# EMBEDDED VALUE IN BLOOMBERG NEWS & SOCIAL SENTIMENT DATA

Bloomberg

CONTENTS

# INTRODUCTION

**When rational arbitrageurs have limited risk-bearing capacity and time horizons, the actions of irrational noise traders can affect asset prices (De Long, Shleifer, Summers, & Waldmann, 1990a). Such actions can be interpreted as being driven by fluctuating investor sentiment. This creates the possibility of trading profitably on the basis of investor sentiment, most obviously by being a contrarian, but, under some circumstances, it may be rational to "jump on the bandwagon" and bet with, rather than against, noise traders (De Long, Shleifer, Summers, & Waldmann, 1990b). Various proxies for investor sentiment have been proposed (Baker & Wurgler, 2006), but perhaps the most direct way to measure sentiment in the stock market is to analyze the words of those who are commenting on stocks. One traditional source of such comments is stories in the news media (Tetlock, 2007). More recently, Google searches and Twitter feeds have been used (Mao, Counts, & Bollen, 2015).**

The high volume and time sensitivity/dependence of news and social media stories necessitates automated processing to extract actionable information, while the unstructured nature of textual information presents challenges that are comfortably addressed by machine-learning techniques. Bloomberg has applied such techniques to identify a news story or tweet as being relevant for an individual stock ticker and to assign a sentiment score to each story or tweet in the feed. In this paper we examine these scores, focusing on whether and how using news and social sentiment information in trading strategies can achieve good risk-adjusted returns.

### BLOOMBERG NEWS & SOCIAL SENTIMENT DATA

We use supervised statistical machine-learning techniques to construct News & Social Sentiment from the story text at Bloomberg. Bloomberg News and Social Sentiment classification engines are trained to mimic a human expert in processing textual information. First, a human expert manually assigns a positive, negative or neutral score to each news story or tweet. The labeling is based on the question "If an investor having a long position in the security mentioned were to read this news or tweet, is he/she bullish, bearish or neutral on his/her holdings?" Then, the annotated data is fed into machine-learning models, such as a support vector machine. Once the model is trained, when new information comes, the model automatically assigns a probability of being positive, negative or neutral to each news story or tweet.

Bloomberg provides two types of sentiment analytics: story-level sentiment and company-level sentiment.

- Story-level sentiment is generated in real time upon the arrival of news or tweets. It consists of two parts: score and confidence. Score is a categorical value, e.g., 1, -1 and 0, which indicates positive, negative and neutral sentiment, respectively. Confidence is a numerical value ranging from 0 to 100, which can be interpreted as the probability of being positive, negative or neutral.
- Company-level sentiment is the confidence-weighted average of story-level sentiment. It only delivers one score as a numerical value ranging from -1 to 1, with -1 being the most negative sentiment and 1 being the most positive sentiment.

For company-level intraday sentiment, the computation covers feeds with a rolling window. News intraday sentiment score is recomputed every two minutes with an eight-hour rolling window, while Twitter intraday sentiment score is recomputed every minute with a 30-minute rolling window. Company-level daily sentiment scores are the confidence-weighted average of the past 24 hours' story-level sentiments for both News and Twitter and are published every morning about 10 minutes before market open.

### TRADING ON SENTIMENT

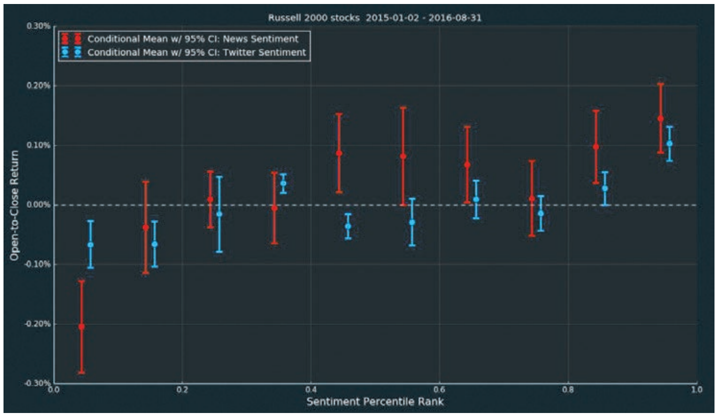
Sentiment can be used as a directional signal for trading purposes. Intuitively, if there is positive information about a particular company we expect the stock price of the company to increase, whereas if there is negative information we expect the stock price to decrease.

In order to show the predictive power of Bloomberg's sentiment data, we construct three different types of systematic equity long/short trading strategies daily sentiment-driven strategy, daily earnings event-driven strategy, and intraday sentiment-driven strategy. In all cases, we assume no transaction costs and no risk management.

#### Strategy I: Daily sentiment-driven strategy

The company-level daily sentiment data is published every day before market open. We work to determine if this data has any predictive power for the open-to-close returns on the same day. To start, we first compute the daily percentile rank of each stock based on the cross-sectional sentiment scores. Then, we estimate the average return, conditioned on the percentile rank across all the stocks and over more than an 18-month period.

In the following graph, we show the conditional average open-to-close return with 95 percent confidence interval for each sentiment percentile rank bucket of Russell 2000 stocks. The y-axis is the open-to-close return, and the x-axis is the percentile rank of the sentiment score. Each percentile rank bucket covers roughly 10 percent of the data points. Due to sentiment clustering, especially for Twitter sentiment, the exact number of data points differs from bucket to bucket.




As clearly shown in the graph, returns conditioned on bucketed News or Twitter sentiment indicate momentum trading opportunity. Stocks ranked in the top quantiles have significant positive average returns, while stocks ranked in the bottom quantiles have significant negative average returns.

Our daily-sentiment-driven strategy builds a daily-rebalanced long/short portfolio based on Bloomberg sentiment daily average scores. The daily sentiment is a lagging indicator as it is an aggregation of the past 24 hours' story-level sentiment. Our daily-sentiment-based strategy is actually exploring if the market has efficiently priced in sentiment information.

Our strategy uses Twitter sentiment as an example and is described as the following:

- Each day before market open, rank all stocks in the given stock universe by their daily-sentiment average scores.
- Construct portfolio holdings in three different variations:
  - **High-Minus-Low portfolio (HML 1/3):** Long (short) the top (bottom) third of stocks ranked by sentiment scores. Stocks in long and short portfolios are equally weighted.
  - **High-Minus-Low portfolio (HML 5%):** Long (short) the top (bottom) 5% of stocks ranked by sentiment scores. Stocks in long and short portfolios are equally weighted.
  - **Proportional portfolio (Prop):** Long (short) stocks with positions proportional to the difference of the sentiment score from its cross-sectional mean. If the sentiment score is above the mean, take a long position; if it is below, take a short position. The further away from the mean, the greater the position.
  - Positions are created at market open and closed out at market close.

The portfolio daily return can be computed as follows:

$$Ret_j = \sum_{i\,\in Long_j} w_{ij}^{Long}\left(\frac{P_{ij}^{close}}{P_{ij}^{open}} - 1\right) - \sum_{i\,\in Short_j} w_{ij}^{Short}\left(\frac{P_{ij}^{close}}{P_{ij}^{open}} - 1\right)$$

Where

$Ret_j$ is the portfolio return on day j;

$P_{ij}^{close}$ is the close price of stock i on day j, $P_{ij}^{open}$ is the open price of stock i on day j;

$Long_j$ is the basket of stocks to long on day j, $w_{ij}^{Long}$ is the weight of stock i in $Long_j$;

$Short_j$ is the basket of stocks to short on day j, $w_{ij}^{Short}$ is the weight of stock i in $Short_j$;

- For HML portfolio, $w_{ij}^{Long} = \frac{1}{\#\ of\ Stocks\ in\ Long_j}$, $w_{ij}^{Short} = \frac{1}{\#\ of\ Stocks\ in\ Short_j}$
- For proportional portfolio, $w_{ij}^{Long} = \frac{ss_{ij}^{Long} - \mu_j}{\sum_{i \in Long_j}(ss_{ij}^{Long} - \mu_j)}$, $w_{ij}^{Short} = \frac{\mu_j - ss_{ij}^{Short}}{\sum_{i \in Short_j}(\mu_j - ss_{ij}^{Short})}$

In the backtesting, we tried four different holding periods:

- "Same O2O" is the open-to-open return from the previous day to the same day as the sentiment score. The score as computed may be viewed as a rough proxy for the contemporaneous impact of news or tweets.
- "Same O2C" is the open-to-close return on the same day as the sentiment score. This is theoretically attainable but requires quick action — trading a few minutes after observing the score.
- "Next C2C" is the close-to-close return from the same day to the next day. In other words, after observing the sentiment score at 9:20 AM, you wait until 4:00 PM to trade.
- "SO2NC" is just the sum of "Same O2C" and "Next C2C." It stands for "same-day open to next-day close."

We backtest this strategy for S&P 500 stocks, Russell 3000 stocks and Russell 2000 stocks in order of descending average market cap. The backtesting period is from January 2, 2015, to August 31, 2016.

The most statistically significant returns are for "Same O2O," and this is consistent across all stock universes. This is in line with the intuition that news should drive contemporaneous return, but this return is not exploitable. The "Same O2C" also shows some statistical significance for low- and mid-cap universes, e.g., Russell 2000 and Russell 3000 stocks, and results in an exploitable trading strategy.

Equity curves for the strategies for Russell 2000 stocks are shown below, along with a performance statistics table. The benchmark index ETF (IWM) equity curve is calculated with open-to-close returns to be consistent with the sentiment strategy. The results for other portfolios are included in Appendix.

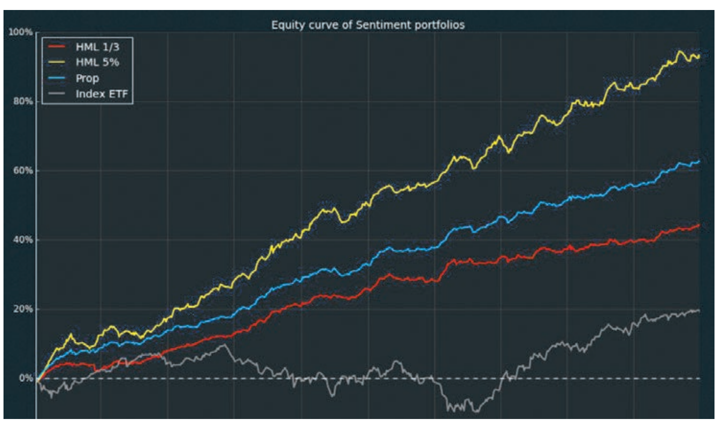



Illustration for Russell 2000 Stocks

| | Beta | Annualized Ret | Annualized Vol | Sharpe | Average # of Short | Average # of Long |
|---|---|---|---|---|---|---|
| HML 1/3 | -0.05 | 26% | 6% | 4.25 | 232 | 386 |
| HML 5% | -0.09 | 56% | 12% | 4.80 | 58 | 59 |
| Proportional | -0.04 | 38% | 6% | 5.87 | 796 | 381 |
| Index ETF (IWM) | 1.00 | 12% | 14% | 0.80 | N/A | N/A |

The performance statistics show that all sentiment portfolios outperform the benchmark index ETF (IWM) significantly and the realized betas are all very close to zero, which means very small market exposure. Also, based on our backtesting results, the more diversified portfolio, i.e., the Proportional portfolio, improves the risk-adjusted return substantially.

**Strategy II: Daily earnings event-driven strategy**

U.S. publicly traded companies are required to file their earnings report with the SEC every quarter. An earnings release shows the profitability of the company in the past quarter and also gives guidance for the future potential performance of the company. Stocks are likely to move significantly on earnings days based the actual earnings results. With the earnings event-driven strategy, we show that Bloomberg News and Twitter sentiment data prior and leading up to the market open of earnings day can be used to explore the earnings day return.

The earnings strategy goes long or short on stocks on their earnings days based on Bloomberg News/Twitter sentiment daily average scores. Our strategy is the following:

On each day, if there are companies scheduled to release earnings between current market open and the next market open:

- Long those with positive sentiment and short those with negative sentiment.

A portfolio is not necessarily long/short balanced, thus to reduce market exposure, we short market ETF if the portfolio has only long positions if the portfolio has only short positions, we long market ETF. Stocks in long and short portfolios are equally weighted.

- Positions are created at the current market open and close out at the next market open.

In the backtesting, we compared three sentiment sources: News only, Twitter only, and News/Twitter combined. For the combined version, we go long on stocks only if both News and Twitter sentiment scores are positive; we go short on stocks only if both these measures are negative.

The portfolio daily return can be computed as follows:

$$Ret_j = \sum_{i\,\in Long_j} \frac{1}{N_j^{Long}} \left( \frac{P_{i(j+1)}^{open}}{P_{ij}^{open}} - 1 \right) \mathbb{I}(N_j^{Long} > 0) + \left( \frac{M_{(j+1)}^{open}}{M_j^{open}} - 1 \right) \mathbb{I}(N_j^{Long} = 0)$$

$$- \sum_{i\,\in Short_j} \frac{1}{N_j^{Short}} \left( \frac{P_{i(j+1)}^{open}}{P_{ij}^{open}} - 1 \right) \mathbb{I}(N_j^{Short} > 0) - \left( \frac{M_{(j+1)}^{open}}{M_j^{open}} - 1 \right) \mathbb{I}(N_j^{Short} = 0)$$

Where

$Ret_j$ is the portfolio return on day j;

$P_{ij}^{open}$ is the open price of stock i on day j;

$M_j^{open}$ is the open price of benchmark market ETF on day j;

$Long_j$ is the basket of stocks to long on day j, $N_j^{Long}$ is the number of stocks in $Long_j$;

$Short_j$ is the basket of stocks to short on day j, $N_j^{Short}$ is the number of stocks in $Short_j$.

We backtest the strategy for S&P 500 stocks, Russell 3000 stocks and Russell 2000 stocks in order of descending average market cap. The backtesting period is from January 2, 2015, to August 31, 2016. Based on our results, this strategy works better for S&P 500 stocks. We believe that is true because S&P 500 companies attract more attention and analyst coverage, so their average sentiment from news and social sources just before earnings are reported is more likely to contain earnings-related information.

However, even for S&P 500 stocks, the signal-to-noise ratio is very low at stock level and improves at portfolio level. One way to refine this strategy is to use topic codes to filter out irrelevant information. For example, if we are interested only in earnings-related information, we can just aggregate earnings stories or tweets to get earnings-related sentiment scores, which may further enhance the signal. We will test this in our future work.

Equity curves of the strategy for S&P 500 stocks are shown below, along with a performance statistics table. The benchmark index ETF (SPY) equity curve is calculated with open-to-open returns in order to be consistent with the sentiment strategy. The results for other portfolios are included in Appendix.

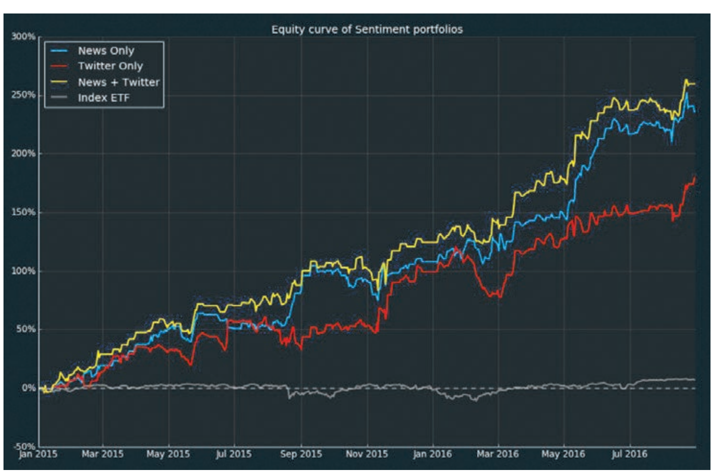



Illustration for S&P 500 Stocks

| | Beta | Annualized Ret | Annualized Vol | Sharpe | Average # of Short | Average # of Long |
|---|---|---|---|---|---|---|
| News Only | -0.08 | 142% | 59% | 2.39 | 2 | 7 |
| Twitter Only | -0.14 | 108% | 61% | 1.76 | 4 | 7 |
| News + Twitter | 0.12 | 156% | 58% | 2.68 | 2 | 5 |
| Index ETF (SPY) | 1.00 | 4% | 15% | 0.29 | N/A | N/A |

The performance statistics show that our strategies based on News only, Twitter only and News/Twitter combined all significantly outperform the benchmark index ETF (SPY). The realized betas are all relatively small by design. More interesting, combining News and Twitter sentiment further boosts the performance in terms of the risk-adjusted return, e.g., the Sharpe ratio.

Due to the long-run sentiment bias, we also notice that long positions are more frequent than short positions for this strategy. For News sentiment, long positions appear 70% of the time and short positions appear 40% of the time over the backtesting period; the average number of long positions is seven and the average number of short positions is two. For Twitter sentiment, long positions appear 70% of the time and short positions appear 50% of time; the average number of long positions is seven and the average number of short positions is four.

**Strategy III: Intraday sentiment-driven strategy**

Bloomberg's story-level sentiment tracks news and tweets in real time, which enables subscribers to respond quickly to the new information in the market. Our intraday strategy longs or shorts stocks based on Bloomberg News intraday story-level sentiment. Since news stories of different companies arrive asynchronously, intraday trading in practice usually involves rebalancing positions according to these asynchronous signals. For simplicity in conveying the main idea, our strategy trades at evenly spaced intervals instead. We assume we only trade during market trading hours, e.g., from 9:30 AM to 4:00 PM for U.S. exchange-listed stocks. The trading idea is described as follows:

- Divide each day's trading hours into N-minute intervals.
- Within each N-minute interval, if there are multiple stories on the same company, we take the average of the scores and confidence.
- At the end of each N-minute interval, long stocks with perfect positive sentiment (average score equals 1 and average confidence equals 100) and short stocks with perfect negative sentiment (average score equals -1 and average confidence equals 100). Stocks in long and short portfolios are equally weighted.
- Close out positions after N minutes.

The portfolio daily return can be computed as the following, $Ret_j = \sum_{k=2}^{M} Ret_{jk}^{Nmin}$

Where

$Ret_j$ is the portfolio return on day j;

$M$ is the number of non-overlapping N-minute intervals in a trading day;

$Ret_{jk}^{Nmin}$ is the portfolio return of the k-th N-minute on day j, and is computed as

$$Ret_{jk}^{Nmin} = \sum_{i \in Long_{jk}} \frac{1}{N_{jk}^{Long}} \left( \frac{P_{ijk}^{close}}{P_{ijk}^{open}} - 1 \right) \mathbb{1}\left(N_{jk}^{Long} > 0\right) - \sum_{i \in Short_{jk}} \frac{1}{N_{jk}^{Short}} \left( \frac{P_{ijk}^{close}}{P_{ijk}^{open}} - 1 \right) \mathbb{1}\left(N_{jk}^{Short} > 0\right)$$

$P_{ijk}^{open}$ is the stock i's open price of the k-th N-minute on day j;

$P_{ijk}^{close}$ is the stock i's close price of the k-th N-minute on day j;

$Long_{jk}$ is the basket of stocks to long at the beginning of the k-th N-minute on day j;

$N_{jk}^{Long}$ is the number of stocks in $Long_{jk}$;

$Short_{jk}$ is the basket of stocks to short at the beginning of the k-th N-minute on day j;

$N_{jk}^{Short}$ is the number of stocks in $Short_{jk}$.

We used 5-minute interval as an example and backtested this strategy for S&P 500 stocks, Russell 2000 stocks and NASDAQ biotechnology stocks. The backtesting period is from December 1, 2015, to March 30, 2016, with intraday 1-minute trade price bars. If there are missing bars for certain 5-minute periods, we drop that 5-minute return. Although this doesn't introduce any upward or downward bias in expectation, to be more realistic, bid/ask intraday bars may be used instead of trade bars. Also, in real trading, the close bar is not really exploitable. The open bar may be used for the next 5-minutes in the backtesting; however, in this case, you need to deal with the overlapping period with new positions of the next 5-minutes.

Based on our results, this strategy works better for small-cap stocks, e.g., Russell 2000 and Nasdaq biotechnology stocks. The equity curve of the strategy for Russell 2000 stocks is shown below, with a performance statistics table. The benchmark index ETF (IWM) equity curve is calculated with open-to-close returns to be consistent with the sentiment strategy. The results for other portfolios are included in Appendix.

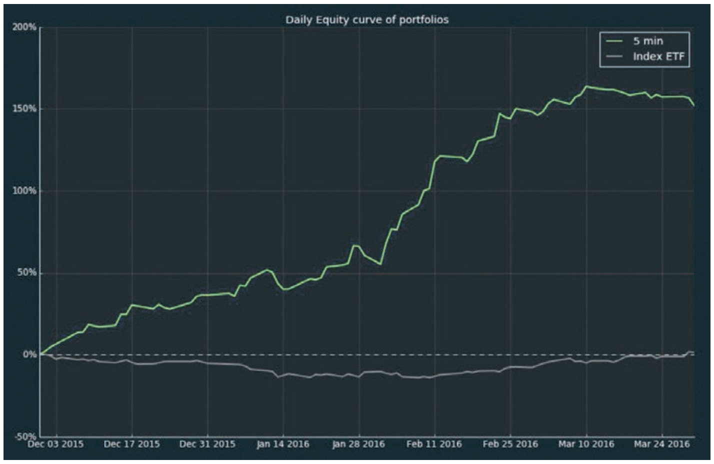



Illustration for Russell 2000 Stocks

| | Beta | Annualized Ret | Annualized Vol | Sharpe |
|---|---|---|---|---|
| News | -0.94 | 467% | 69% | 6.74 |
| Index ETF (IWM) | 1.00 | 4% | 19% | 0.22 |

[1]The point-in-time index members and their corresponding 1-minute price bars were retrieved separately on different days. If any stock changed its ticker during this period, the stock's price bars may be missing. However, this should only affect a few stocks at most.

The performance statistics show that the news story–based strategy significantly outperforms the benchmark index ETF (IWM). Since this is an intraday strategy, which is more subject to the transaction costs, a proper trading cost model should be used for practical purposes. We also backtest this strategy with different interval lengths, e.g., 1 minute, 10 minutes, 30 minutes and 60 minutes. For most of the cases, the best Sharpe ratio is achieved between 5 minutes and 30 minutes, depending on the stock universe. Beyond 30 minutes, we hardly see any meaningful return, which reflects market efficiency in incorporating new information.

## CONCLUSION

In this paper, we demonstrate three different types of trading ideas based on Bloomberg News & Social Sentiment data. According to our backtesting results, the sentiment strategies outperform the corresponding benchmark index ETFs significantly, which strongly demonstrates the value embedded in Bloomberg News & Social Sentiment data.

## APPENDIX

### Additional Backtesting Results

In this appendix, we show more backtesting results for different stock universes.

### Strategy I: Daily Sentiment-driven Strategy

The backtesting period is from January 2, 2015, to August 31, 2016.

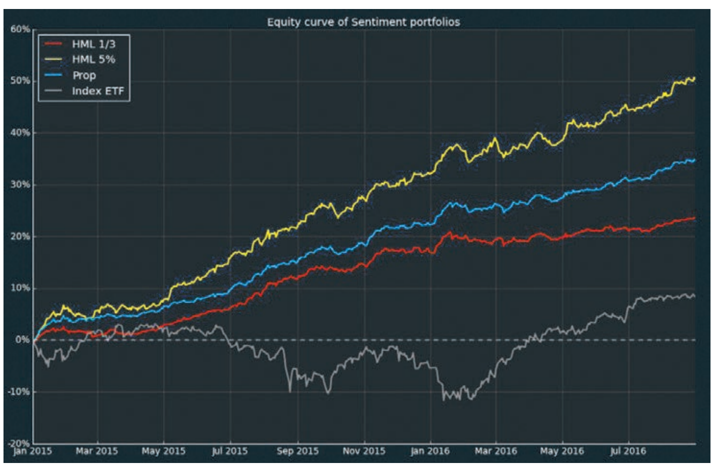



Illustration for Russell 3000 stocks

| | Beta | Annualized Ret | Annualized Vol | Sharpe | Average # of Short | Average # of Long |
|---|---|---|---|---|---|---|
| HML 1/3 | -0.05 | 14% | 4% | 3.29 | 449 | 661 |
| HML 5% | -0.10 | 30% | 8% | 3.94 | 99 | 100 |
| Proportional | 0.06 | 21% | 4% | 4.67 | 1332 | 664 |
| Index ETF (IWV) | 1.00 | 5% | 11% | 0.44 | NaN | NaN |

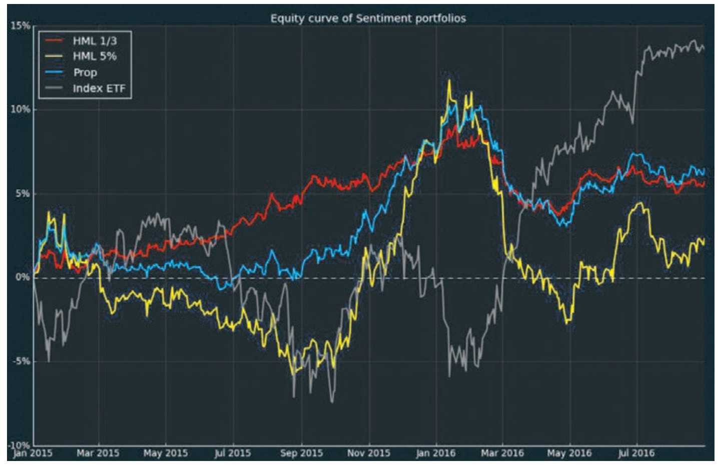



Illustration for S&P 500 stocks

| | Beta | Annualized Ret | Annualized Vol | Sharpe | Average # of Short | Average # of Long |
|---|---|---|---|---|---|---|
| HML 1/3 | -0.08 | 3.42% | 3.71% | 0.92 | 130 | 151 |
| HML 5% | -0.15 | 1.38% | 8.42% | 0.16 | 23 | 23 |
| Proportional | -0.11 | 3.89% | 4.93% | 0.79 | 291 | 160 |
| Index ETF (IWV) | 1.00 | 8.17% | 10.97% | 0.74 | NaN | NaN |

### Strategy II: Daily Earnings Event-driven Strategy

The backtesting period is from January 2, 2015, to August 31, 2016.

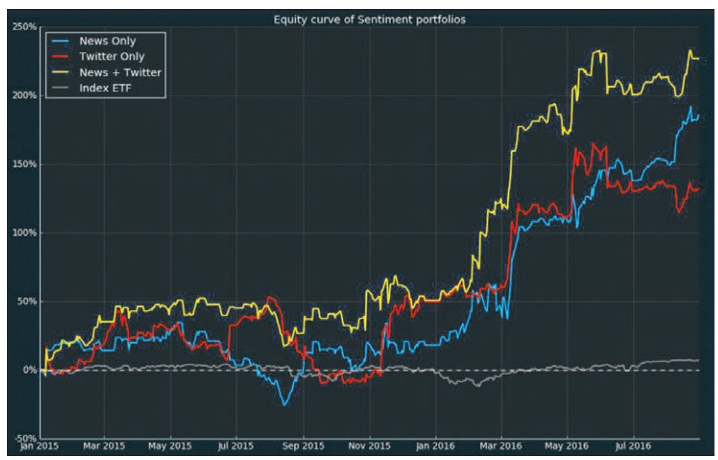



Illustration for Russell 3000 stocks

| | Beta | Annualized Ret | Annualized Vol | Sharpe | Average # of Short | Average # of Long |
|---|---|---|---|---|---|---|
| News Only | 0.14 | 82% | 78% | 1.05 | 4 | 13 |
| Twitter Only | 0.01 | 42% | 81% | 0.52 | 10 | 21 |
| News + Twitter | 0.15 | 52% | 85% | 0.61 | 2 | 8 |
| Index ETF (IWV) | 1.00 | 4% | 14% | 0.27 | NaN | NaN |

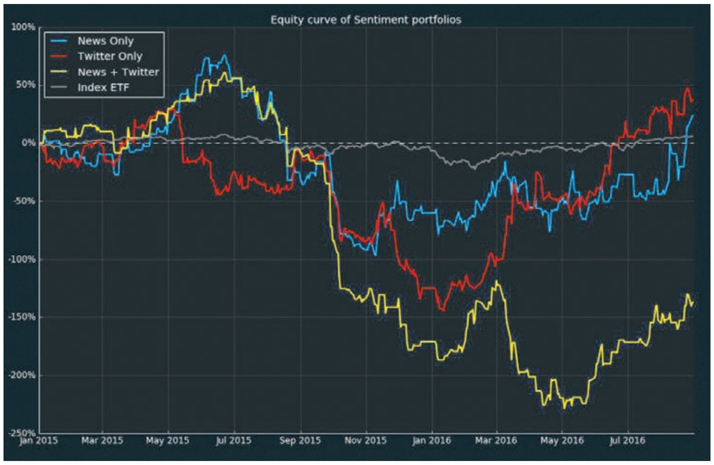



Illustration for Russell 2000 stocks

| | Beta | Annualized Ret | Annualized Vol | Sharpe | Average # of Short | Average # of Long |
|---|---|---|---|---|---|---|
| News Only | 0.42 | 14% | 96% | 0.15 | 3 | 5 |
| Twitter Only | -0.11 | 22% | 95% | 0.23 | 6 | 12 |
| News + Twitter | 0.24 | -83% | 92% | -0.90 | 2 | 3 |
| Index ETF (IWV) | 1.00 | 3% | 17% | 0.19 | NaN | NaN |

### Strategy III: Intraday Sentiment-driven Strategy

The backtesting period is from December 1, 2015, to March 30, 2016, with 1-minute price bars.

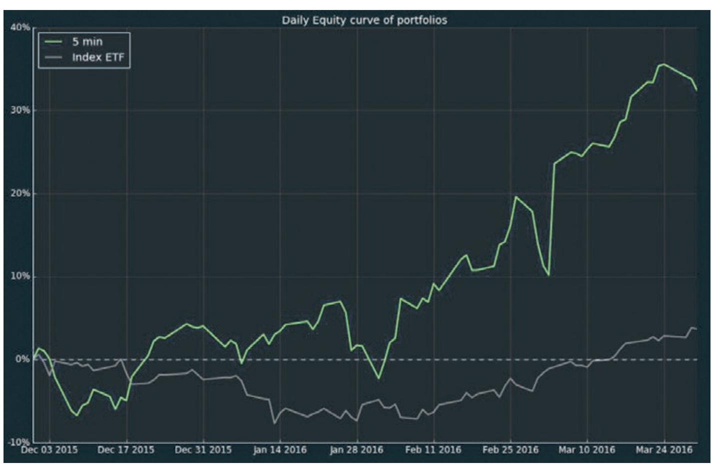



Illustration for S&P 500 stocks

| | Beta | Annualized Ret | Annualized Vol | Sharpe |
|---|---|---|---|---|
| News | -0.30 | 100% | 36% | 2.75 |
| Index ETF (IWM) | 1.00 | 100% | 13% | 0.84 |

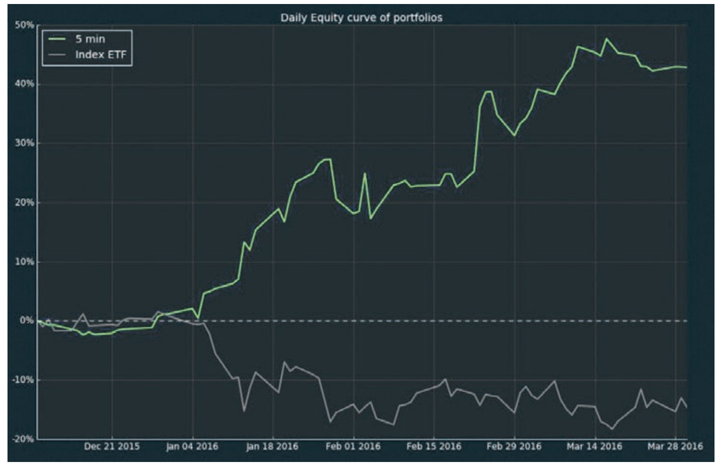



Illustration for Nasdaq biotechnology stocks

| | Beta | Annualized Ret | Annualized Vol | Sharpe |
|---|---|---|---|---|
| News | -0.35 | 146% | 42% | 3.51 |
| Index ETF (IWM) | 1.00 | -48% | 32% | -1.47 |

### Transaction Costs

Transaction costs are an essential component of a successful trading strategy. Without properly taking transaction costs into account, real trading could underperform the backtesting result substantially and even lead to a loss. In general, transaction costs include bid/ask spreads, slippage costs and market impact. However, properly estimating all components depends on the details of trade implementation and order execution, which is beyond the scope of this paper. Below we discuss the impact of transaction costs on the above strategies.

**Strategy I:** Daily sentiment-driven strategy trades small-cap stocks. Daily open-to-close rebalancing will incur a lot of transaction costs, which can wipe out the profit completely. However, we could reduce the transaction costs by holding the portfolio from market open to the next market open and by only trading stocks that need to be rebalanced. For the Russell 2000 stocks, we see about a 30% reduction in transaction costs for the HML 1/3 portfolio.

**Strategy II:** Daily earnings event-driven strategy trades large-cap stocks, which are less affected by transaction costs. With a reasonable transaction cost assumption, the strategy still shows a reasonable Sharpe ratio.

**Strategy III:** Intraday sentiment-driven strategy trades small-cap stocks with a relatively high turnover, making this strategy more subject to transaction costs. Therefore, you definitely need to incorporate a proper transaction cost model into the backtesting. When taking transaction costs into account, we may see that the optimal holding period length increases, say from 5 minutes to 30 minutes, since trading less frequently reduces transaction costs.

## Alternative Aggregation Methodology

Below we propose a new methodology for company-level sentiment aggregation. Instead of just one score representing the average sentiment, the new methodology produces two components: average sentiment and dispersion.

## Alternative Sentiment Score & New Dispersion Indicator

Each news story/tweet is scored with "confidences" of $C_+, C\ , C_n > 0$ for positive, negative and neutral sentiment, respectively. These can be interpreted as "probabilities," and the following identity holds $C_+ + C\ + C_n = 1$.

- **Background:** These probabilities are formed from output of three SVMs, each of which helps with a binary classification of a story/tweet as Positive Vs. Neutral, Positive Vs. Negative and Negative Vs. Neutral, respectively, using various features that are constructed from the text analysis of the story/tweet.

The probabilities $C_+, C\ , C_n$ are essentially a function of the output of the three SVMs, and we derive final labels $L \quad \{Positive, Negative, Neutral\}$ for each story/tweet based on the probability values $C_+, C\ \& C_n$, essentially assigning the class with highest probability as the label for the story.

- **Sentiment Average:** For each story $i$, we define a story-specific sentiment polarity score $S^i \in [-1,1]$ simply as $C_+^i \quad C^i$. This passes the smell test: S values that are highly positive should correspond to positive stories (or stories with high "positive probability"), with negative values to negative stories and values around zero to neutral stories; however, this may be not be fully consistent with the currently used labeling.

For the average sentiment calculation, we simply propose an average of the sentiment polarity scores from each story that is part of the set, e.g.

$$\text{Average Sentiment} = \mu = \frac{\sum_{i=1}^{N} S^i}{N} = \frac{\sum_{i=1}^{N}(C_+^i - C_-^i)}{N} = \overline{C_+} - \overline{C_-}$$

Here, $\overline{C_+}, \overline{C_-}$ are the average positive and negative sentiment scores.

- **Sentiment Dispersion:** To calculate the overall dispersion metric to go with the average sentiment, we need to track two components. One is the variance of the average sentiment across different stories, the second is the specific variance of the sentiment per story.

Sentiment dispersion = Inter-story variance + story-specific dispersion, which simplifies to

$$\text{Dispersion} = \overline{C_+} + \overline{C_-} - \mu^2$$

## Backtesting on Alternative Aggregation Method

We backtest Strategy I: Daily Sentiment-driven Strategy for Russell 2000 stocks using the new methodology sentiment score and dispersion indicator. The backtesting period is from January 2, 2015, to March 31, 2016.

## Effect of Dispersion

Below we discuss how the dispersion indicator can improve Sharpe ratios based on Twitter sentiment. We construct four different variations of portfolio holdings:

- **High-Minus-Low portfolio (HML 1/3):** Long (short) the top (bottom) third of stocks ranked by sentiment score. Stocks in long and short portfolios are equally weighted.
- **High-Minus-Low with dispersion portfolio (HML 1/3 w/dispersion):** Long (short) the top (bottom) third of stocks ranked by sentiment score, and filtered by dispersion indicator. It is the same as HML 1/3, except that stocks with dispersion below the cross-sectional median are removed. Stocks in long and short portfolios are equally weighted.
- **Proportional portfolio (Prop):** Long (short) stocks with positions proportional to the distance of the sentiment score from the cross-sectional mean. If the sentiment score is above the mean, take a long position; if it is below, take a short position.
- **Proportional dispersion portfolio (Prop w/dispersion):** Long (short) stocks with positions proportional to the distance of the sentiment score from the cross-sectional mean andfiltered by the dispersion indicator. It is the same as Proportional portfolio, except that stocks with dispersion below the cross-sectional median are removed.

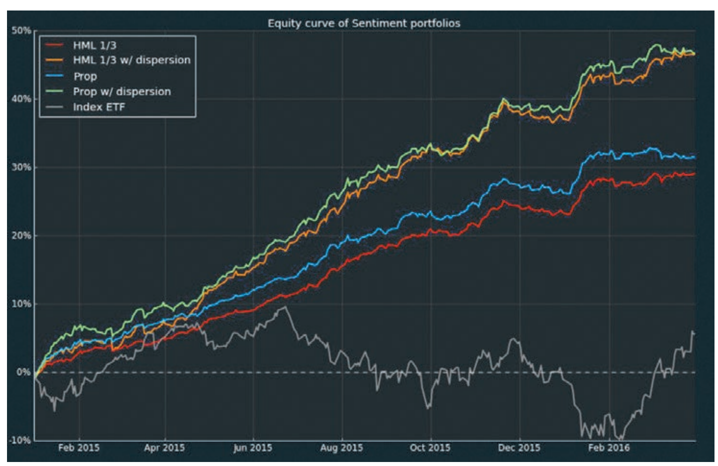



Illustration for Russell 2000 stocks

| | Beta | Annualized Ret | Annualized Vol | Sharpe | Average # of Short | Average # of Long |
|---|---|---|---|---|---|---|
| HML 1/3 | -0.04 | 23% | 4% | 5.35 | 426 | 425 |
| HML 1/3 + dispersion | -0.08 | 37% | 7% | 5.48 | 197 | 325 |
| Prop | -0.06 | 25% | 5% | 5.06 | 752 | 529 |
| Prop + dispersion | -0.07 | 38% | 7% | 5.39 | 265 | 375 |
| Index ETF (IWM) | 1.00 | 5% | 15% | 0.30 | NaN | NaN |

[2]The story-level sentiment data provided covers period from Jan. 1, 2015, to March 31, 2016.

According to the backtesting results, adding the dispersion indicator improves strategy performance for both HML 1/3 and Proportional portfolios. We believe that the dispersion indicator captures the conflicting market sentiments for a company. When dispersion is small, it means market views are quite in line with each other and the market is more efficient in pricing in the converging views; when dispersion is large, it means market sentiments are quite different and the market is less efficient in pricing in diverging views. Our backtesting results suggest long/short stocks with diverging market views provide better risk-adjusted returns.

**Effect of Combining News & Twitter Sentiment**

Below we show that combining News and Twitter sentiment can further boost the performance of the sentiment portfolio in terms of risk-adjusted return. We construct the HML 1/3 portfolio based on three types of sentiment:

- **News new value:** Long (short) the top (bottom) third of stocks ranked by News sentiment scores. Stocks in long and short portfolios are equally weighted.
- **Twitter new value:** Long (short) the top (bottom) third of stocks ranked by Twitter sentiment scores. Stocks in long and short portfolios are equally weighted.
- **News + Twitter:** Long (short) the top (bottom) third of stocks ranked by both News and Twitter sentiment scores. In other words, stocks in the long leg have to be in the top third of both News and Twitter sentiment; stocks in the short leg have to be in the bottom third of both News and Twitter sentiment. Stocks in long and short portfolios are equally weighted.
- **News + Twitter w/dispersion:** Long (short) the top (bottom) third of stocks ranked by both News and Twitter sentiment scores, respectively, filtered by the dispersion indicator (stocks with dispersion above the cross-sectional median are filtered out). This can be seen as combining "HML 1/3 + dispersion" portfolio of News and Twitter. Stocks in long and short portfolios are equally weighted.

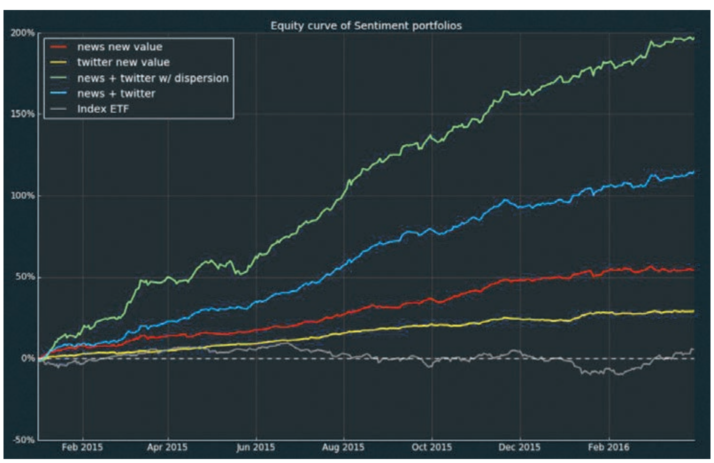



Illustration for Russell 2000 stocks

| | Beta | Annualized Ret | Annualized Vol | Sharpe | Average # of Short | Average # of Long |
|---|---|---|---|---|---|---|
| News Only | -0.15 | 44% | 9% | 5.08 | 147 | 345 |
| Twitter Only | -0.04 | 23% | 4% | 5.35 | 426 | 425 |
| News + Twitter | -0.13 | 92% | 15% | 6.22 | 55 | 116 |
| News + Twitter w/ dispersion | -0.18 | 158% | 26% | 6.07 | 24 | 46 |
| Index ETF (IWM) | 1.00 | 5% | 15% | 0.30 | NaN | NaN |

Based on our backtesting results, combining News and Twitter sentiment generates a stronger signal, which improves strategy performance significantly.

**Effect of Transaction Costs**

In the following graph, we show the equity curves of the same daily sentiment-driven strategy as in Strategy I from top of the appendix but include transaction costs. We assume 20 bps average round-trip costs for both the long and short legs. The results below show the "News + Twitter w/ dispersion" portfolio still has a reasonably good Sharpe ratio.

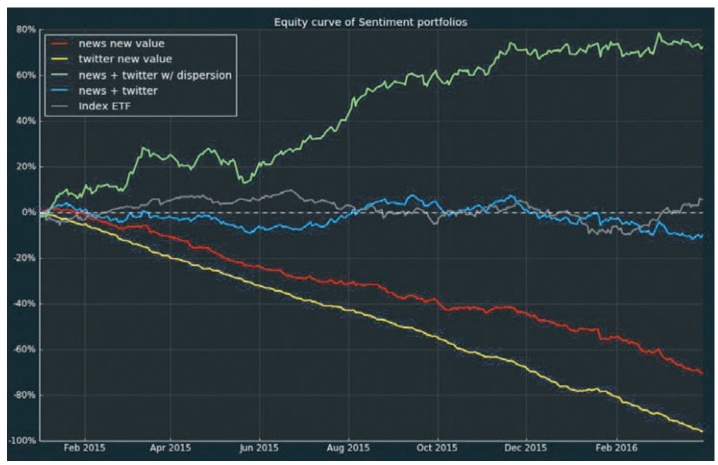



Illustration for Russell 2000 stocks

| | Beta | Annualized Ret | Annualized Vol | Sharpe | Average # of Short | Average # of Long |
|---|---|---|---|---|---|---|
| News Only | -0.15 | -57% | 9% | -6.58 | 147 | 345 |
| Twitter Only | -0.04 | -77% | 4% | -17.71 | 426 | 425 |
| News + Twitter | -0.13 | -9% | 15% | -0.61 | 55 | 116 |
| News + Twitter w/ dispersion | -0.18 | 58% | 26% | 2.21 | 24 | 46 |
| Index ETF (IWM) | 1.00 | 5% | 15% | 0.30 | NaN | NaN |

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