSE	CRK	NYSE	EZPW	NASDAQ	IBKR	NASDAQ	MANU	NYSE	OII	NYSE	SE	NYSE	VMC	NYSE		
BIDU	NASDAQ	CRUS	NASDAQ	FBN	NYSE	ICE	NYSE	MAR	NYSE	OIS	NYSE	SIG	NYSE	VMW	NYSE		
BIG	NYSE	CVGW	NASDAQ	FBR	NYSE	IFT	NYSE	MATX	NYSE	OWW	NYSE	SIMG	NASDAQ	VRTX	NASDAQ		
BKI	NYSE	CVS	NYSE	FCX	NYSE	IMMR	NASDAQ	MBI	NYSE	OXY	NYSE	SIMO	NASDAQ	VRX	NYSE		
BKW	NYSE	CVX	NYSE	FDO	NYSE	INFA	NASDAQ	MBT	NYSE	OZM	NYSE	SINA	NASDAQ	VVUS	NASDAQ		
BLOX	NYSE	CWH	NYSE	FDS	NYSE	ININ	NASDAQ	MCF	NYSE	P	NYSE	SNH	NYSE	WAB	NYSE		

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