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Daily expectations of returns index☆

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ABSTRACT

The paper introduces a daily index for expectations of returns based on tweets that express a directional prediction about the stock market index. I develop a dictionary that includes lexicon of traders to identify and classify opinionated tweets. The results show that (1) the Twitter Expectations of Returns Index (TERI) is positively correlated with weekly changes in net long position of investment managers, (2) expectations index of high followers accounts predicts stock market returns, and (3) private information is the primary source of return predictability.

1. Introduction

I introduce a daily index for expectations of returns by aggregating directional forecasts about the S&P500 index expressed on Twitter. I have used Twitter's search tools to download tweets about U.S. stock market index every half an hour since 2013 and developed a dictionary based on the lexicon used by traders to identify and classify opinionated tweets. The daily expectations of returns index is the simple average of numerical score associated with positive, negative and neutral forecasts. The index provides a high frequency empirical measure of expectations of returns and could be used to test or estimate theoretical models that aim to shed light on the drivers and dynamic of investors' expectations about future stock market returns.

Twitter Expectations of Returns Index (TERI) is positively correlated with a number of market-based and survey-based measures of expectations of returns. The opinions posted by high followers accounts predict stock market returns but there is no evidence of predictability in the opinions of low followers accounts. The paper explores private information and demand pressure from retail investors as potential sources of return predictability and provides evidence that favors private information as the main source of short-term return predictability.

TERI has two important advantages over investor optimism surveys. First, survey participants have no incentive to express their true opinion because individual opinions are not disclosed with survey results. Accounts that have a large number of followers have the incentive to tweet their true opinion to maintain their reputation. User description of accounts in the sample show that almost two third of high followers accounts are controlled by traders or businesses. The share of this group among low followers accounts is 44%. Traders and businesses that provide products and services related to the financial markets would not put their reputation at risk by misleading their followers with malicious tweets or posting an opinion that contradicts their true beliefs. Second, surveys assign equal weight to individual opinions when aggregating the responses. Twitter data provides the number of followers of the account that posts a tweet. The number of followers can be used to filter out random opinions from the dataset and only keep opinions that are likely to be posted by informed market participants. In this paper, I construct two indexes from expectations of high and low followers accounts. The opinions of high followers accounts contain private information that lead to return predictability on major

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economic news announcement days. The opinions of low followers accounts show no return predictability so they have no useful private information. Moreover, their expectations index is correlated with daily shocks to mutual fund flows. This indicates that their opinions are, to some extent, driven by sentiment. Survey-based measures ignore the information heterogeneity of opinions by assigning equal weight to opinions of all participants. In addition, survey results are usually reported in weekly or monthly frequency but the index for expectations of returns can be constructed in daily frequency.

In recent years, Twitter has become a major source of information and an effective communication tool for investors and public companies. In April 2013, U.S. Securities and Exchange Commission (SEC) issued a press release stating that companies can use social media outlets such as Facebook and Twitter to announce key information.[1] Stock market participants use Twitter to share their information with others and receive real-time information about the stock market and individual companies. There are several anecdotal stories that highlight the role of Twitter in providing information to the market and significant effects on stock prices following the release of information on Twitter. For instance, Carl Icahn, an activist investor, tweeted about his large position in Apple on August 13th 2013. As the result, the stock surged by over four percent in a few seconds. Almost two years later on April 28th 2015, a data mining company obtained Twitter's quarterly earning and posted it on Twitter before the scheduled release time. Twitter's stock plummeted by twenty percent following the early release of its earning and trading was halted by NYSE. Given the widespread use of Twitter among stock market participants, it is a natural choice to study the link between expectations of future returns and asset prices.

Text analysis is an important element of extracting useful information from internet message boards and social media networks. I develop a special purpose finance dictionary to classify opinionated tweets. The dictionary includes a large set of word combinations from the lexicon of traders in the financial markets and detects opinions expressed in a tweet. With small changes, the dictionary could be used to extract information from short messages in similar studies. This approach is different from the methodology of other papers in the literature. Antweiler and Frank (2004) use Naive Bayes as the main algorithm to classify messages. Tetlock (2007) and Da et al. (2015) count the number of words in different categories using the Harvard IV dictionary. Both methods are shown to be effective in practice given the data sources used in the studies. In this paper, a number of word combinations are defined as indicators for bullish, bearish and neutral tweets. If a tweet contains one of the bullish word combinations, it is placed in the bullish category and is associated with the numeric score of +1. The details of message classification is provided in Section 2. Given that traders express their opinion by announcing their current option or ETF positions and the Harvard dictionary is not structured for the vocabulary of traders, using a finance dictionary is more effective than alternative methods in extracting opinions expressed in a tweet.

There are several studies that focus on the information content of social media messages but there are three important differences between this study and previous work. First, I use the number of followers of Twitter accounts to filter out random opinions from the dataset. It is later shown that the number of followers is a useful proxy for the quality of private signals. The second distinction is the text analysis methodology used to extract opinions from the tweets. I develop a finance dictionary that is designed to include the lexicon of traders and investors. Several studies, such as Tetlock (2007), Li (2008), Chen et al. (2014) and Da et al. (2015) count the number of words in different categories to extract opinions from a text. The papers show that counting the number of words is an effective method to extract the sentiment of a lengthy text such as an article or a newspaper column. Counting the number of positive or negative words is not an effective method to extract an individual's outlook from a tweet because traders often provide their view using few words from the lexicon of financial markets. Moreover, individuals sometimes express their views by announcing their recent trades. General language dictionaries are not designed to catch those opinions expressed using technical terms or trades. Third, the universe of tweets included in this study is limited to those that mention the S&P500 index or an ETF that tracks the index. Other studies, such as Bollen et al. (2011) and Zhang et al. (2011), explore the relationship between "Twitter mood" and the stock market returns by using a random sample of tweets that are not necessarily related to the stock market. Mao et al. (2015) examines the return predictability of tweets that mention the words "bullish" or "bearish".

The rest of the paper is organized as follows. Section 2 describes the details of Twitter data and the methodology of constructing the Twitter Expectations of Returns Index (TERI). Section 3 investigates the relation between expectations of returns and the stock market returns. The relationship between TERI and other proxies for expectations of returns is explored in Section 4. Section 5 presents a model for expectations of returns and uses a dynamic regression in a Markov switching model to examine the state dependent role of past prices and economic conditions on expectations of returns. Section 6 concludes the paper.

2. Measuring expectations of returns

This section provides some details about the underlying opinions and the methodology of aggregating those opinions to create a daily index for expectations of returns.

2.1. Why twitter data?

Before discussing the details of Twitter data, I provide a comparison of Twitter and alternative data sources used in other studies. It is important to emphasize that one of the objectives of this paper is to create a daily measure of expectations of returns that aggregates private information of a disperse group of individuals.

[1] www.sec.gov/news/press-release/2013-2013-51.htm.

Tetlock (2007) measures the sentiment of a daily column in Wall Street journal. The paper shows that the media sentiment predicts short-term stock returns because either the media reports investor sentiment before it is fully incorporated in stock prices or sentiment of media influences investor sentiment. Tetlock (2007) measures the media sentiment from the writings of a small number of writers. The data sample used in this study includes opinionated tweets from 48,996 unique accounts. Using Twitter data allows measuring expectations of a large number of individuals.

Da et al. (2015) present a daily measure of households sentiment based on internet search volume for negative words such as "recession" or "bankruptcy". They show that their measure of sentiment is broadly consistent with theories of investor sentiment. Da et al. (2015) provide evidence for return predictability of their index. Predictability is primarily the result of return reversal following temporary mispricing of risky assets. While measuring investor sentiment through households search behavior is useful in some applications, it is impossible to learn about expectations of informed investors from aggregate search volume because Google's Search Volume Index (SVI) counts all searches for a given keyword. Tetlock (2007) and Da et al. (2015) attribute their return predictability results to fluctuations in investor sentiment. While TERI is also related to investor sentiment, I show that the expectations of high followers accounts predict short-term returns because they have private information. It is shown in Section 3 that the evidence for return predictability on event days is significantly stronger than that of non-event days. Event days are days on which a major economic news is announced. In addition, the positive relation between TERI and next day market return is not reversed on future days. Short-term return reversal is a notorious characteristic of sentiment-driven return predictability. See Da et al. (2015).

Cookson and Niessner (2019) use opinions from StockTwits to study sources of disagreement among investors. StockTwits is often described as Twitter for traders and investors. While it might seem that a platform focused on trading and investing is ideal for measuring expectations of returns, I show that Twitter is a better source of data for constructing an information-based measure of expectations.

Business news media and investor relations of public companies are two important sources of information for traders and investors. I compare Twitter and StockTwits to find out which platform is more likely to generate opinions based on information. I consider a list of ten major business news networks and newspapers.[2] All of the major news outlets have an official account on Twitter but only three of them are officially represented on StockTwits.[3] Weak presence of major business news outlets on StockTwits indicates lack of significant demand for business news from StockTwits users.

Investor relations of public companies are another important source of company specific information. To compare Twitter and StockTwits, I consider 20 largest companies of the S&P500 index and count the number of companies that have official account on the two platforms.[4] 19 out of the 20 largest U.S. public companies are officially represented on Twitter but only 4 have official accounts on StockTwits.[5] Fig. 1 shows a snapshot of Microsoft's page on Twitter and StockTwits. Similar to the previous argument, largest U.S. companies would have communicated more through StockTwits had the users sought company news on the platform. Given that all major news outlets and most public companies are on Twitter, it is reasonable to assume that Twitter users are more likely than StockTwits users to post an information-based opinion about stock market. It should be acknowledged that being certain about the basis of opinions is difficult because individuals do not specify how they form their expectations.

2.2. Data

I have used Twitter's search tools to download stock market tweets in real-time every half an hour since 2013. More specifically, I collect tweets that mention the S&P500 index or an Exchange Traded Fund (ETF) that tracks the daily return of the index. For instance, tweets that mention the index or any of the ticker symbols "SPY", "SSO", "SDS", "UPRO", or "SPXU" are included in the dataset. These tickers represent the ETFs that correspond to unleveraged and leveraged long and short positions on the S&P500 index.[6] Every half an hour, a search query is sent to Twitter's server and tweets that mention at least one of the search words in their text are downloaded and stored. The data sample includes 6,187,003 tweets posted over 1279 trading days between December 2, 2013 and December 31, 2018.

2.3. Opinionated tweets

The objective is to create an index for expectations of future returns. Since most of the tweets that mention the stock market index or its ETFs provide no opinion about future returns, we need a systematic approach to identify opinionated tweets. One approach is to use a general dictionary such as Harvard IV dictionary to identify and classify opinionated tweets.[7] The dictionary assigns a large number of words to 182 categories such as "Positive", "Strong", and "Weak". Each word is assigned to one or more categories in the Harvard dictionary and one could analyze a text by counting the number of words assigned to different categories. The main disadvantage of an off the shelf dictionary is that it is not structured to capture opinions expressed using the lexicon of traders.

[2] CNBC, Bloomberg, Fox Business, CNN Money, Yahoo finance, Wall Street Journal, Financial Times, Reuters, Dow Jones and Business Insider.

[3] Bloomberg, Yahoo finance and CNN Money.

[4] The list of 20 largest companies includes Microsoft, Apple, Amazon, Facebook, Berkshire Hathaway, JP Morgan, Alphabet, Johnson and Johnson, Exxon Mobil, Visa, Procter and Gamble, Bank of America, UnitedHealth Group, Walt Disney, Mastercard, Cisco, AT&T, Pfizer, Home Depot, Verizon.

[5] Berkshire Hathaway is the only company in the list that does not have an official account on Twitter. Microsoft, Visa, AT&T and Verizon are the four companies in the top 20 list that have an official StockTwits account.

[6] Tweets that mention at list one of the following are included in the dataset: sp500, s&p500,s&p 500, $spx, $spxu, $spxs, $spy, $sso, $sds, $upro, $ivv, $sh, $voo.

[7] see Tetlock (2007) and Da et al. (2015).

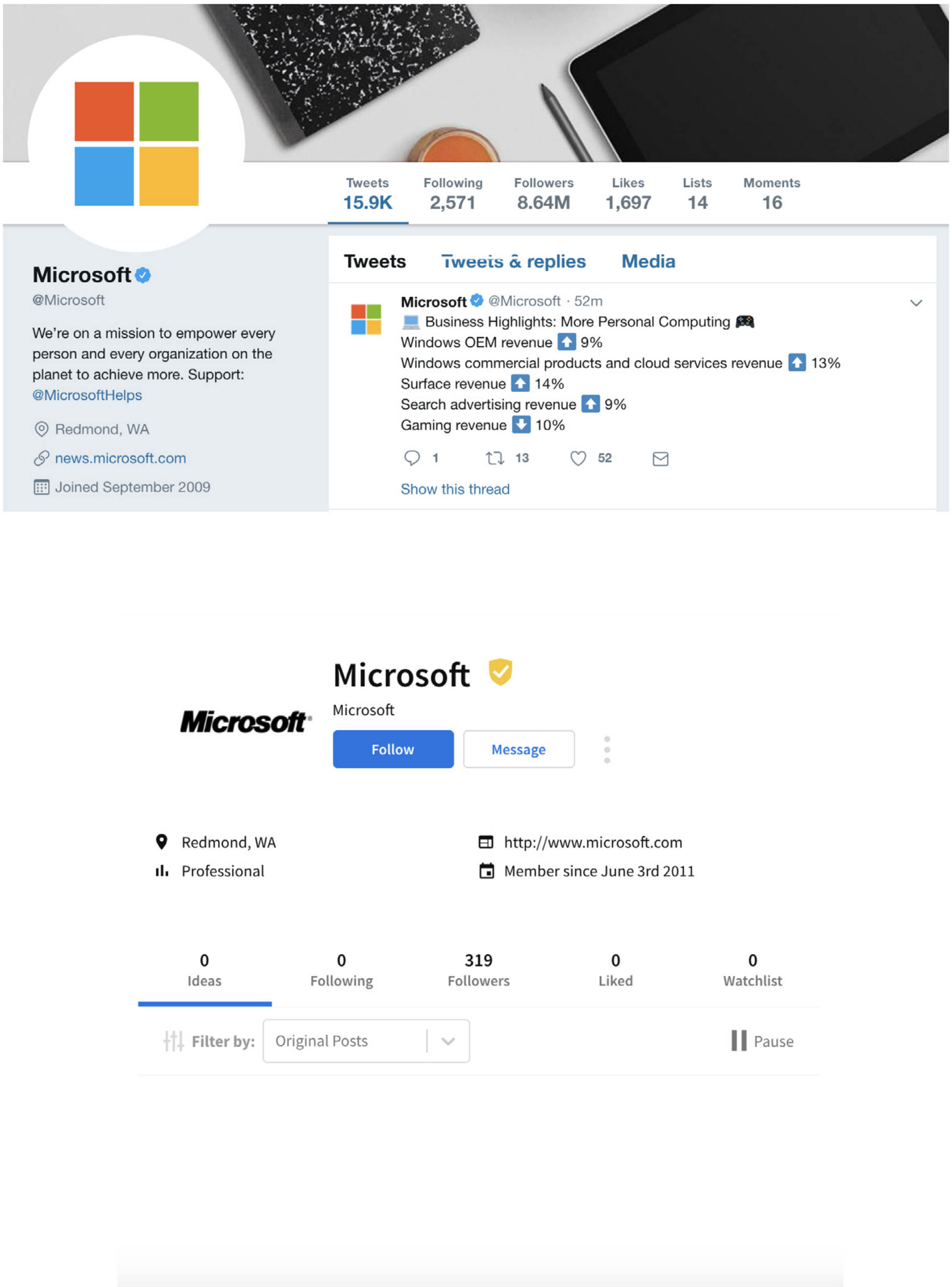

Fig. 1. Microsoft's Page on Twitter and StockTwitts.
The top picture is a snapshot of Microsoft's page on Twitter and the bottom picture shows company's page on StockTwitts. Both snapshots are taken on July 18, 2019.

Traders usually express their opinion using words that convey a different message according to a general language dictionary such as the Harvard dictionary. For example, traders often use the word "Bullish" to express a positive outlook. The closest word to bullish in the Harvard dictionary is "Bull" which is placed in "Male" category.

Another approach to identify opinionated tweets is to develop a dictionary that includes the lexicon of traders and investors. I studied a large number of tweets and created a list of 433 word combinations that traders use to express an opinion about the stock market index. The full list of word combinations is provided in the online appendix. Each one of the word combinations belong to one of the three categories of positive, negative and neutral. Every tweet in the dataset is compared with all the word combinations

Table 1
Examples of positive, neutral and negative tweets.

Score	Category	Text
+1	Positive	I am long $SPXL $TNA $TQQQ coming into today.
+1	Positive	Bought $SPY 227 calls .59
+1	Positive	Trade: SELL −1 $SPY PUTS: JUL15 200 0.91.
+1	Positive	added to some longs $SPX
+1	Positive	A Tight Range with a Slightly Bullish Bias Next Week (Says the OI) $SPX $SPY
0	Neutral	$SPX Waiting on housing number at top of the hour.
0	Neutral	$SPY watch 169.84 here
0	Neutral	$SPY also below 10sma — be patient – look for relative strength – sit on your hands if needed
0	Neutral	Staying flat for now. Good day $SPX $SPY
−1	Negative	Slightly bearish setup for the day on $SPY.
−1	Negative	Pressing my shorts with an objective to move 20% net short this morning on any future strength. $SPY
−1	Negative	Weekly S&P 500 ChartStorm — Bearish Beacons Building $SPY
−1	Negative	Bonds and stocks are now overbought.$TLT $SPY
−1	Negative	Still looking for more downside. $SPX

and is placed in the opinionated group if it contains all words of at least one word combination. An opinionated tweet is then placed in one of the three categories of positive, negative and neutral depending on the word combination that identifies it as an opinionated tweet. In order to make sure that the dictionary identifies and classifies the opinionated tweets correctly, I randomly selected 100 opinionated tweets, and determined the category of their opinion manually. Then, compared the results of automatic classification to those of manual classification and made changes to the dictionary to improve the automatic classification. I repeated the process multiple times until the automatic classification correctly classified over 90 percent of the tweets.

To illustrate the process of finding opinionated tweets and placing them in their category, suppose that a trader has positive outlook on the stock market and expresses this view by posting a tweet that indicates buying call option on the S&P500 index ETF (ticker symbol SPY), so a tweet that contains the words “bought", “spy", “call" in this order is placed in positive category. Similarly, a tweet that contains the words “increase", “spy", “short" in this order is identified as negative because it indicates that a trader expects further drop in equity prices and is willing to increase the size of an existing short position. The words “will", “buy", “if" put a tweet in neutral category because they indicate a decision to buy the equity index conditional on some event. Table 1 provides some examples of actual positive, neutral, and negative tweets. The combination of words that identifies the category of each opinionated tweet is underlined. The placement of tweets in the categories is independent of daily returns in the stock market and is determined only by the content of tweets.

In order to externally test the validity of tweet categorization method, I had a number of survey participants determine the category of some randomly selected tweets and compared their responses to the result of categorization by the dictionary. I briefly explain the details of the study before discussing the results. I randomly selected a total of 200 tweets (70 positive, 70 negative and 60 neutral) and used Prolific to recruit 30 survey participants.[8] The survey was only open to participants who study finance or economics. The participants were given ample time to read and determine the category of the tweets. For each tweet, the category with the highest number of votes is considered the group’s selection and it is compared with the category determined by the dictionary. The results indicate that the participants and the dictionary selected the same category for 84 percent of the tweets. This means that the participants and the dictionary disagree on the category of 16 percent of the tweets. Further investigation of the source of disagreement shows that the dictionary fails to correctly identify the category of 6 percent of the tweets while the participants select an incorrect category for 10 percent of the tweets. The participants fail to determine the correct category of some tweets because they might not be familiar with the lexicon of traders or do not know the payoff structure of various trading strategies using options.

The dictionary finds 213,583 opinionated tweets over 1279 trading days in the sample.[9] Fig. 2 shows the distribution of daily number of opinionated tweets. Fig. 3 provides the distribution of the number of followers of 48,996 unique accounts that posted at least one opinionated tweet during the sample period.

2.4. Twitter expectations of returns index (TERI)

Directional predictions are usually expressed in the form of a direct prediction stated in a tweet or announcement of a recent trade. Opinionated tweets are identified using the dictionary developed for this study and are assigned to positive, neutral and negative categories. A numerical score is assigned to each opinionated tweet. All positive tweets are coded as +1, neutral tweets as 0 and negative tweets as −1.[10] Twitter Expectations of Returns Index (TERI) for a given time period is the average of numerical

[8] Prolific.ac is a website that allows researchers to recruit survey participants for research studies. Participant could be pre-screened based on their demographics and a number of characteristics.

[9] Multiple tweets from the same account during a day are counted as one opinion.

[10] Tweets that mention both positive and neutral word combinations are coded as +1 and those that mention negative and neutral combinations are coded as −1.

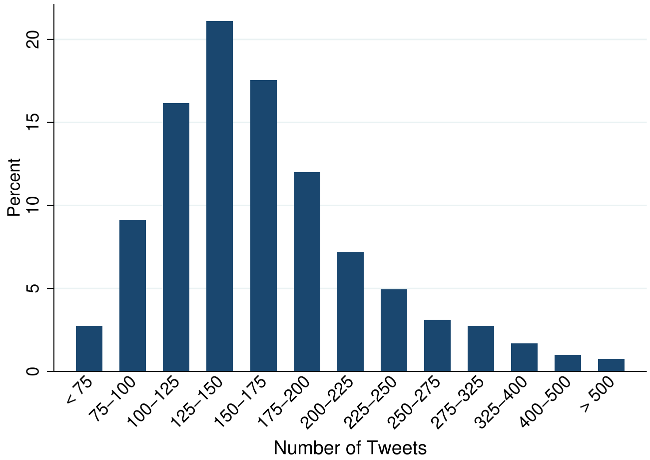

Fig. 2. Distribution of the Daily Number of Opinionated Tweets.

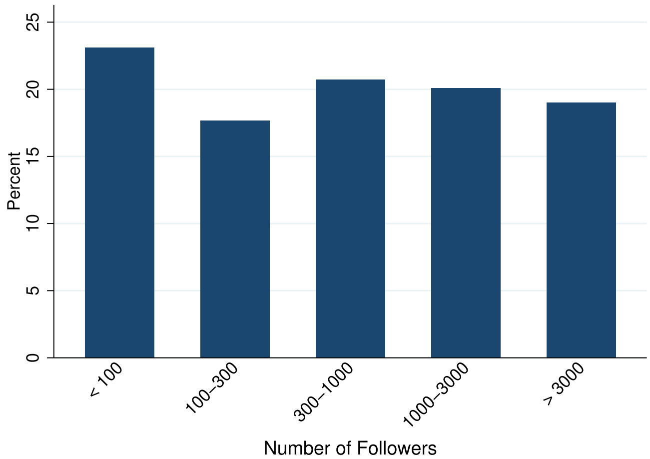

Fig. 3. Distribution of the Number of Followers.

score of the opinionated tweets posted during that period.

$$TERI_t = \frac{\sum_{i=1}^{n_t} s_i}{n_t}, \tag{1}$$

where s_i is the numeric score associated to the tweet i and $s_i \in \{-1, 0, +1\}$ and n_t is the number of opinionated tweets posted during the time period t. The daily index is a number between -1 and $+1$. If all the tweets on a given day express a negative outlook for the stock market, TERI would be -1, which is the most bearish value for the expectations of return. Conversely, the index takes the most bullish value of $+1$ if every tweet expresses a positive outlook.[11]

For each tweet, Twitter provides the number of followers of the account that posted the tweet. I create two indexes, denoted by $TERI_t^I$ and $TERI_t^U$, using opinionated tweets posted by high followers (informed) and low followers (uninformed) accounts. The idea is that accounts with a large number of followers are more likely to post informed predictions. If we assume that the number of followers of each account is the equilibrium value given by the information marketplace to the opinions posted by that account, separating opinions based on the number of followers takes into account the differences between the quality of information. Although the number of followers might not always reflect the quality of information, it is a useful observable variable to filter out noise from the measure of expectations of returns. The cutoff for the number of followers is 500. That is, opinionated tweets posted by accounts with more than 500 followers are used to construct the index of the informed group and similarly tweets posted by accounts with less than 500 followers are used in constructing the index for the uninformed group. The cutoff threshold of 500 is chosen because it almost splits the data in half. The daily average number of tweets posted by the informed and uninformed group

[11] TERI is assumed to be zero on twelve trading days that there is no opinionated tweets.

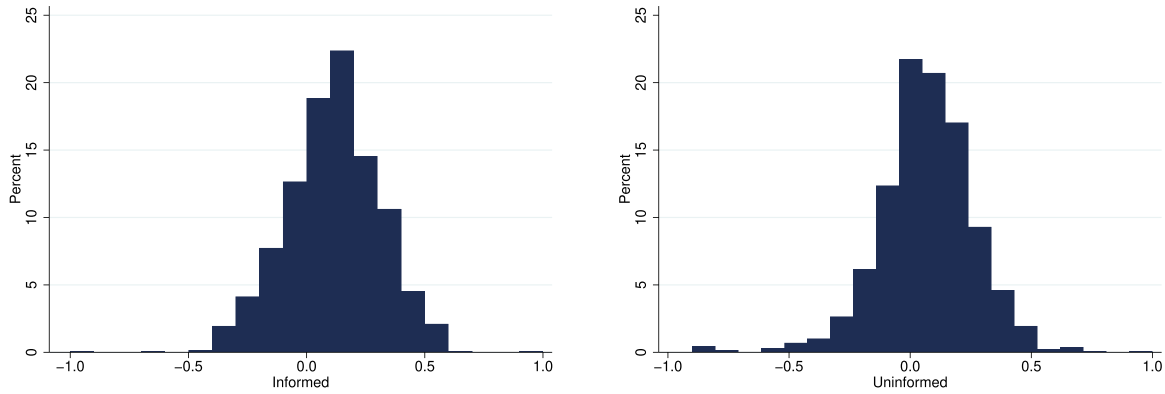

Fig. 4. Distribution of daily TERI for the Informed and Uninformed group.

is 81 and 86 respectively. Fig. 4 shows the distribution of daily index for the informed and uninformed groups. Both indexes have a positive mean over the sample period because the stock market index advances in most years between 2013 and 2018.

It is shown in Section 3 that opinions of high followers accounts predict the direction of future stock market changes significantly better than what could be the result of random guessing. The same cannot be said about opinions of low followers accounts. There is also more evidence related to return predictability that justifies the labels "informed" and "uninformed" for the opinions of high and low followers accounts respectively. Creating separate index for the informed and uninformed groups is possible because the number of followers is observable in the Twitter data. This is a clear advantage of TERI over survey-based measures of expectations of returns that assign equal weight to all participants in a survey.

Before discussing the relationship between TERI and stock market returns, a brief comment about the incentive of the informed group to express their true opinion is in order. Accounts that post opinionated tweets about the stock market and have large number of followers are often controlled by individuals or businesses that provide research, newsletter or other investment related products. It is reasonable to assume that they care about their reputation and would not damage their credibility by posting malicious tweets. In order to verify the validity of this argument, I look for evidence in the data. Twitter provides users with the option to write few sentences in the "user description" box when they create an account. Many users use the space to provide information about their personal and professional interests or business services that they provide individually or through their employer. I search the user description of all accounts in the informed and uninformed groups for keywords that could indicate the user is affiliated with a business related to financial markets. I also include keywords that identify individuals who call themselves "trader", "expert" or educators. The goal is to estimate the fraction of users that care about their reputation and are less likely to post opinions that contradict their true expectations. The complete list of keywords is provided in Appendix A. Using this methodology, I break down all users in the dataset into three categories across the informed and uninformed groups. The distribution of users is provided in Table 2. Users that their description includes at least one of the keywords of Table A.1 are placed in "Business or Trader" category. If the user description of an account does not include any of the keywords, the user is considered "Unknown". The Unknown category includes users that post opinions about stock market but their user description does not directly show that they trade stocks or work for a financial services firm. For instance, a user with the description "I love life and dark chocolate" is classified as Unknown. Finally, those who leave their user description blank are placed in the "Blank" category. Table 2 shows that 66% of accounts in the informed group are controlled by individuals or businesses related to the financial markets. These accounts are less likely to mislead their followers by posting a tweet that contradicts their true opinion. The share of Business or Trader accounts in the uninformed group is about 44%. Given that the share of Business or Trader accounts in high followers accounts is significantly higher than that of low followers accounts, it is not surprising that there is more evidence of private information in opinions of the informed group. The identity of participants in survey-based measures of expectations is not disclosed and they do not have any incentive to express their true expectations of returns. Having access to the identity of individuals or businesses that tweet their expectations is another advantage of TERI over survey-based measures of expectations of returns.

3. TERI and stock market returns

3.1. Directional forecasts

Since opinionated tweets are assigned to three groups based on their directional forecast, it is useful to compare the forecasts with the sign of subsequent returns and measure the fraction of opinions that correctly predict the direction of future stock market changes. I define directional moment for k days in the future as the average proportion of correct minus incorrect forecasts of the sign of stock market return over the subsequent k days. For illustration, suppose that 10 opinionated tweets are posted on day t. Three of the ten tweets forecast a positive return, two have a negative outlook and five tweets are labeled neutral. If the realized return between day t and $t+k$ is positive, then three tweets predicted the direction correctly and two predictions were incorrect.

Table 2
Share of various types of accounts in the universe of all accounts that posted at least one opinionated tweet during the sample.
"Trader & Business" accounts are those that their user description includes one of the keywords in Appendix A. These accounts are likely to be controlled by individual traders or businesses that offer services related to financial markets. "Unknown" group includes accounts that their description does not indicate interest in finance or economics and there is no indication of affiliation with a business. Providing user description is optional on Twitter and "Blank" group covers accounts that left their user description blank.

	High followers (informed)	Low followers (uninformed)
Business or Trader	66%	44%
Unknown	26%	31%
Blank	8%	25%

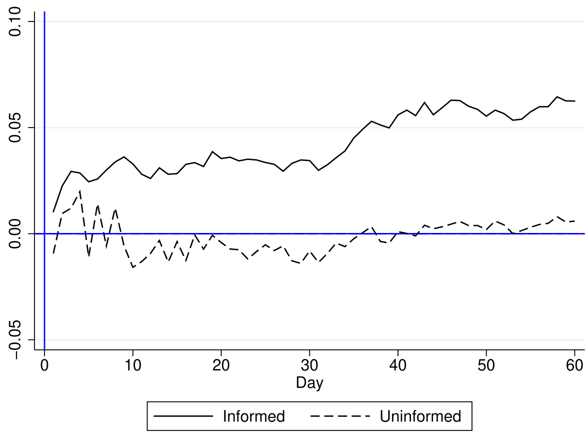

Fig. 5. Directional moments over 60 days*.
* Directional moments are computed as the average over all tweets of a variable that is +1 (−1) if the tweet correctly (incorrectly) predicts the direction of the subsequent stock market return and 0 if the tweet has a neutral opinion.

Neutral tweets are not considered correct nor incorrect. The directional moment over k days is 0.1, which is the difference between 0.3 and 0.2. The directional moment shows how well the forecasts predict future direction of the stock market. If individuals have no information and their tweets are simply guesses about the future returns, they have 50 percent chance of being correct and the directional moment is zero. Fig. 5 shows the directional moments for up to 60 trading days in the future for the informed and uninformed groups. The number of correct and incorrect forecasts of the uninformed group are almost equal and their directional moments hover around zero regardless of the forecast horizon. The directional moments are positive for the informed group over any forecast horizon between 1 and 60 trading days. The positive directional moments indicate that the forecasts of the informed group are more correct than incorrect and the label "informed" is justified for the group. If we assume that tweets are random guesses and contain no useful information about future stock market returns, we can analytically find the standard deviation of directional moments. Under the null hypothesis of no information, a tweet is neutral with probability p and positive or negative with probability $(1-p)/2$. The variance of directional moment for the tweet is $1-p$. Since there are 213,583 tweets, the standard deviation of directional moment for any horizon is $\sqrt{(\frac{1-p}{213583})}$. Based on the data sample, $p = 0.35$ and the standard deviation of directional moment for any horizon under the null hypothesis is 0.0017. Fig. 5 shows that we cannot reject the null of no information for the uninformed group but can strongly reject the null for the informed group.

3.2. Correlation with past and future returns

Literature has shown that there is empirical evidence for the influence of past returns on investors' expectations of future returns (See Brown and Cliff (2004) and Greenwood and Shleifer (2014)). In this section, I examine the correlation between TERI and past stock market returns to learn more about the role of past returns in expectations of returns. Fig. 6 shows the correlations between TERI and past, current and future stock market returns for the informed and uninformed groups. The expectations of the informed group are positively correlated with past returns up to 10 trading days or two weeks. In order to see how quickly the expectations are incorporated in asset prices, I examine the forward correlations. Fig. 6 shows that the contemporaneous correlation between the expectations of the informed group and the stock market's return is 0.25 but a significant part of expectations is incorporated in stock prices quickly and the correlation with one day forward return is less than 0.1. Forward correlations gradually fall to zero

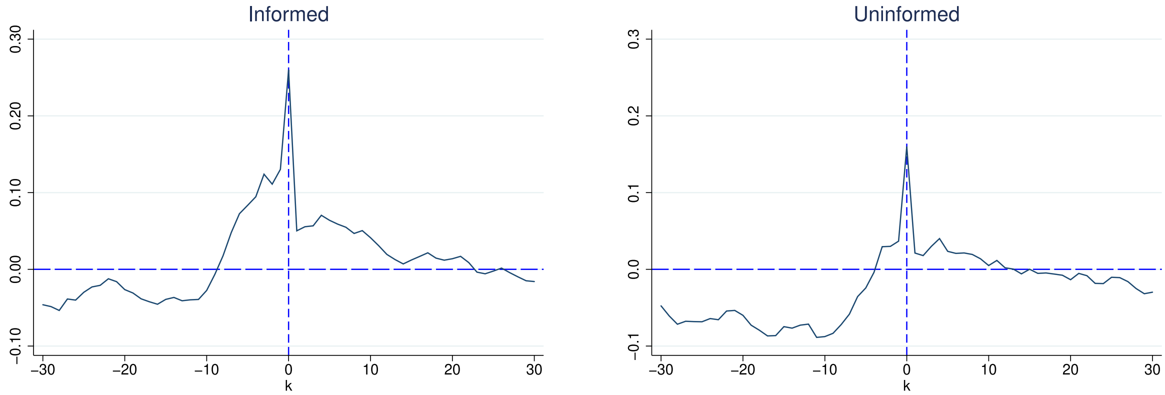

Fig. 6. Correlation between TERI and stock market returns.

in about 20 trading days. The correlations between the expectations of the uninformed group and stock market returns exhibit a similar pattern but the correlations are weaker than those of the informed group.

3.3. Return predictability

In this section, I examine short-term return predictability of $TERI_t^I$ and $TERI_t^U$ for the stock market index. I regress future returns of the S&P500 index on the expectations of returns index. Following Da et al. (2015), I include the CBOE volatility index, changes in ADS business conditions index, changes in news-based measure of economic policy uncertainty (EPU) and five lagged returns of the S&P500 index as control variables. I estimate the coefficient of $TERI$ in the following regression

$$Ret_{t+k} = \alpha + \beta TERI_t^j + \gamma Z_t + \epsilon_{t+k} \tag{2}$$

where $j \in \{I, U\}$, Ret_{t+k} is the stock market's return on day $t+k$, and Z_t is the vector of control variables. Tables 3 and 4 show the return predictability results of $TERI_t^I$ and $TERI_t^U$. The first and second columns of both tables show the regression results when $TERI_t$ is used to predict R_{t+1} and R_{t+2} respectively. The third column provides the predictability results for cumulative market returns over two days. Tables 3 and 4 show that the expectations of the informed group predict short-term returns and there is no evidence of return predictability for expectations of the uninformed group. Moreover, there is no evidence of return reversal which usually occurs when sentiment causes asset prices to temporarily rise or fall.

In order to shed some light on the source of return predictability, I consider a number of possibilities and look for evidence in the data. It is possible that high followers accounts possess information about market's reaction to economic news. In that case, the evidence for return predictability should be stronger on event days. To test this hypothesis, I split the trading days into two groups of "event" days and "non-event" days. Event days include trading days on which major economic news is released. More specifically, event days are days that non-farm payroll, ADP employment, ISM services, GDP, inflation, industrial production, leading indicators, retail sales, auto sales and new home sales are released to the public. I run separate predictability regressions using observations of event days and non-event days. In other words, I investigate the extent to which expectations of the informed group predict the market return on event days and compare the predictability to that of non-event days. Table 5 shows the results. There is a strong evidence of predictability on event days but the coefficient of $TERI^I$ is positive and not significant on non-event days.

The other possibility is that high followers accounts influence the expectations of their followers and predictability is the result of portfolio decisions by a large number of retail investors who follow the informed group. If retail investors change their portfolio based on opinions of the informed group, there should be evidence of such trading activity in mutual fund flows data. Given that individual investors as a group hold most of mutual fund assets, daily mutual fund flows reflect aggregate trading activities of retail investors. I obtained daily flow data to U.S. equity mutual funds from Informa Financial Intelligence and tested the effect of $TERI$ on contemporaneous and future daily funds flow. The funds flow data covers the period from 2014 to 2018. I demean the fund flows time series and apply a fractionally integrated ARMA model to extract daily fund flow innovations. The flows data fits the $ARFIMA(1,d,1)$ model well and the integration parameter is 0.35.[12] Autoregressive and moving average terms are significant at the 5 percent level and the integration parameter is significant at the 1 percent level. I estimate the coefficients of the following regression

$$flow_{t+k} = \alpha + \beta TERI_t^j + \gamma Z_t + \epsilon_{t+k} \tag{3}$$

where $flow_{t+k}$ is innovations in equity mutual fund flow on day $t+k$ and Z_t is the vector of control variables that include five lagged daily returns, log VIX, changes in ADS and changes in EPU. Columns (1) and (4) of Table 6 show the regression results for

[12] I follow the methodology of Da et al. (2015) to extract the innovations of fund flow data. Their estimate of the integration parameter is 0.4.

Table 3
Return predictability regressions of opinions expressed by high followers (informed) accounts.
$TERI^I$ is twitter expectations of returns constructed from the forecasts posted by accounts with more than 500 followers. Ret_{t+k} is the return of the s&p500 index on day $t+k$, $[ret_{t+1}, ret_{t+2}]$ is cumulative stock market return from $t+1$ to $t+2$, vix is log of cboe volatility index, ΔADS is daily changes in the ads business conditions index, ΔEPU is daily changes in the news-based measure of economic policy uncertainty.

	(1) Ret_{t+1}	(2) Ret_{t+2}	(3) $[Ret_{t+1}, Ret_{t+2}]$	(4) Ret_{t+3}	(5) Ret_{t+4}	(6) Ret_{t+5}
$TERI^I$	0.257**	0.133	0.389**	0.125	0.204*	0.021
	(0.118)	(0.119)	(0.167)	(0.119)	(0.119)	(0.120)
VIX	0.088	0.132	0.209	0.097	0.204**	0.155
	(0.102)	(0.102)	(0.144)	(0.103)	(0.103)	(0.103)
ΔADS	−1.879	−1.855	−3.750	−1.966	−1.968	−1.251
	(2.458)	(2.463)	(3.464)	(2.477)	(2.477)	(2.482)
ΔEPU	−0.012	0.078	0.066	0.071	−0.036	−0.038
	(0.049)	(0.049)	(0.069)	(0.050)	(0.050)	(0.050)
Ret_{t-1}	−0.038	0.022	−0.014	−0.064**	−0.021	0.012
	(0.029)	(0.029)	(0.041)	(0.029)	(0.029)	(0.029)
Ret_{t-2}	0.020	−0.058**	−0.037	−0.022	0.015	0.017
	(0.029)	(0.029)	(0.040)	(0.029)	(0.029)	(0.029)
Ret_{t-3}	−0.060**	−0.022	−0.082**	0.005	0.015	−0.046
	(0.029)	(0.029)	(0.041)	(0.029)	(0.029)	(0.029)
Ret_{t-4}	−0.008	−0.008	−0.016	0.013	−0.048	−0.036
	(0.029)	(0.029)	(0.041)	(0.029)	(0.029)	(0.029)
Ret_{t-5}	−0.022	0.024	0.002	−0.059**	−0.031	−0.004
	(0.029)	(0.029)	(0.041)	(0.029)	(0.029)	(0.029)
Constant	−0.234	−0.333	−0.540	−0.233	−0.535*	−0.386
	(0.275)	(0.276)	(0.388)	(0.277)	(0.277)	(0.278)
Observations	1,279	1,279	1,279	1,279	1,279	1,279
Adjusted R-squared	0.003	0.003	0.005	0.005	0.005	0.000

Standard errors are in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

Table 4
Return predictability regressions of opinions expressed by low followers (uninformed) accounts.
$TERI^U$ is twitter expectations of returns constructed from the forecasts posted by accounts with less than 500 followers. Ret_{t+k} is the return of the s&p500 index on day $t+k$, $[ret_{t+1}, ret_{t+2}]$ is cumulative stock market return from $t+1$ to $t+2$, vix is log of cboe volatility index, ΔADS is daily changes in the ads business conditions index, ΔEPU is daily changes in the news-based measure of economic policy uncertainty.

	(1) Ret_{t+1}	(2) Ret_{t+2}	(3) $[Ret_{t+1}, Ret_{t+2}]$	(4) Ret_{t+3}	(5) Ret_{t+4}	(6) Ret_{t+5}
$TERI^U$	0.099	0.022	0.119	0.116	0.114	−0.120
	(0.119)	(0.119)	(0.168)	(0.120)	(0.120)	(0.120)
VIX	0.075	0.125	0.189	0.092	0.195*	0.151
	(0.102)	(0.102)	(0.144)	(0.103)	(0.103)	(0.103)
ΔADS	−1.711	−1.721	−3.446	−1.996	−1.894	−1.028
	(2.465)	(2.467)	(3.475)	(2.480)	(2.483)	(2.485)
ΔEPU	−0.011	0.079	0.068	0.071	−0.036	−0.036
	(0.049)	(0.049)	(0.070)	(0.050)	(0.050)	(0.050)
Ret_{t-1}	−0.031	0.026	−0.004	−0.061**	−0.016	0.014
	(0.029)	(0.029)	(0.041)	(0.029)	(0.029)	(0.029)
Ret_{t-2}	0.021	−0.057**	−0.035	−0.021	0.015	0.017
	(0.029)	(0.029)	(0.040)	(0.029)	(0.029)	(0.029)
Ret_{t-3}	−0.057**	−0.021	−0.078*	0.006	0.017	−0.045
	(0.029)	(0.029)	(0.041)	(0.029)	(0.029)	(0.029)
Ret_{t-4}	−0.009	−0.009	−0.018	0.013	−0.048*	−0.038
	(0.029)	(0.029)	(0.041)	(0.029)	(0.029)	(0.029)
Ret_{t-5}	−0.021	0.024	0.003	−0.057*	−0.030	−0.005
	(0.029)	(0.029)	(0.041)	(0.029)	(0.029)	(0.029)
Constant	−0.179	−0.300	−0.453	−0.215	−0.496*	−0.365
	(0.274)	(0.274)	(0.387)	(0.276)	(0.276)	(0.276)
Observations	1,279	1,279	1,279	1,279	1,279	1,279
Adjusted R-squared	−0.000	0.002	0.001	0.005	0.003	0.001

Standard errors are in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

$k = 0$. Funds flow data shows no significant evidence of demand pressure from retail investors in response to opinions expressed

Table 5
Return Predictability of TERI on Event Days and Non-Event Days.
$TERI^I$ ($TERI^U$) is Twitter Expectations of Returns constructed from the forecasts posted by accounts with more (less) than 500 followers. Ret_{t+1} is stock market's return on event days. "Event Days" are days that non-farm payroll, ADP employment, ISM services, GDP, inflation, industrial production, leading indicators, retail sales, auto sales and new home sales are released to the public. All other trading days in the sample are "Non-Event Days". Control variables are log of CBOE volatility index, changes in ADS business conditions index, changes in news-based index of economic policy uncertainty and five lags of the stock market return.

	Event Days Ret_{t+1}	Non-Event Days Ret_{t+1}	Event Days Ret_{t+1}	Non-Event Days Ret_{t+1}
$TERI_t^I$	0.580***	0.061		
	(0.199)	(0.148)		
$TERI_t^U$			0.207	0.049
			(0.224)	(0.140)
Controls	Yes	Yes	Yes	Yes
Observations	476	803	476	803
Adjusted R-squared	0.007	0.003	−0.009	0.003

Standard errors are in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

Table 6
Regressions of Equity Fund Flows on TERI.
$flow_{t+k}$ is innovations in fund flows to U.S. equity mutual funds on day $t+k$. $TERI^I$ ($TERI^U$) is Twitter Expectations of Returns constructed from the forecasts posted by accounts with more (less) than 500 followers. Control variables are log of CBOE volatility index, changes in ADS business conditions index, changes in news-based index of economic policy uncertainty and five lags of the stock market return.

	(1) $flow_t$	(2) $flow_{t+1}$	(3) $flow_{t+2}$	(4) $flow_t$	(5) $flow_{t+1}$	(6) $flow_{t+2}$
$TERI_t^I$	0.085	0.023	0.087			
	(0.085)	(0.084)	(0.085)			
$TERI_t^U$				0.153*	0.087	0.052
				(0.084)	(0.084)	(0.084)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,258	1,258	1,258	1,258	1,258	1,258
Adjusted R-squared	0.015	0.011	0.002	0.017	0.011	0.002

Standard errors are in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

by the informed group. Column (4) shows that the coefficient of $TERI^U$ is positive and statistically significant in the regression of funds flow on opinions of uninformed group. Since the uninformed group do not have many followers, the positive relation between daily fund flows and opinions of the uninformed group shows that $TERI^U$ is, to some extent, driven by the sentiment of retail investors. Da et al. (2015) and a number of other studies highlight reporting issues in funds flow data that lead to reporting part of the flow of day t on day $t+1$. To account for the effect of delayed reporting of funds flow, columns (2), (3), (5) and (6) of Table 6 show the regression results for $k = 1, 2$. The main results remain the same except that the coefficient of $TERI^U$ is not statistically significant.

In summary, the evidence in the data favors private information over demand pressure as the source of short-term stock market predictability. This result is different from the findings of Tetlock (2007) and Da et al. (2015) that attribute return predictability of their indexes to fluctuations in investor sentiment.

4. Comparison to other measures

In order to validate TERI, as a measure of investors' expectations of returns, it is useful to examine the correlation between the index and other measures that gauge investors' expectations. Table 7 shows the correlation between TERI and a number of alternative measures. The correlations are reported in two columns. The first column shows the correlations between alternative measures and expectations of returns posted by high followers accounts, denoted by $TERI^I$. The second column shows similar correlations when the index is constructed from opinions of the uninformed group. The alternative measures for expectations of returns are classified in three groups.

Table 7
Correlation between TERI (Twitter Expectations of Returns Index) and alternative measures for expectations of returns.
"$TERI^I$" is the daily index for expectations of returns constructed from the opinionated tweets posted by accounts with more than 500 followers.
"$TERI^U$' is the expectations of accounts with less than 500 followers.
"Δ Asset Managers Net Long" and "Δ Leverage Money Net Long" are weekly changes in net long positions of asset managers and hedge funds on the S&P500 futures and options contracts.
"AAII bull-bear spread" is the difference between the percentage of bullish and bearish investors in the weekly AAII surveys.
ADVDEC is the number of advancing stocks divided by the number of declining stocks in NYSE.
VIX is log CBOE volatility index.
Put/Call Ratio is the number of put options on the S&P500 index divided by the number of call options.
ΔADS is changes in the business conditions index from the Federal Reserve Bank of Philadelphia.

	$TERI^I$	$TERI^U$
CFTC Commitment of Traders		
Δ Asset Managers Net Long	0.24***	0.11*
Δ Leverage Money Net Long	−0.17***	−0.04
Survey-based Sentiment Index		
AAII bull-bear spread	0.23***	0.11*
Market-based Measures		
ADVDEC	0.25***	0.18***
VIX	−0.10***	−0.01
Put/Call Ratio	−0.13***	−0.04
Business Conditions Index		
ΔADS	0.06**	0.08***

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The first group includes measures that indicate changes in net position of speculators. Every week, CFTC aggregates regulatory transaction data and reports open interest and changes in long and short positions in the futures and options market.[13] Market participants often monitor the weekly changes to learn about expectations of others. The first two rows in Table 7 show the correlation between TERI and changes in net long position of institutional asset managers and leverage funds respectively.[14] TERI shows positive correlation with weekly changes in net long position of asset managers that include pension funds, insurance companies, mutual funds and institutional investment managers. Conversely, there is a negative correlation between TERI and changes in net long position of leverage funds that are typically hedge funds.

The second group includes a survey-based measure of sentiment. American Association of Individual Investors (AAII) conducts a sentiment survey and measures the percentage of individual investors who are bullish, bearish, and neutral on the stock market for the next six months. Every individual who subscribes to the AAII services can submit a vote in the weekly surveys. The proportion of investors in each group is measured based on the data received each week by Wednesday and the results are reported on Thursdays. The survey was first conducted in July 1987.[15] Positive and statistically significant correlation between TERI and the bull-bear spread of the weekly AAII survey shows that they both pick up expectations of returns from different data sources.[16]

The third group includes a number of market based variables that are often used as measures of investor optimism. Market based measures are usually available in daily frequency but they could be influenced by other factors unrelated to investors' expectations (see Baker and Wurgler (2007)). The daily TERI is positively related to advance to decline ratio, which is a measure of market breadth. There is also a negative correlation between TERI and measures of fear such as CBOE volatility index (VIX) and the put–call ratio of short-term options on the S&P500 index.

The correlations reported in Table 7 indicate that TERI is broadly consistent with alternative measures of expectations of returns. Modest correlations show that there is a common component in TERI and three types of proxies for investors' expectations of returns. Moreover, positive and statistically significant correlation between TERI and changes in the ADS business conditions index shows that economic news is part of the information set that affects the expectations of investors about future returns.[17] The second column of Table 7 shows that the correlations are generally weaker when TERI is constructed from the opinions of less informed accounts.

[13] CFTC stands for Commodity Futures Trading Commission.

[14] Since the commitment of traders data is available in weekly frequency, a weekly measure of TERI is created to compute its correlation with weekly changes in net long positions. The weekly TERI is a simple average of daily TERI over a week.

[15] Source: www.aaii.com/sentimentsurvey.

[16] There are other survey-based measures of investors' expectations but since they are reported in monthly frequency, I only consider AAII survey in the survey-based measures.

[17] Aruoba et al. (2009) use a number of macroeconomic variables of different frequencies and construct the ADS index as a daily measure of business conditions. The ADS index is obtained from the Federal Reserve Bank of Philadelphia and includes seasonally adjusted value of quarterly real GDP, industrial production, manufacturing and trade sales, personal income minus transfer payments, monthly payroll employment, and weekly jobless claims.

Three comments about the correlations table and predictability results of Section 3.3 are in order. First, hedge funds are often considered "smart money" so the negative correlation between opinions of the informed group and changes in net long position of hedge funds might seem puzzling. We should note that CFTC reports aggregate transactions in futures and options market. Given that many hedge funds use equity index derivatives to hedge their market risk, it is not surprising that their demand for hedging motivated trades increases (decreases) when expectations of returns are high (low) and the cost of buying protection is low (high). Second, Table 7 shows that there is a positive and statistically significant correlation between opinions of high followers accounts and the bull-bear spread of the weekly AAII survey of individual investors. The expectations of individual investors are known to have little information about future stock market returns. One might argue that the positive correlation between $TERI^I$ and the AAII survey contradicts the predictability results reported in Section 3.3. It is important to note that $TERI^I$ is constructed from opinions of high followers accounts and the label "informed" does not mean that all individuals in the group have information about future returns. Some of the opinions in $TERI^I$ could come from uninformed individuals that happen to have large number of followers. For instance, some of the opinions are posted by technical traders and they, by definition, use past prices to form opinions about future returns. Their expectations are correlated with the sentiment of individual investors who form their expectations based on past returns. Third, the results of Section 3.3 show that the evidence of predictability is only significant on event days. There are, on average, less than two event days in a week so the weekly expectations of returns index, which is the average of daily expectations over a week, includes a large number of opinions posted on non-event days.[18] The opinions posted on non-event days have little predictability about returns and are positively correlated with the sentiment of individual investors measured by AAII survey.

In order to compare the accuracy of $TERI^I$ in predicting future returns with that of the alternative measures, I run a horse race of future returns on Twitter expectations and all the other alternative measures listed in Table 7. I run the following regression

$$R_{t+1} = \alpha_0 + \alpha_1 TERI_t^I + \beta Z_t + \epsilon_t \tag{4}$$

R_{t+1} is next-day return and Z_t is the vector of control variables that includes all the alternative measures of expectations of returns in Table 7. Since the AAII survey results and the CFTC data are available in weekly frequency, I carry each weekly observation forward for four trading days until the next observation is available. Table 8 shows the standard deviation of $TERI^I$ and the alternative measures to facilitate computing economic magnitudes. It also shows the estimated coefficients of the independent variables in (4). The last column of Table 8 shows stock market's next-day return following a one standard deviation change in $TERI^I$ and other measures. Based on the results in Table 8, a one standard deviation increase in Twitter expectations of returns leads to a statistically significant positive price change of 5 basis points. Two observations stand out in the results. First, $TERI^I$ is the only measure with a statistically significant coefficient. Second, the magnitude of next-day return following a one standard deviation increase in Twitter expectations is greater than that of any other alternative measure of expectations. $TERI^I$ is the clear winner of this race.

While I acknowledge that it is hard to provide conclusive evidence on what could be causing superiority of Twitter expectations, I provide a number of possible explanations. First, $TERI^I$ is constructed from the opinions of high followers accounts. Having access to the number of followers in Twitter data makes it possible to filter out opinions of potentially uninformed individuals from the measure of expectations. Twitter expectations of high followers accounts is a more accurate measure of expectations compared to surveys-based measures because surveys such as AAII do not exclude potentially uninformed opinions from their results. Second, market based measures and CFTC commitment of traders data could be significantly affected by trades unrelated to expectations of returns such as hedge trades. Opinionated tweets often indicate individuals' expectations of future returns. It is very unusual that an investor shares his hedge trades on Twitter.

5. A model for expectations of returns

The main focus of this section is on the factors that drive investors' expectations of returns on a daily basis. I only consider the expectations of the informed group. Examination of opinionated tweets indicate that a number of individuals form their outlook using technical analysis. This group uses recent price changes to form an opinion about future prices. There is also another group of individuals that use fundamental analysis to forecast future returns. This group often mention macroeconomics data points such as unemployment, inflation, retail sales and etc. to justify their prediction. I start with a simple model that expresses expectations of returns as a function of lagged stock market return and changes in economic conditions. The lagged return picks up the effect of recent price changes on expectations and changes in economic conditions captures the effect of fundamentals on the expectations of returns. Lagged TERI is included to take into account persistence of expectations. In addition, I include log of volatility index to control for the negative effect of volatility on investors' expectations. I estimate the parameters of the following model

$$TERI_t^I = \alpha + \rho TERI_{t-1}^I + \beta Ret_{t-1} + \gamma \Delta ADS_t + \nu VIX_t + \epsilon_t \tag{5}$$

where $TERI_t^I$ is Twitter Expectations of Returns Index constructed from opinions of accounts with more than 500 followers, Ret_{t-1} is one day lagged return of the S&P500 index, ΔADS_t is the daily change in ADS business conditions index and VIX_t is log of CBOE volatility index. The regression results are reported in Table 9. Consistent with the results of other studies in the literature about extrapolative behavior of some investors, daily expectations of returns expressed on Twitter are influenced by past returns. There is also a positive relation between changes in economic conditions and expectations of returns.

[18] 476 of 1279 trading days in the data are event days. Given that there are five trading days in a week, there are on average 1.86 event days in a week.

Table 8
Horse race of future returns on Twitter Expectations of Returns Index (TERI) and alternative measures for expectations of returns.
Column (1) shows the standard deviations to facilitate computing economic magnitudes. Column (2) reports the coefficients and their standard deviation in the regression of future returns on $TERI^I$ and alternative measures listed in Table 7. Column (3) is the product of columns (1) and (2) and indicates the expected next-day return following a one standard deviation increase in the measures. Next-day returns are in basis points.

	(1) Std. Dev.	(2) Ret_{t+1}	(3) bps
$TERI^I$	0.199	0.248**	5.0
		(0.122)	
Δ Asset Managers Net Long	0.626	−0.016	−1.0
		(0.045)	
Δ Leverage Money Net Long	0.573	−0.021	−1.2
		(0.045)	
AAII bull-bear spread	0.127	−0.030	−0.4
		(0.195)	
ADVDEC	1.099	−0.018	−2.0
		(0.022)	
VIX	0.253	0.146	3.7
		(0.102)	
Put/Call Ratio	0.371	−0.028	−1.0
		(0.066)	
ΔADS	0.009	−2.059	−1.9
		(2.484)	
Observations		1,279	
R-squared		0.006	

Standard errors are in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

Table 9
Model for expectations on returns, Regression results of $TERI^I$ on its lag and other independent variables.
$TERI^I$ is Twitter Expectations of Returns constructed from the forecasts posted by accounts with more than 500 followers. Ret_{t-1} is one day lagged return of the S&P500 index, ΔADS_t is daily changes in the ADS business conditions index from the Federal Reserve Bank of Philadelphia and VIX_t is log of CBOE volatility index.

	$TERI_t^I$
Ret_{t-1}	0.012*
	(0.007)
ΔADS_t	0.874
	(0.562)
$TERI_{t-1}^I$	0.272***
	(0.028)
VIX_t	−0.048**
	(0.021)
Observations	1278
Adjusted R-squared	0.09

Standard errors are in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

5.1. State dependent model for expectations of returns

In this section, I explore state dependent effect of economic news and past returns on expectations of returns. I consider two states of the world. In state 1, investors are optimistic and state 2 represents the times when investors are pessimistic about future returns in the stock market. The hypothesis is that the role of fundamental and technical analysis in forming the opinions of investors is different depending on whether investors have positive or negative bias. I estimate the following Markov switching dynamic regression model

$$TERI_t^I = \alpha_{s_i} + \rho TERI_{t-1}^I + \nu VIX_t + \beta_{s_i} Ret_{t-1} + \gamma_{s_i} \Delta ADS_t + \epsilon_t \tag{6}$$

The difference between Eqs. (3) and (2) is that the coefficients of lagged return, changes in the ADS index and the constant are state dependent. The model assumes that investors switch between the states of optimism and pessimism based on an unobservable state variable. The coefficients are estimated using the maximum likelihood method and the results are reported in Table 10. In the state

Table 10
Markov switching model of expectations of returns. Dynamic regression results of daily index for expectations of returns, denoted by $TERI^I$, with two unobservable states and the role of fundamental and technical analysis in those states.
Ret_{t-1} is one day lagged return of the S&P500 index and represents the role of technicals in expectations of returns. ΔADS is changes in the business conditions index from the Federal Reserve Bank of Philadelphia and represents the role of fundamentals in the expectations of future returns, VIX_t is log of CBOE volatility index.

	$TERI_t^I$		
	Optimistic		Pessimistic
Ret_{t-1}	0.015**		−0.001
	(0.007)		(0.014)
ΔADS_t	0.646		2.354**
	(0.851)		(1.172)
$TERI_{t-1}^I$		0.076**	
		(0.034)	
VIX_t		−0.102***	
		(0.029)	
Observations		1278	

Standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

dependent model of expectations of returns, lagged return is significant when investors are optimistic and changes in economic conditions is significant when investors are pessimistic. Investors extrapolate past returns when they are optimistic about future returns. When investors are pessimistic, they pay less attention to recent returns and their expectations are mainly influenced by changes in economic conditions.

5.2. Robustness test

This section provides a number of robustness tests to show that the state dependent relationship between expectations of returns and fundamentals or technicals is robust if more controls are added to the Markov switching model. Table 11 shows the regression results when additional controls are included in the benchmark dynamic regression model. The first three columns show the results in the "optimistic" state and the three columns in the right provide the results in "pessimistic" state. In regressions of columns (1) and (4), changes in the slope of yield curve is included as a state independent variable to take into account the effect of term premium on the expectations of returns. In order to account for the effect of short term interest rates on expectations, the yield on two years treasury note is included in the regression and the results are reported in columns (2) and (5). In addition, columns (3) and (6) provide the regression results when long term interest rate is included as an additional control. According to Table 11, the results of Section 5.1 are robust to a variety of controls that involve the effect of interest rates on expectations of stock market returns.

5.3. State dependent expectations and return predictability

It was shown in Section 3 that expectations of the informed group predict stock market returns. The results of Section 5.1 and 5.2 show that lagged return is a significant factor in forming the expectations of the informed group when they are optimistic. This section sheds light on the link between state dependent expectations and return predictability.

On a given day, the current state is not known with certainty but we can estimate the probability of being in each state from the estimated transition probabilities. I use the probability estimates to label every trading day in the data as optimistic or pessimistic. More specifically, a given trading day is labeled optimistic if the probability of being in optimistic state is greater than the probability of being in pessimistic state and conversely, I consider a trading day pessimistic if the estimated probability of pessimism is greater than that of optimism. Given that the evidence of return predictability is mostly evident on event days, I only consider the event days over optimistic and pessimistic states for predictability regressions. I include the usual controls that are log volatility index, ADS business conditions index, economic policy uncertainty index and five lagged returns. The results of predictability regressions on optimistic and pessimistic days are reported in Table 12. While there is evidence for predictability on event days of both optimistic and pessimistic days, the evidence is weaker on optimistic event days. Sections 5.1 and 5.2 show that investors condition their expectations on economic conditions on pessimistic days. As the result, the evidence for return predictability is stronger on pessimistic event days. On optimistic days, past return is the major factor that shapes investor expectations so it is not surprising that the evidence for return predictability is weaker on optimistic event days.

Table 11
Robustness tests. Markov switching model of expectations of returns with a number of state independent variables. Dynamic regression results of daily index for expectations of returns, denoted by $TERI^I$, with two unobservable states.
Ret_{t-1} is one day lagged return of the S&P500 index, ΔADS is changes in the business conditions index from the Federal Reserve Bank of Philadelphia, VIX_t is log of CBOE volatility index, $\Delta slope_t$ is the difference between the yield of 10 and 2 years U.S. treasury notes, $\Delta Yld2_t$ is the yield of 2 years U.S. treasury notes and $\Delta Yld10_t$ is the yield of 10 years U.S. treasury notes.

	$TERI^I_t$					
	Optimistic			Pessimistic		
	(1)	(2)	(3)	(4)	(5)	(6)
Ret_{t-1}	0.016**	0.016**	0.017**	0.003	0.002	0.004
	(0.007)	(0.007)	(0.008)	(0.014)	(0.014)	(0.014)
ΔADS_t	0.604	0.654	0.631	2.500**	2.437**	2.510**
	(0.857)	(0.854)	(0.850)	1.157	1.164	(1.170)
$TERI^I_{t-1}$	0.081**	0.075**	0.083**	0.081**	0.075**	0.083**
	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)	(0.035)
VIX_t	−0.091***	−0.094***	−0.088***	−0.091***	−0.094***	−0.088***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
$\Delta slope_t$	0.393***			0.393***		
	(0.117)			(0.117)		
$\Delta Yld2_t$		0.385**			0.385**	
		(0.174)			(0.174)	
$\Delta Yld10_t$			0.486***			0.486***
			(0.123)			(0.123)
Observations	1278					

Standard errors are in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

Table 12
Return Predictability of $TERI^I$ on Optimistic and Pessimistic Event Days.
Ret_{t+1} is stock market's return on event days. Event days are days that non-farm payroll, ADP employment, ISM services, GDP, inflation, industrial production, leading indicators, retail sales, auto sales and new home sales are released to the public. "Optimistic" ("Pessimistic") days are trading days that the probability of being in optimistic (pessimistic) state is greater than that of being in pessimistic (optimistic) state. $TERI^I_t$ is Twitter Expectations of Returns on a day prior to an event day and is constructed from the expectations of accounts with more than 500 followers. Control variables are log of CBOE volatility index, changes in ADS business conditions index, changes in news-based index of economic policy uncertainty and five lags of the stock market return.

	Event Days	
	Optimistic	Pessimistic
	Ret_{t+1}	Ret_{t+1}
$TERI^I_t$	0.454*	1.018***
	(0.244)	(0.389)
Controls	Yes	Yes
Observations	329	146
Adjusted R-squared	0.013	0.065

Standard errors are in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

6. Conclusion

Every day, a large number of people go online and share their opinion about different topics including asset prices on Twitter. This paper introduces a daily index for expectations of returns based on tweets that provide a directional forecast about U.S. stock market index. I use a special purpose finance dictionary to identify and classify opinionated tweets and create a daily expectations of returns index for informed and uninformed accounts. The informed index consists of predictions made by accounts with more than 500 followers and similarly, the uninformed index includes forecasts of accounts that have less than 500 followers. I show that the expectations of returns index is positively correlated with a weekly survey-based and a number of daily market-based measures. Moreover, the expectations index is positively correlated with changes in net long position of money managers.

It is shown that the index constructed from opinions of high followers accounts predicts stock market returns. The evidence in the data favors private information over demand pressure as primary source of return predictability. The evidence for return predictability is much stronger on trading days that major economic news is announced. The index of opinions posted by low followers accounts is correlated with shocks to daily mutual fund flows and is driven by the sentiment of individual investors.

I show that the expectations of returns are influenced by recent returns and changes in economic conditions. However, the role of these two factors depends on the optimism of investors. Investors extrapolate recent returns to future when they are optimistic

Table A.1
The following keywords in the user descriptions are used to identify businesses and individuals that are traders or offer services related to the financial markets.

Broker	Research	News	Strategist
platform	service	education	analyst
analysis	trading	information	director
charting	mentoring	advis	founder
ceo	business	technical	signal
manager	journalist	producer	economy
finance	market	website	subscribe
company	companies	news letter	macro
partner	consultant	investment	blog
hedge	fund	options	futures
stocks	editor	writer	forex
entrepreneur	macro	http	management
derivative	commodity	spx	chief officer
etf	economics	trade	expert
investor	professor	portfolio	mba
economist	investing	stock	

but their expectations are influenced by changes in economic conditions when they are pessimistic. As the result, evidence for return predictability on optimistic event days is weaker than that of pessimistic event days.

Appendix A. Trader or business

See Table A.1.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jempfin.2019.10.004.

References

Antweiler, Werner, Frank, Murray Z., 2004. Is all that talk just noise? The information content of internet stock message boards. J. Finance 59 (3), 1259–1294.
Aruoba, S. Borağan, Diebold, Francis X., Scotti, Chiara, 2009. Real-time measurement of business conditions. J. Bus. Econom. Statist. 27, 417–427.
Baker, Malcolm, Wurgler, Jeffrey, 2007. Investor sentiment in the stock market. J. Econ. Perspect. 21 (2), 129–151.
Bollen, Johan, Mao, Huina, Zeng, Xuaojun, 2011. Twitter mood predicts stock market. J. Comput. Sci. 2, 1–8.
Brown, Gregory W., Cliff, Michael T., 2004. Investor sentiment and the near-term stock market. J. Empir. Financ. 11 (1), 1–27.
Chen, Hailiang, De, Prabuddha, Hu, Yu (Jeffrey), Hwang, Byoung-Hyoun, 2014. Wisdom of crowds: The value of stock opinions transmitted through social media. Rev. Financ. Stud. 27 (5), 1367–1403.
Cookson, J. Anthony, Niessner, Marina, 2019. Why don't we agree? evidence from a social network of investors. J. Finance (forthcoming).
Da, Zhi, Engelberg, Joseph, Gao, Pengjie, 2015. The sum of all FEARS: Investor sentiment and asset prices. Rev. Financ. Stud. 28 (1), 1–32.
Greenwood, R., Shleifer, A., 2014. Expectations of returns and expected returns. Rev. Financ. Stud. 27 (3), 714–746.
Li, Feng, 2008. Annual report readability, current earnings, and earnings persistence. J. Account. Econ. 45, 221–247.
Mao, Huina, Counts, Scott, Bollen, Johan, 2015. Quantifying the effects of online bullishness on international financial markets. ECB Stat. Paper 9 (2015).
Tetlock, Paul C., 2007. Giving content to investor sentiment: the role of media in the stock market. J. Finance 62 (3), 1139–1168.
Zhang, Xue, Fuehres, Hauke, Gloor, Peter A., 2011. Predicting stock market indicators through Twitter I Hope it is not as bad as I fear. Proc. Soc. Behav. Sci. 26, 55–62.