# Social media indicator review

June 2018

### Research Signals

In March 2014, we introduced a set of social media indicators, in partnership with Social Market Analytics, Inc., that classify the text content in daily Twitter posts to construct a family of social media signals. With four years of live data since the initial roll out and over 6 years of out of sample history since SMA's inception, we revisit this developing discipline for gauging investor sentiment at a time when President Trump's predilection for tweeting consumes the news media, with some suggesting the social media service was the big winner of the 2016 US election, and has now joined the S&P 500.

- For names at the extreme tails (3 standard deviations) of the factor distribution, we report notable S-Score™ average daily return spreads of 0.163% since the factor went live, with robustness to longer 10-day holding periods and to long-only strategies
- When focusing on frequently tweeted names, average daily return spreads improve to 0.215% and more than double the stand-alone result at the 10-day time horizon
- Social media sentiment differentiates outperformers from underperformers across high momentum and low momentum buckets, and across high short interest and low short interest buckets, validating the sentiment is not fully captured by common factors


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## Introduction

Through our partnership with Social Market Analytics, Inc. (SMA), we provide a suite of social media indicators constructed to capture timely information gleaned from Twitter posts (#Alpha: Extracting market sentiment from 140 characters). SMA operates in data services and provides analysis of social media data streams to estimate market sentiment at the stock level. The resulting measures are based on analysis of the text content in daily Twitter posts. Tweets are filtered for financial trading relevance and scored for market sentiment content. Tweet scores are then aggregated for each stock to produce a sentiment measurement from which the indicators are derived.

Research Signals' 22 social media factors using SMA sentiment data contain both derived and directly passed through indicators covering the following broad categories:

- Tweet sentiment quantifies alpha-generating sentiment from a previously untapped source of information flow of tweets filtered for financial trading relevance and scored for market sentiment content
- Tweet volume identifies increased interest in a stock
- Relative value computes scores relative to the market and/or the stock's recent history and provides a clearer view of sentiment levels
- Changing sentiment measures 1-day to 20-day look back signals to identify trends in the sentiment signals
- Dispersion assesses the number of unique tweet sources to gauge the validity of a signal

In this report, we review factor performance since the model's inception, with focus on a key predictive factor, S-Score™. We also analyze S-Score™ interactions with short-term price momentum and short interest factors. Rounding out the report, we go beyond the stock level and consider application of sentiment aggregated at the market level.

## Data and methodology

S-Score™ measures a stock's aggregated raw sentiment score normalized to the average and standard deviation of the past 20 days. It is a gauge of the deviation of a stock's sentiment intensity level from a normal state computed as a z-score of weighted raw sentiment scores. While the underlying measure is highly dependent on tweet volume, the z-score normalization adjusts for this impact. Positive (negative) scores are aligned with positive (negative) sentiment and considered a buy (sell) signal.

We analyze several strategies for performance analytics of S-Score™. First, we detail results at the tails of the underlying factor distribution with a score >=3 (<=-3), in other words, a current relative sentiment score of at least 3 (-3) standard deviations away from the normal aggregate sentiment level, indicating positive (negative) sentiment. We also detail performance at scores of +/- 2 and on a decile ranking basis providing larger targeted sets, but our results indicate that the factor's strength is in identifying names at the extreme tails of the distribution.

Updates may at times be sparse as messaging on Twitter expressing market sentiment for any stock may be variable in time and volume, with some top or bottom scoring names only having one or two tweets. While we can make a case that these are potentially important tweets, we study the signal strength after removing names with sparse tweet volumes. For this we apply a filter for a minimum S-Volume™ (number of indicative tweets) of 3 to adjust the S-Score™ signal for confirmed information content (see Table A1 in the Appendix for the impact on portfolio sizes).

Data coverage for the live period at IHS Markit begins 1 March 2014 and runs through 30 March 2018, and full period analytics begin 1 December 2011. While data and factor scores are available on an intraday basis, performance analytics in this report are based on pre-open data, published at 8:55 AM EST. Daily average open-to-close returns are reported, along with varying holding periods ranging from 1 to 20 business days (overlapping periods) to check for persistence beyond the open-to-close period given that the signal is a known high-turnover strategy. Our coverage universe is the US Total Cap, representing 98% of cumulative market cap or 3,000+ stocks. We also have results available for the large cap universe, though performance is not shown here given the similarity to the full universe as a consequence of the significant concentration of tweets among large caps.

## Performance results

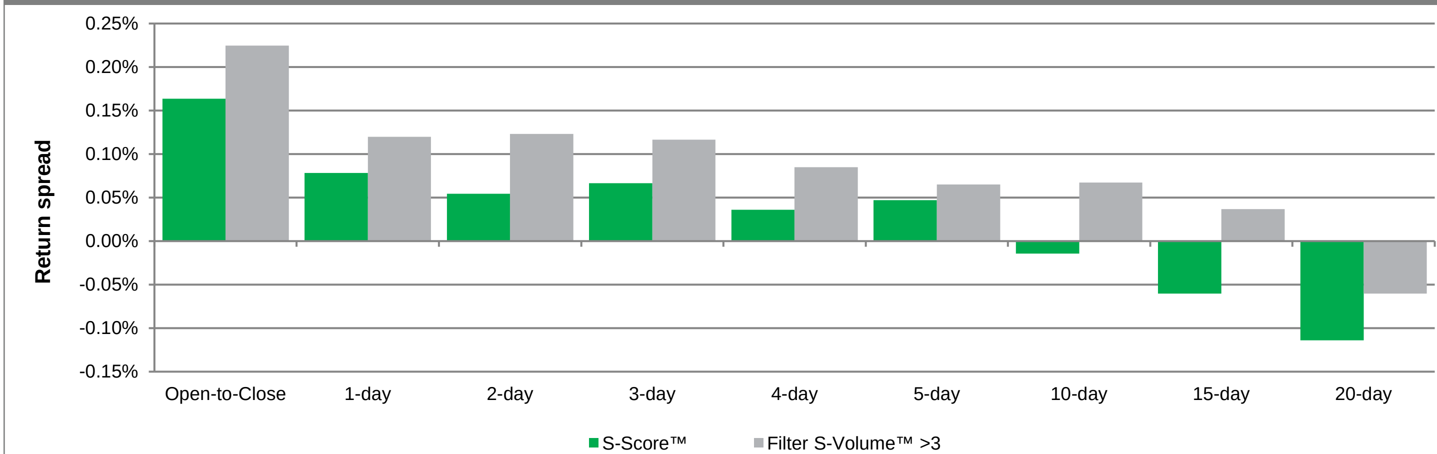
First, for the factor's live period, we analyze spread performance which is the difference between equal-weight average returns for the buy portfolio less the sell portfolio (Table 1) and feature the results at the extreme +/-3 tail (Figure 1). We also include longer term results since the factor went live (1 December 2011) in the Appendix (see Table A2).

S-Score™ open-to-close return spreads at the +/-3 tail averaged 0.164% since March 2014, with an annualized Sharpe ratio of 2.5. Signal power persisted to longer holding periods out to five days (0.047%), though not exceeding the open-to-close average. We also detail longer term daily cumulative returns at each tail since the factor's inception (Figure 2), demonstrating a cumulative return of 179% for longs versus -14% for shorts and 135% for the market. For reference, we also include pre-close long and short signals. We note that the pre-close signal works better than the pre-open signal when trading at the close, as expected considering the importance of acting upon the signals with low latency.

At the broader +/- 2 and decile tails, performance was weaker at the shorter time horizons. However, decile spreads were stronger over longer holding periods posting at 0.037% and 0.102%, respectively, out to 15 days.

Figure 1

**S-Score™ +/-3 tail average return spreads, 1 Mar 2014 - 30 Mar 2018**




Source: IHS Markit

Table 1

**S-Score™ average return spreads (%), 1 Mar 2014 – 30 Mar 2018**

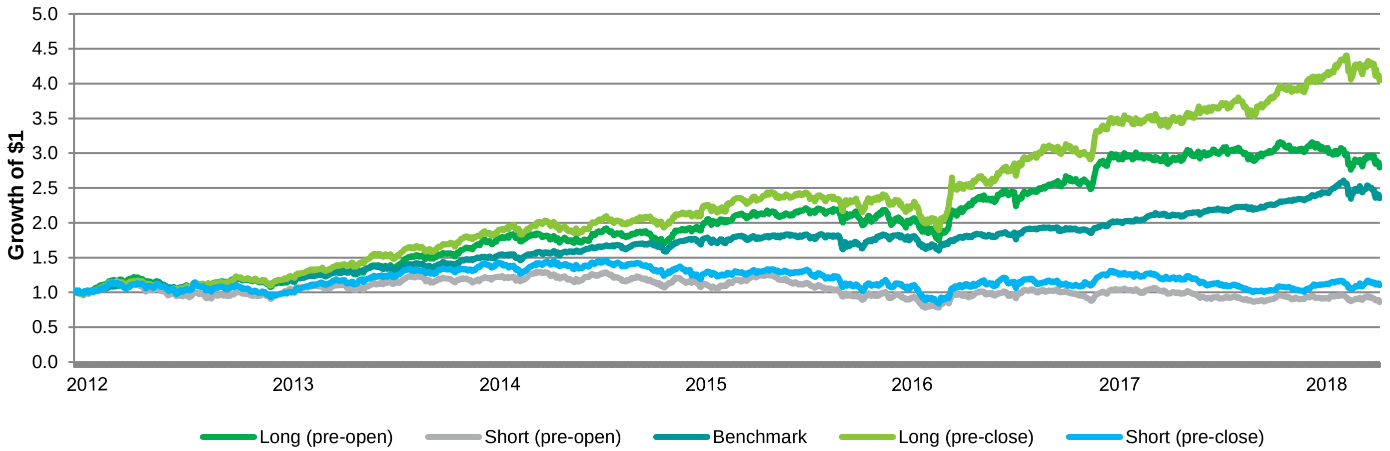
| Strategy | Open-to-close (%) | 1-day (%) | 2-day (%) | 3-day (%) | 4-day (%) | 5-day (%) | 10-day (%) | 15-day (%) | 20-day (%) |
|---|---|---|---|---|---|---|---|---|---|
| S-Score™ | | | | | | | | | |
| +/-3 tail spread | 0.164 | 0.078 | 0.054 | 0.066 | 0.036 | 0.047 | -0.014 | -0.060 | -0.114 |
| +/-2 tail spread | 0.134 | 0.036 | 0.028 | 0.037 | 0.036 | 0.037 | 0.054 | 0.037 | 0.000 |
| Decile spread | 0.099 | 0.034 | 0.052 | 0.070 | 0.079 | 0.079 | 0.095 | 0.102 | 0.095 |
| Filter S-Volume™ >3 | | | | | | | | | |
| +/-3 tail spread | 0.225 | 0.120 | 0.123 | 0.116 | 0.085 | 0.065 | 0.067 | 0.037 | -0.060 |
| +/-2 tail spread | 0.181 | 0.049 | 0.055 | 0.060 | 0.063 | 0.065 | 0.087 | 0.081 | 0.051 |
| Decile spread | 0.125 | 0.042 | 0.075 | 0.085 | 0.100 | 0.097 | 0.125 | 0.140 | 0.139 |

Source: IHS Markit



Figure 2

**S-Score™ +/-3 tail daily cumulative return**




Source: IHS Markit



Turning to the filtered strategies, outcomes were robust to these additional checks, under the caveat of more limited portfolio sizes. With the filter for S-Volume™>3, average open-to-close spreads at the +/- 3 tail improved to 0.225%, and continued to exceed the stand-alone factor results at each holding period. Indeed, the 15-day spread posted at 0.037%, remaining in positive territory. Lastly, the live period data suggests that the signal may peak at the 5-day horizon, with longer holding period results showing some signs of decay at the tightest tail, though the less stringent +/- 2 and decile tail results peaked at the 10- and 15-day horizons, respectively.

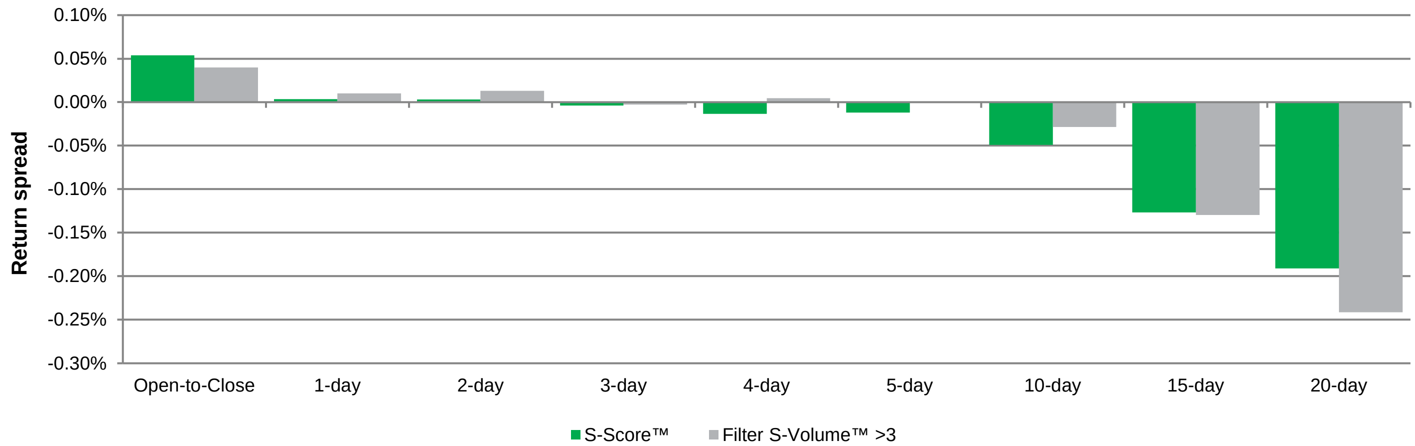
Full period time series of cumulative 1-day returns for the filtered strategies are included in the Appendix (see Figure A1). Our empirical results show a cumulative return of 177% for the S-Volume™>3 filtered buy portfolio compared to a -45% loss for the sell portfolio. Again, we remark on the skew to positive sentiment (as observed in Table A1 in the Appendix) producing a higher number of securities on average for S-Score™ >3 than <-3, a matter to be acutely aware of when implementing the signal in a portfolio.

Taking into account long-only strategies, we focus next on performance for just the buy portfolio (Table 2) and again feature the results at the extreme +3 tail (Figure 3). We remark that the portfolios remain reasonably sized for our analysis given our findings that the distribution of scores demonstrates a skew toward positive sentiment signals. Performance is reported as returns in excess of the market proxied by the SPDR S&P 500 ETF (SPY).

S-Score™ open-to-close excess returns at the +3 tail averaged 0.054%, exceeding both the +2 tail (0.042%) and decile (0.036%) strategies, with an annualized Sharpe ratio of 1.2. Under the S-Volume™ >3 filter, excess returns were somewhat stronger up to the 10-day horizon. However, results overall confirm the benefits of the signal for long-only portfolio managers as a short term signal.

Figure 3

**S-Score™ +3 tail excess returns, 1 Mar 2014 - 30 Mar 2018**




Source: IHS Markit © 2018 IHS Markit

Table 2

**S-Score™ average return spreads (%), 1 Mar 2014 – 30 Mar 2018**

| Strategy | Open-to-close (%) | 1-day (%) | 2-day (%) | 3-day (%) | 4-day (%) | 5-day (%) | 10-day (%) | 15-day (%) | 20-day (%) |
|---|---|---|---|---|---|---|---|---|---|
| S-Score™ | | | | | | | | | |
| +3 tail - SPY | 0.054 | 0.004 | 0.003 | -0.004 | -0.014 | -0.012 | -0.049 | -0.127 | -0.191 |
| +2 tail - SPY | 0.042 | -0.007 | -0.001 | -0.008 | -0.018 | -0.016 | -0.052 | -0.119 | -0.193 |
| Decile 1 - SPY | 0.036 | 0.000 | 0.011 | 0.004 | -0.006 | -0.009 | -0.047 | -0.116 | -0.193 |
| Filter S-Volume™ >3 | | | | | | | | | |
| +3 tail - SPY | 0.040 | 0.010 | 0.013 | -0.003 | 0.005 | 0.000 | -0.029 | -0.129 | -0.241 |
| +2 tail - SPY | 0.034 | -0.009 | -0.003 | -0.015 | -0.014 | -0.024 | -0.072 | -0.158 | -0.257 |
| Decile 1 - SPY | 0.027 | -0.003 | 0.010 | -0.006 | -0.008 | -0.022 | -0.072 | -0.155 | -0.249 |

Source: IHS Markit © 2018 IHS Markit

## Short-term momentum and short interest interactions

Next, we review S-Score™ interactions with short-term price momentum and short interest factors, two commonly used sentiment signals in quantitative models. For this analysis we compute factor rank correlations between S-Score™ and 5-day Industry Relative Return and Demand Supply Ratio, a measure of the amount of shares borrowed in the market relative to the lendable inventory of the stock. Note that we typically sort 5-day Industry Relative Return in ascending order given its strong predictive power as a price reversal metric; however, for this analysis we sort it in descending order to capture the actual price appreciation that may potentially explain tweet sentiment. Demand Supply Ratio is sorted in its usual ascending order, favoring the least shorted names.

We review concurrent daily correlations along with lead/lag correlations up to five days using 5-day Industry Relative Return and Demand Supply Ratio ranks as the leading signals (Table 3). Statistics are again computed over the US Total Cap universe for the full analysis period from 1 December 2011 through 29 March 2018.

The same day rank correlation between S-Score™ and 5-day Industry Relative Return (0.115) is the strongest on average. However, considering the fact that S-Score™ uses pre-market open data and 5-day Industry Relative Return uses end-of-day data, the positive correlation is, in fact, confirming the outperformance of S-Score™ open-to-close returns.

On the other hand, using 5-day Industry Relative Return as a leading signal we can test if positive sentiment reflects prior positive price momentum. Given the mostly neutral correlations observed particularly from time *t+2* (0.014) to *t+5* (-0.024), the results suggest that S-Score™ is not solely driven by price momentum and thus contains additional aspects of underlying investor sentiment.

For Demand Supply Ratio, the rank correlations are around zero across all lags. The implication is that short interest does not forecast social media sentiment.

Table 3

**S-Score™ average daily rank correlations, 1 Dec 2011 – 29 Mar 2018**

| | t | t+1 | t+2 | t+3 | t+4 | t+5 |
|---|---|---|---|---|---|---|
| 5-day Industry Relative Return | 0.115 | 0.086 | 0.014 | -0.006 | -0.016 | -0.024 |
| Demand Supply Ratio | 0.007 | 0.007 | 0.007 | 0.007 | 0.006 | 0.006 |

Source: IHS Markit © 2018 IHS Markit

Given our findings that the S-Score™ signal is not captured fully by 5-day Industry Relative Return or Demand Supply Ratio, we next test the social media signal conent across factor distributions. Our analysis is based on equal-weighted open-to-close returns using a double sorting across quintile groups (Table 4). The overlap of stocks is fairly evenly distributed across quintile groups, with slightly higher counts for stocks commonly ranked in the top and bottom quintiles with 5-day Industry Relative Return and across the top quintile for Demand Supply Ratio.

We find that S-Score™ Q1 baskets consistently outperform Q5 across each momentum and short interest quintile bucket. The largest spread for 5-day Industry Relative Return was associated with Q5, the lowest momentum bucket, with a spread of 0.125% between the positive and negative sentiment. This indicates that sentiment differentiates between price reversals and further price deterioration among the stocks performing the worst. For Demand Supply Ratio, the largest spread also occurred in Q5 at 0.106%. Thus, we find added value by applying the social media sentiment on top of these signals.

Table 4

**Average open-to-close returns (%) across 5-day Industry Relative Return and Demand Supply Ratio, 1 Dec 2011 – 29 Mar 2018**

| | | High S-Score™ | | | | Low S-Score™ | |
|---|---|---|---|---|---|---|---|
| | | Q1 | Q2 | Q3 | Q4 | Q5 | Q1-Q5 spread |
| High momentum | Q1 | -0.001 | 0.010 | -0.002 | -0.009 | -0.048 | 0.047 |
| | Q2 | 0.062 | 0.016 | 0.015 | 0.015 | -0.005 | 0.068 |
| | Q3 | 0.066 | 0.041 | 0.022 | 0.015 | 0.000 | 0.067 |
| | Q4 | 0.091 | 0.026 | 0.034 | 0.015 | -0.006 | 0.097 |
| Low momentum | Q5 | 0.073 | 0.003 | -0.014 | -0.030 | -0.051 | 0.125 |
| Least shorted | Q1 | 0.054 | 0.033 | 0.031 | 0.029 | 0.013 | 0.042 |
| | Q2 | 0.076 | 0.049 | 0.037 | 0.027 | 0.012 | 0.064 |
| | Q3 | 0.079 | 0.029 | 0.037 | 0.014 | 0.013 | 0.066 |
| | Q4 | 0.060 | 0.017 | 0.018 | 0.022 | -0.018 | 0.078 |
| Highest shorted | Q5 | -0.012 | -0.031 | -0.064 | -0.080 | -0.118 | 0.106 |

Source: IHS Markit © 2018 IHS Markit

## Market sentiment

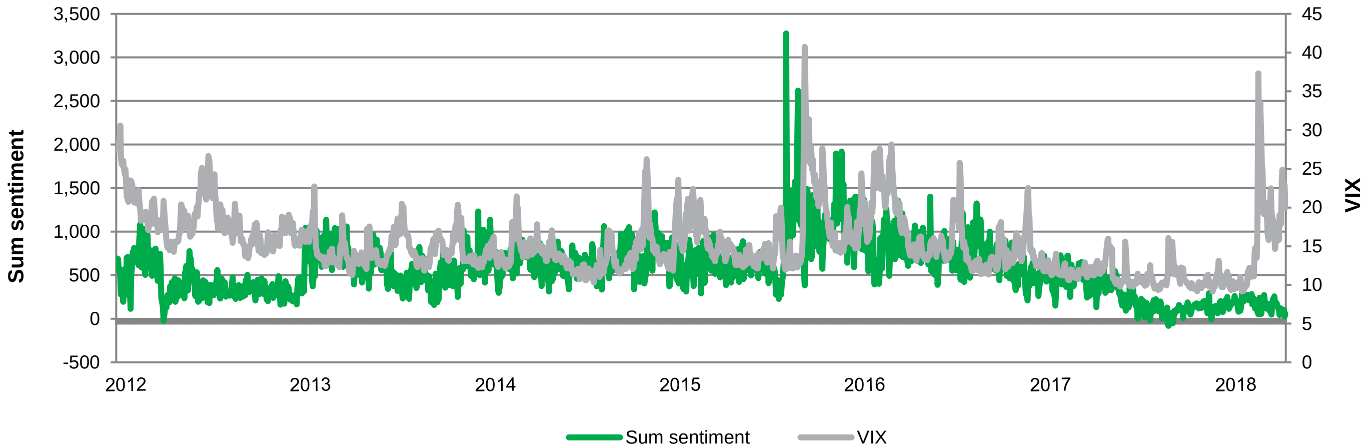
Lastly, we move beyond stock level sentiment and consider aggregated raw sentiment scores at the market level, and the ability to use market sentiment to forecast market returns and volatility, measured by the S&P 500 (SPX) and VIX, respectively. First, we aim to replicate results found in Deutsche Bank's 2017 paper on the SMA data, which found correlation between the VIX and an aggregated Social Media Sentiment Index. For this analysis, we sum daily Raw-S values across the US Total Cap universe, measuring the average sentiment per tweet at the market level. For reference, time series of monthly average sentiment per tweet, computed as the ratio of aggregate sentiment versus the sum of S-Volume™, and aggregate volume is included in the Appendix (see Figures A2 and A3, respectively), where we remark on the increase in volume in mid-2015 as SMA increased their confirmed accounts used in tweet sentiment estimates.

Following their methodology, we confirm a positive correlation between social media sentiment levels and VIX (Figure 4), and a negative correlation between the sentiment index and SPX (Figure 5). However, we note that these three time series are non-stationary, so we turn to correlations between daily changes in the index levels, as well as lead-lag relationhips with changes in market sentiment (Table 5). As an example to add more clarity to the interpretation of the data, the VIX 1-day lag correlation of -0.03 with sum sentiment (upper left value in the table) is the correlation between the daily change in the sum of sentiment with the VIX change from the prior day.

Overall, the results reveal weak correlations between the changes in sentiment and changes in VIX and SPX. The strongest relationship occurs between contemporaneous changes in sentiment and VIX (-0.09), where the negative relationship indicates that when the VIX is down sentiment is up, which makes intuitive sense. We also find a similarly strong relationship with contemporaneous change in SPX and change in sentiment (0.07). As the time frame is extended, the relationships disappear, with very low correlations between sentiment and future VIX and SPX changes. We conclude that overall market sentiment cannot be used to forecast changes in VIX nor changes in expected market returns.

Figure 4

**Sum sentiment and VIX**

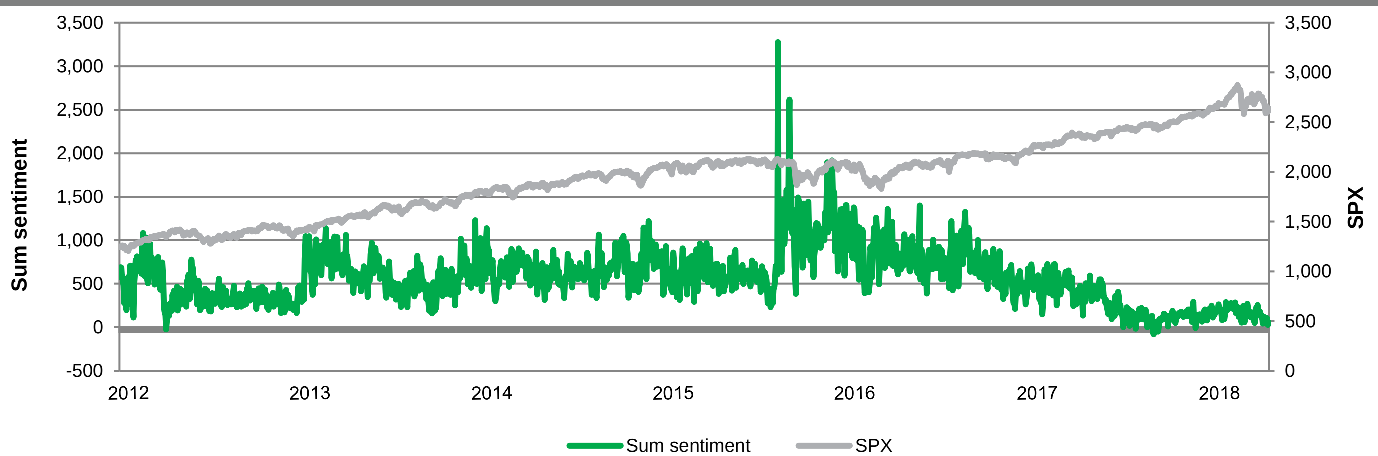



Source: IHS Markit



Figure 5

**Sum sentiment and SPX**




Source: IHS Markit

Table 5

**Correlations of 1-day changes in S-Score™ with 1-day changes in VIX and SPX, 1 Dec 2011 – 29 Mar 2018**

| | Sum sentiment | Sum volume | Average sentiment |
|---|---|---|---|
| VIX 1-day lag | -0.03 | 0.04 | -0.04 |
| VIX | -0.09 | -0.05 | -0.09 |
| VIX +1 day | 0.02 | -0.02 | 0.02 |
| VIX +2 day | 0.01 | 0.01 | 0.00 |
| SPX 1-day lag | 0.02 | 0.02 | 0.03 |
| SPX | 0.07 | 0.02 | 0.08 |
| SPX +1 day | 0.00 | -0.01 | 0.00 |
| SPX +2 day | -0.02 | 0.00 | -0.02 |

Source: IHS Markit



## Conclusion

We revisit our social media indicators sourced in partnership with SMA which analyzes social media data streams to estimate market sentiment. The factors are based on analysis of the text content in daily Twitter posts which are filtered for financial trading relevance and scored for market sentiment content.

We focus on the main predictive factors, S-Score™, along with applying a filter for a minimum S-Volume™ of 3 to adjust the S-Score™ signal for confirmed information content in addressing random effects that may arise from sparse tweets. S-Score™ open-to-close return spreads at the +/-3 tail averaged 0.163%, persistent to 5-day (0.073%) and 10-day (0.051%) holding periods. On a cumulative basis, we report a return of 179% for buy-rated stocks versus -14% for sell-rated stocks and 135% for the market.

Focusing again on +/-3 tail performance with the S-Volume™ >3 filter, average open-to-close spreads improved to 0.215%, and continued to exceed the stand-alone factor results at each holding period. The open-to-close returns cumulated to 177% for the S-Volume™>3 filtered buy portfolio compared to a -45% loss for the sell portfolio.

Next, considering application to long-only strategies and in light of the skew to positive sentiment which produces a higher number of securities on average at positive tails, we review excess returns for the buy portfolios. S-Score™ open-to-close excess returns at the +3 tail averaged 0.061%. Excess returns were somewhat weaker under the S-Volume™ >3 filter, however, results overall confirm the benefits of the signal for long-only portfolio managers.

We also review S-Score™ interactions with short-term momentum and short selling activity based on factor rank correlations with 5-day Industry Relative Return and Demand Supply Ratio, respectively, as leading signals. The mostly neutral correlations observed across all lags for Demand Supply Ratio and particularly from time $t+2$ (0.014) to $t+5$ (-0.024) for 5-day Industry Relative Return suggest that social media signals are not captured by price movement or short interest and thus contain additional aspects of underlying investor sentiment. In addition, we find added value by applying the social media sentiment on top of these signals as S-Score™ differentiates outperformers from underperformers across high and low momentum and short interest quintile baskets.

Lastly, we test for a relationship between aggregated sentiment scores at the market level and VIX and SPX. We confirm a positive correlation between social media sentiment levels and VIX and a negative correlation with SPX. We also find a negative relationship between VIX changes and sentiment changes, and a positive relationship between market returns and VIX changes, though the correlation with future SPX and VIX changes is very low, indicating that sentiment is not a useful predictor of future changes in market returns and volatility.

# Appendix

## SMA factor methodology

Our social media data is sourced from SMA, which analyzes social media data streams to estimate market sentiment. More specifically, metrics are estimated from analysis of Twitter message stream that are converted into actionable indicators in their family of measures called S-Factors™, designed to capture the signature of financial market sentiment. However, not all tweets for a particular stock are useful. Only tweets that pass SMA's filtering processes and identified as "indicative" tweets posted by confirmed accounts are used in sentiment estimates.

The methodology involves a 3-step process:

1) The **Extractor** collects tweet content and source information using a source agnostic retrieval platform that extracts all signals for designated financial terms and symbols. SMA's servers poll API's of Twitter and GNIP with access to over 500 million daily tweets.
2) The **Evaluator** filters the tweets to only include "indicative" tweets, those with relevant sentiment to the particular stock. The process utilizes established Natural Language Processing algorithms, enhanced and tuned for performance in the domain of financial markets. The Evaluator identifies words, phrases and stock symbols in the captured tweets, then removes duplicates and applies re-tweet policies to reduce the noise level of the tweet stream from sources such as "spamming" users. Lastly, it analyzes the set of relevant tweets with respect to SMA ratings for the Twitter accounts that are the originators of the captured tweets.
3) The **Calculator** analyzes the tweet language using a Sentiment Dictionary tuned for performance in the financial market domain with relevant, industry-specific terms. Sentiment level for each word parsed from a tweet is obtained from the dictionary. SMA's Sentiment Dictionary uses a multi-pass approach by identifying phrases that have content and sentiment levels of relevance to financial market activity. Raw sentiment level is the simple aggregate of all indicative tweet sentiment levels captured during the prior 24 hours. Lastly, a normalization and scoring process calculates the final sentiment measures.

## Tables and figures

Table A1

**S-Score™ average counts, 1 Dec 2011 – 30 Mar 2018**

| Strategy | Buy portfolio | Sell portfolio |
|---|---|---|
| S-Score™ | | |
| +/-3 tail | 67 | 28 |
| +/-2 tail | 152 | 73 |
| Decile | 156 | 158 |
| Filter S-Volume™ >3 | | |
| +/-3 tail | 41 | 15 |
| +/-2 tail | 96 | 40 |
| Decile | 101 | 87 |

Source: IHS Markit

Table A2

**S-Score™ average return spreads (%), 1 Dec 2011 – 30 Mar 2018**

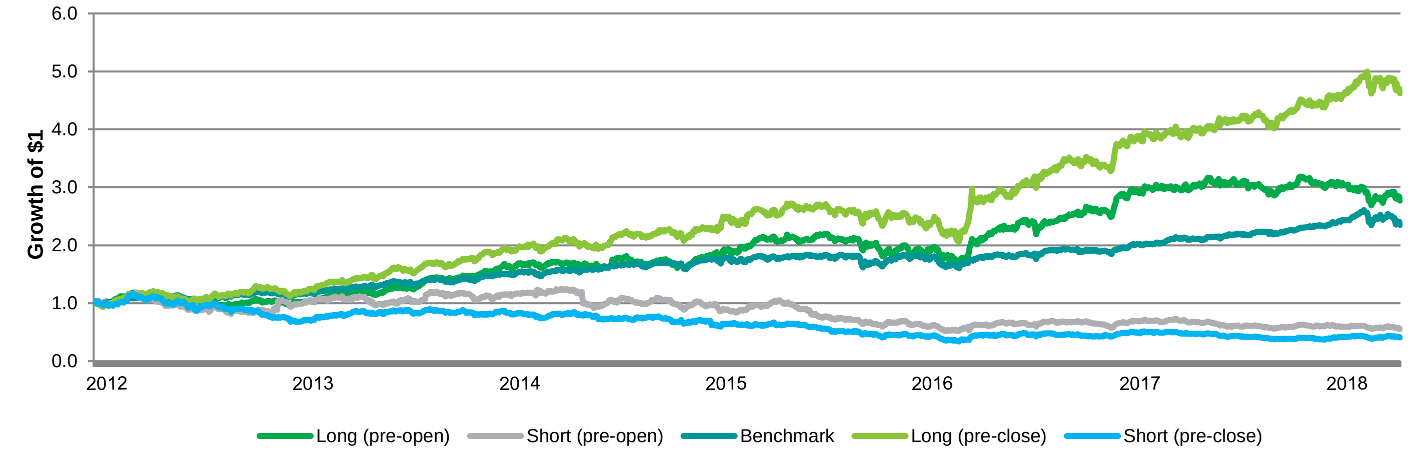
| Strategy | Open-to-close (%) | 1-day (%) | 2-day (%) | 3-day (%) | 4-day (%) | 5-day (%) | 10-day (%) | 15-day (%) | 20-day (%) |
|---|---|---|---|---|---|---|---|---|---|
| S-Score™ | | | | | | | | | |
| +/-3 tail spread | 0.163 | 0.073 | 0.054 | 0.063 | 0.060 | 0.073 | 0.051 | 0.027 | -0.014 |
| +/-2 tail spread | 0.126 | 0.039 | 0.027 | 0.025 | 0.034 | 0.034 | 0.069 | 0.078 | 0.053 |
| Decile spread | 0.104 | 0.032 | 0.038 | 0.047 | 0.056 | 0.059 | 0.085 | 0.105 | 0.081 |
| Filter S-Volume™ >3 | | | | | | | | | |
| +/-3 tail spread | 0.215 | 0.096 | 0.090 | 0.084 | 0.076 | 0.101 | 0.100 | 0.115 | 0.0132 |
| +/-2 tail spread | 0.170 | 0.044 | 0.032 | 0.028 | 0.045 | 0.064 | 0.104 | 0.143 | 0.125 |
| Decile spread | 0.138 | 0.042 | 0.054 | 0.056 | 0.069 | 0.075 | 0.113 | 0.147 | 0.103 |

Source: IHS Markit



Figure A1

**S-Score™ +/-3 tail with S-Volume™ >3 filter daily cumulative return**

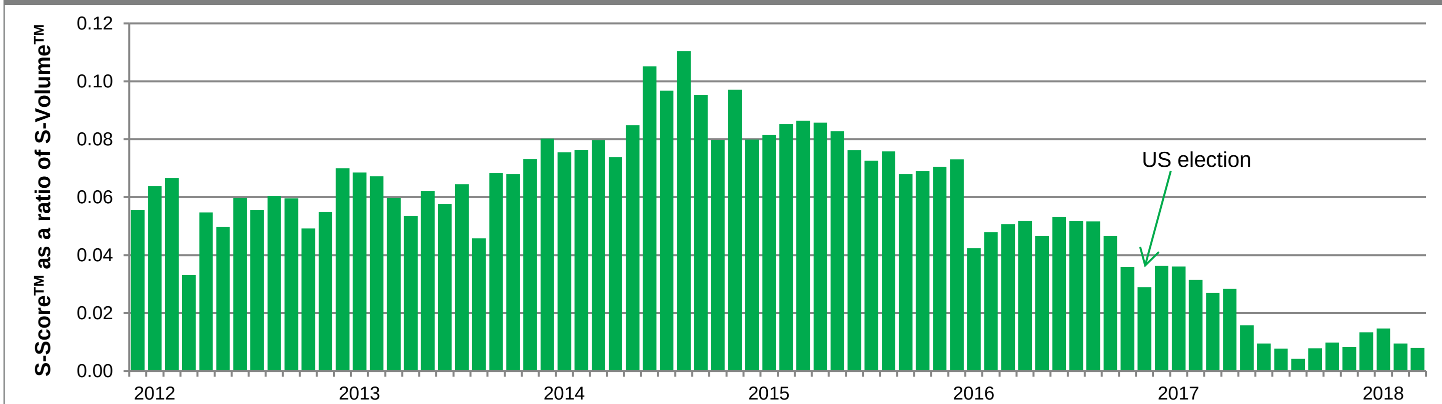



Source: IHS Markit



Figure A2

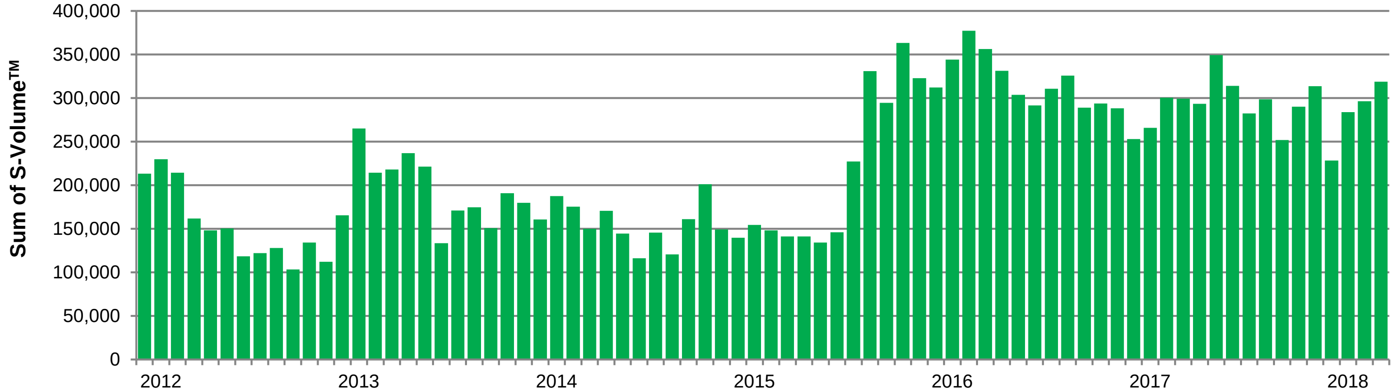
**Aggregate market sentiment**




Source: IHS Markit

Figure A3

**Aggregate volume**




Source: IHS Markit



# References

Deutsche Bank Securities Inc. “Translating Words to Numbers”, 16 June 2017.

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