Natural Language Processing – Part II: Stock Selection

Alpha Unscripted: The Message within the Message in Earnings Calls

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Astute investors have shifted their attention to explore the information content in unstructured data sets to differentiate their alpha[1]. S&P Global Market Intelligence's earnings call transcripts data is one such example that may offer that differentiated source of alpha. In this paper, we explore and highlight a number of **sentiment- and behavioral-based alpha insights** first introduced in our NLP primer. This work provides empirical support by enumerating the profitability of those insights in the U.S. market. High-level findings from this report include:

- **Sentiment-based signals**: Firms whose executives and analysts exhibited the **highest positivity in sentiment**[2] during earnings calls outperformed their counterparts by 4.14% annually with significance at the 1% level. Firms with the **largest year-over-year positive sentiment change** and firms with the **strongest positive sentiment trend** outperformed their respective counterparts by 3.07% and 3.96% annually with significance at the 1% level (Exhibit 3).

- **Behavioral-based signals:** Firms whose executives provided the most transparency by using the **simplest language** and by **presenting results with numbers** outperformed their respective counterparts by 2.11% and 4.43% annually with significance at the 1% level (Exhibit 6).

- **Sentiment- and behavioral-based signals are not subsumed by commonly used alpha and risk signals**. After adjustments[3], the signals generated excess long-short returns ranging from 1.65% to 3.64% annually with significance at the 1% level (Exhibit 14). The sentiment- and behavioral-based signals had some of the **highest information ratios** among all considered strategies (Exhibit 4) and are lowly and negatively correlated with each other (Exhibit 15).

- Positive language from **the unscripted responses by the executives during the Q&A drove the overall predictability** of the positive sentiment signal (Exhibit 5).

- The **sentiment of CEOs has historically been more important than the sentiment of other executives** (Exhibit 9). A strategy based on the sentiment of CEOs generated 3.63% per year on a long-short basis with significance at the 1% level (Exhibit 7).

- **The aggregate sentiment of analysts historically enhanced the predictability of the 3-month FY1 EPS analyst revision signal** (Exhibit 11). A strategy using the aggregate sentiment of analysts from earnings calls yielded 4.24% per year on a long-short basis with significance at the 1% level (Exhibit 10).

[1] Other examples may be more sophisticated modeling (e.g., non-linear) and execution efficiency.
[2] Positive sentiment is defined using Loughran & McDonald's dictionary (Exhibit 1).
[3] A.1 Factor Definitions

1. Introduction

There has been an industry-wide push into unstructured data sets[4] as investors race to harness the information content in these newly created, voluminous data points to gain an informational edge. With a myriad of data sets in existence and the list only growing, where should investors prioritize their efforts?

Our view is that not all unstructured data sets are created equal. They could be binned into two categories: primary versus non-primary. Primary in this context is defined as: i) the data is the **furthest up the information chain containing the most relevant and most timely information**; ii) the data has **an unequivocal relation to publicly traded firms** or could be easily rolled up to them; iii) the data contains information that **sheds light on the future prospects** of those firms.

One such example is the earnings call transcripts data, as it contains first-hand, relevant information that is unequivocally related to the firm that holds the call. The call contains forward looking elements that may be telegraphed **directly** - for instance via the sentiment of the executives who speak during the call, or may be telegraphed **indirectly** - for instance via the level of transparency that the executives provide during the call such as the simplicity of their language or the abundance of references to numbers.

The following sections discuss the elements of an earnings call, the intuitions underlying our signal construction, and the empirical results of our earnings call transcript research.

2. Earnings Calls

The table below highlights some of the unique features and the nuances of the earnings call transcripts data set that is reflected in the construction of our stock selection signals.

Description	A conference call between the management of a publicly traded company, sell-side analysts and other attendees to discuss the firm's latest financial results
Major Sections	Three major sections: i) **prepared remarks** by executives ii) **questions** by sell-side analysts iii) **unscripted responses** by executives to analysts' questions
Major Participants	Executives (predominately CEOs and CFOs) and analysts; Executives say about 83% of all words (43% in the prepared remarks). Analysts say about 16% of the words in the form of questions (Exhibit A.2).

[4] See Section 2.1.2 in the NLP primer for details.

Length	Average length is 48 minutes (Exhibit A.3).
Sentiment	Average sentiment on calls is positive since calendar Q1 2008 and as of Q4 2017 it is at the highest level in the past 10 years (Exhibit A.4).

Source: S&P Global Market Intelligence Quantamental Research, as of 02/01/2018.

3. Signals, Intuition & Construction

The stock selection signals in this paper are separated into two categories: sentiment- and behavioral-based. Our **ex-ante hypothesis for sentiment-based signals** is that firms whose calls exhibit the most positivity should outperform historically. Our **ex-ante hypothesis for behavioral-based signals** is that when firms experience financial distress whether transitory or otherwise, executives may soften the bad news by providing different degrees of transparency that are telegraphed directly or indirectly in ways that can be captured quantitatively.

3.1 Sentiment-Based Signals

We leverage the work of Loughran & McDonald's (LM) sentiment word lists to construct four proxies of sentiment level: **positivity**, **negativity**, **net positivity** and **positivity-to-negativity** (see Exhibit 1). Throughout the paper, we show empirical results for sentiment-based signals that use one or more of these four base metrics as inputs.

Exhibit 1: Four Proxies to Measure Sentiment Level

Signal	**Construction**	**Sort Order**	**Intuition**
Positivity	# positive words / # total words	D	The frequency of usage of positive words by executives in an earnings call may reveal their (true) sentiment about their firm's future prospects
Negativity	# negative words / # total words	A	Executives use negative words in an earnings call when compelled to fulfill legal or fiduciary obligations; the absence of negative words is viewed favorably in our narrative
Net Positivity	(# positive words - # negative words) / # total words	D	Takes into account both positive and negative words
Positivity to Negativity	# positive words / # negative words	D	Similar to net positivity but amplifies the magnitude of the difference between positive and negative word frequency

Note: D = descending sort; A = ascending sort

Source: S&P Global Market Intelligence Quantamental Research, as of 02/01/2018.

Then, the four base metrics from above are used in the following three-ways:

i) **Sentiment level** (Exhibit A.5 for formula)

ii) **Year-over-year (YoY) change in sentiment level** (Exhibit A.5 for formula)

- To mitigate the impact of seasonality in a firm's business performance with retailers as the most pronounced example such that the comparison between the two quarters is more comparable.

iii) **Change in sentiment trend relative to the previous eight calls** (Exhibit A.5 for formula)

- The intuition is that the sentiment trend signal is able to capture inflection points and accelerations better.

3.2 Behavioral-Based Signals

Language complexity, **presenting using more numbers** and **analyst favoritism** are three examples of indirect signals that may occur during a call that telegraphs the level of transparency that a firm is willing to provide. A high level of transparency in our narrative is viewed favorably.

3.2.1 Language Complexity: Gunning Fog Index

We use the **Gunning fog index** as a proxy for language complexity. It has two inputs: **average words per sentence** and **the proportion of polysyllabic words in a call** where we deem words that have three syllables or more as polysyllabic. The Gunning fog index outputs an integer value between 10 and 18 inclusive where each integer can be interpreted as the number of years of formal education one needs in order to understand a text. For example, a value of 16 signifies the need for a bachelor's degree in order to understand the text (Exhibit 2 for formula).

3.2.2 Presenting Results with More Numbers

A second way that executives may soften bad news is through the use of numbers in their presentation. One way to capture this is using the **proportion of numerical values that are presented on a call**. Intuitively, words are imprecise. While numbers could still be distorted they are less subject to distortion and interpretation. **An abundant usage of numbers in a call is viewed favorably in our narrative and suggests the firm is exuding objectivity, transparency and confidence about their future prospects** (Exhibit 2 for formula).

3.2.3 Analyst Favoritism

A third way that executives may soften bad news is through **analyst favoritism**[5], i.e., whether a firm is picking the most bullish analysts to ask questions. Intuitively, if a firm is experiencing financial distress whether transitory or not, executives at the firm may call on select analysts who are more optimistic on the firm's future prospects and may ask questions that are easier to answer. Specifically, we **define favoritism by comparing the**

[5] Cohen, L., Lou D. and Malloy C. J. "Playing Favorites: How Firms Prevent the Revelation of Bad News." SSRN August 13 2014 https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2479542

average difference in percent terms of FY1 EPS forecast, price target or stock recommendation[6] between the group of analysts who are selected to ask questions and the group of analysts who are not (See Exhibit 2 for formula).

Exhibit 2: Construction and Intuition of Behavioral-Based Signals

Signal	Construction	Sort Order
Transparency: Language Complexity	Gunning Fog Index = 100 * (average words per sentence + % of polysyllabic words in a call) where the polysyllabic cutoff is 3+ syllables	A
Transparency: Presenting Using More Numbers	Ratio = Numerical Tokens / Total Word Tokens	D
Transparency: Analyst Favoritism	% Difference = (A – B) / Abs(B) • A = average metric of analysts called on • B = average metric of analysts not called on • metric = {FY1 EPS estimate, price target, numerical stock recommendation}	A

Note: D = descending sort; A = ascending sort

Source: S&P Global Market Intelligence Quantamental Research, as of 02/01/2018.

4. Empirical Results

Earnings calls are events[7] that occur on different dates. In order to have achieve breadth in the cross-section, we apply a look-back window of four calendar months to construct each of our monthly rebalancing strategies. For example, at the end of April when we are rebalancing and constructing our portfolio, we look at all calls that have taken place since January of the same year and extract the information that is from the most recent earnings call to construct the signal for a stock. At the end of May, we construct our portfolio by looking back as far as February.

All long-only and long-short returns in our back-test are equal-weighted, are rebalanced monthly at month end and are binned into quintiles where the top (bottom) quintile or the long (short) portfolio contains the 20% of stocks with the best (lowest) signal ranks in the cross-section. All signals are industry-neutral (GICS Level 3) to mitigate industry tilts. The **definitions of columns** in the exhibits containing back-test results are in Exhibit A.6.

[6] It is based on a 1-5 scale where 1 is strong buy and 5 is strong sell. The scale is historically standardized across brokers and takes into account scale changes at brokers.
[7] Generally, event-driven signals lack a sufficient number of stocks for portfolio construction and the timing of the next event is unknown.

4.1 Results - Sentiment Based Signals

Historically, **sentiment level, change in sentiment level and change in sentiment trend where sentiment is defined as the proportion of LM's positive words in a call are historically predictive of future stock returns in the Russell 3000 universe (see rows 1, 3, 5 in Exhibit 3)** since May 2010[8]. This suggests that empirically sentiment may be another driver of future stock returns in the cross-section in addition to value, momentum, quality and so forth. In section 5, we will examine whether the results of the sentiment-based signals are subsumed by value, momentum and quality signals. Results for sentiment-based signals where the sentiment is defined using negativity, net positivity or positivity-to-negativity can be found in the appendix (starting in A.10).

The second noteworthy observation is that the long-sides of the sentiment-based strategies contribute meaningfully and significantly (i.e., >50%) to the overall long-short strategies (compare the values in column 6 to the values in column 9 in Exhibit 3), which is desirable since there are impediments against shorting stocks.

Exhibit 3: Sentiment-Based Signals
where sentiment = # of LM's positive words in a call
Russell 3000 May 2010 – December 2017

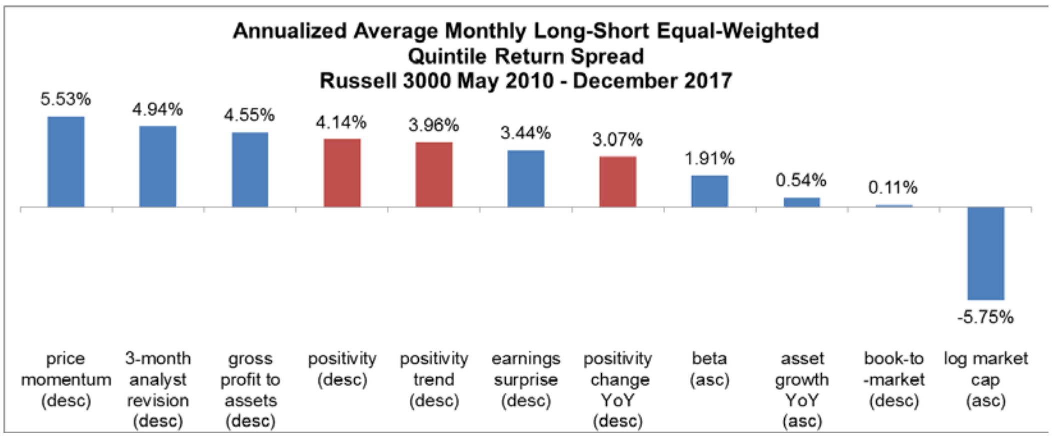
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Sentiment-Based Signals	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Positive Level	D	201005	494	0.016	67.4%	2.35%	1.26	64.1%	4.14%	1.56	65.2%
[2]	p-value	NaN	NaN	NaN	0.000	0.001	0.001	NaN	0.005	0.000	NaN	0.002
[3]	YoY Change in Positive Level	D	201005	446	0.011	64.1%	1.32%	0.72	59.8%	3.07%	1.10	58.7%
[4]	p-value	NaN	NaN	NaN	0.000	0.005	0.048	NaN	0.047	0.003	NaN	0.076
[5]	Change in Positive Trend from previous 8 calls	D	201005	425	0.011	67.4%	2.48%	1.27	60.9%	3.96%	1.48	65.2%
[6]	p-value	NaN	NaN	NaN	0.000	0.001	0.001	NaN	0.028	0.000	NaN	0.002

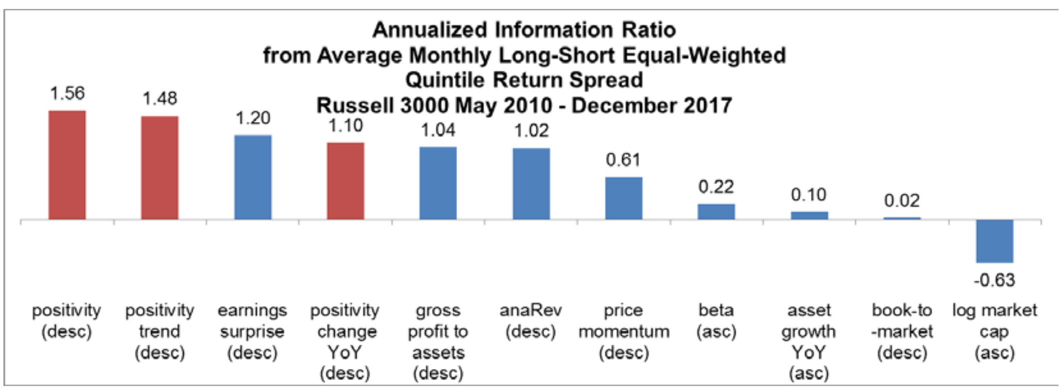
Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

[8] Earnings call transcripts data starts in 2008. In the body of the paper, we show results starting in May 2010 such that results for sentiment level, change in sentiment level and change in sentiment trend have the same sample period. See results in A.3 starting in May 2008 where available.

Third, the economic performance of the sentiment-based signals may appear modest with annualized long-short return spreads ranging from 307 to 414 basis points (bps). However, when the economic performance of these signals is compared to that of commonly used alpha and risk signals such as value, momentum and quality, the economic performance of the sentiment-based signals is comparable in the sample period (Exhibit 4). The sentiment-based signals, however, have some of the highest information ratios (i.e., a measure of risk-and-reward tradeoff) among all strategies during our sample period. **This suggests that the sentiment-based strategies had a higher consistency of yielding positive economic performance on a monthly basis** in our sample period (Exhibit 4).

Exhibit 4: Economic Performance and Information Ratio of Sentiment-Based Signals
Russell 3000 May 2010 – December 2017





See A.1 Factor Definitions. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

Which Section is More Important - Prepared Remarks versus Q&A?

In this section, we deconstruct each of the calls into its prepared remarks and the Q&A section to ascertain which of the two is driving the overall predictability, if any.

Our results indicate that it is the positivity from the responses during the Q&A section that is the driving force. It seems intuitive that investors would value the Q&A section more, since it is in a live unscripted setting where executives have little choice but to answer the questions in a timely manner. Under such conditions, their unscripted answers may reveal their true sentiment intentionally or otherwise regarding the future prospects of the firm.

The economic performance at the overall call level is almost entirely driven by the economic performance of the responses by the executives during the Q&A. The positivity in the prepared remarks historically seems to dilute the predictive power at the overall call level (Exhibit 5).[9]

Exhibit 5: Prepared Remarks vs. Answers during the Q&A

Russell 3000 May 2010 – December 2017

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Sentiment-Based Signals: Prepared Remarks vs. Answers during Q&A	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Positive Level	D	201005	494	0.016	67.4%	2.35%	1.26	64.1%	4.14%	1.56	65.2%
[2]	p-value	NaN	NaN	NaN	0.000	0.001	0.001	NaN	0.005	0.000	NaN	0.002
[3]	Positive Level Prepared Remarks	D	201005	493	0.013	64.1%	1.09%	0.52	57.6%	2.39%	0.86	60.9%
[4]	p-value	NaN	NaN	NaN	0.000	0.005	0.155	NaN	0.117	0.019	NaN	0.028
[5]	Positive Level Q&A Answers	D	201005	479	0.016	73.9%	2.04%	1.14	59.8%	4.02%	1.47	67.4%
[6]	p-value	NaN	NaN	NaN	0.000	0.000	0.002	NaN	0.047	0.000	NaN	0.001

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

Discordance in Sentiment between the Prepared Remarks and the Q&A Section

The results from Exhibit 5 above beg the question to what happens when there is discordance in sentiment between the prepared remarks and the responses during the Q&A. Intuitively, the prepared remarks are carefully crafted and well-rehearsed. They tend to paint the firm in the best light even if it is unwarranted. It is during the Q&A where the true sentiment of executives may surface. Our ex-ante hypothesis is that firms exhibiting the largest difference or percent change in terms of sentiment between the responses during the

[9] The average market-adjusted long returns and long-short returns between the prepared remarks and the Q&A sections are not statistically significant even at the 10% level, however.

Q&A and the prepared remarks should outperform historically. Empirically, however, signals that try to capture the discordance in sentiment between the two sections do not seem to generate any meaningful historical predictive results (appendix A.13).

4.2 Results - Behavioral-Based Signals

Historically, firms whose executives used more basic language outperformed those firms whose executives used more complex language by about 211 bps annually at the 5% significance level (see row 1 Exhibit 6). Firms whose executives used more numbers when presenting results during the prepared remarks outperformed firms whose executives used less numbers historically yielding 443 bps per year (see row 3 Exhibit 6). Firms whose executives selectively picked on the most bullish analysts, however did not underperform (nor outperform) historically.

Exhibit 6: Behavioral-Based Signals

Russell 3000 May 2010 – December 2017

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Behavioral-Based Signals	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Language Complexity - Gunning fog index	A	201005	494	0.009	62.0%	0.72%	0.42	53.3%	2.11%	0.82	57.6%
[2]	p-value	NaN	NaN	NaN	0.000	0.016	0.244	NaN	0.466	0.025	NaN	0.117
[3]	Concreteness - % Numerical Tokens in Prepared Remarks	D	201005	493	0.013	69.6%	1.99%	1.13	58.7%	4.43%	1.58	67.4%
[4]	p-value	NaN	NaN	NaN	0.000	0.000	0.002	NaN	0.076	0.000	NaN	0.001
[5]	Transparency - Analyst Conviction Dispersion in FY1 EPS Forecasts	A	201005	280	0.011	65.2%	-0.38%	-0.14	44.6%	3.45%	0.83	55.4%
[6]	p-value	NaN	NaN	NaN	0.022	0.002	0.706	NaN	0.251	0.023	NaN	0.251

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

What our results do show is that firms where the collective forecasts of analysts, who are called on to ask questions, have the least discordance outperformed historically (see row 5 Exhibit 6) by 345 bps annually on a long-short basis at the 5% significance level. One plausible explanation is that firms whose executives provide more transparency result in a smaller discordance in analyst forecasts because analysts need to make less (subjective) assumptions (Ang and Ciccone (2001); Ali, Liu, Xu and Yao(2012)) in their modeling. One metric that may measure the level of transparency at a firm is one of the behavioral-based signals that we introduced earlier – presenting with more numbers. The return correlation between this signal and the low discordance in analyst forecasts signal historically yields a fairly strong positive correlation of 0.54 (Exhibit 15). This suggests that firms whose executives presented with more numbers also had lower discordance in analyst forecasts.

Like the sentiment-based signals, the behavioral-based signals had modest economic performance since May 2010 ranging from 211 bps to 443 bps on a long-short return basis. The signal presenting with more numbers performed the best historically with the highest information ratio of 1.58 among all signals (Exhibit A.16).

4.3 Executives and Sentiment

In this section, executive speaker type is examined. The executives are identified in the earnings call data set via meta-tags which connect earnings call transcripts to S&P Global Market Intelligence's Professionals data set (e.g., Tim Cook is the current CEO of Apple Inc. and his historically unique professional identifier tag is 169601).

Which Executives Appear on Calls?

We limit our analysis to executives with the word 'Chief' in their title and who are on the earnings calls (i.e., say at least one word). We bin the executives into three buckets: Chief Executive Officer (CEO), Chief Financial Officer (CFO) and non-CEO and non-CFO C-Suite executives.[10] CEOs and CFOs appear on almost every call - approximately 96.4% and 96% of the times, respectively.[11]

Is Executive Sentiment Historically Predictive?

Our results suggest that sentiment level, sentiment change, and sentiment trend where sentiment is defined as the proportion of LM's positive words spoken by the CEOs and CFOs have all been historically predictive of future stock returns (Exhibit 7 and 8). The findings reinforce and serve as an additional robustness check on our earlier results at the overall call level, since executives in aggregate speak about 83% of all words on calls. When neither a firm's CEO nor CFO appears on a call, the signals that capture the aggregate sentiment for non-CEO and non-CFO C-Suite executives are historically just noise (see A.18).

[10] (see list here A.17)

[11] % CEO present = 477/495 = 96.4% and % CFO present = 475/495 = 96.0% where 477 (475) are the average firm counts in a quintile bin where CEOs (CFOs) spoke during earnings calls since May 2012. 495 is the average firm count in a quintile bin since May 2012 where firms had earnings calls.

Exhibit 7: Sentiment Level and Sentiment Change
Russell 3000 May 2012 – December 2017

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	CEO Sentiment	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Positivity	D	201205	477	0.013	73.5%	2.27%	1.10	58.8%	3.63%	1.30	67.6%
[2]	p-value	NaN	NaN	NaN	0.000	0.000	0.011	NaN	0.114	0.003	NaN	0.002
[3]	YoY Positivity Change	D	201205	429	0.006	60.3%	1.02%	0.62	57.4%	2.04%	0.94	61.8%
[4]	p-value	NaN	NaN	NaN	0.030	0.068	0.146	NaN	0.182	0.029	NaN	0.038
[5]	Positivity Trend	D	201205	404	0.006	63.2%	1.13%	0.54	60.3%	1.86%	0.81	60.3%
[6]	p-value	NaN	NaN	NaN	0.027	0.021	0.199	NaN	0.068	0.059	NaN	0.068

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

Exhibit 8: Sentiment Level and Sentiment Change
Russell 3000 May 2012 – December 2017

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	CFO Sentiment	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Positivity	D	201205	475	0.013	66.2%	1.58%	0.81	60.3%	3.02%	0.97	66.2%
[2]	p-value	NaN	NaN	NaN	0.004	0.005	0.059	NaN	0.068	0.024	NaN	0.005
[3]	YoY Positivity Change	D	201205	419	0.007	61.8%	0.92%	0.57	52.9%	1.82%	0.75	57.4%
[4]	p-value	NaN	NaN	NaN	0.019	0.038	0.180	NaN	0.545	0.077	NaN	0.182
[5]	Positivity Trend	D	201205	399	0.007	61.8%	1.81%	1.00	61.8%	3.00%	1.40	63.2%
[6]	p-value	NaN	NaN	NaN	0.015	0.038	0.020	NaN	0.038	0.001	NaN	0.021

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

Which Sentiment Is More Important – CEO's or CFO's?

The economic performance of sentiment for CEOs and CFOs is comparable in our sample period.[12] One question comes to mind is whether the sentiment of CEOs is more or less important than the sentiment of CFOs.

We assess the importance of the two sets of the signals that capture the aggregate sentiment of the CEOs and the CFOs by controlling one against the other and see whether one subsumes the other. **Our results indicate that it is the sentiment of CEOs that is**

[12] The average market-adjusted long returns and long-short returns between the CEOs positivity and the CFOs positivity are not statistically significant even at the 10% level, however.

historically the most meaningful or predictive whereas the sentiment of CFOs gets attenuated or subsumed completely by the sentiment of CEOs. See Exhibit 9.

Exhibit 9: Sentiment Level and Sentiment Change
Russell 3000 May 2012 – December 2017

Positive Sentiment	CEO Standalone	CFO Standalone	CEO Controlled for CFO	CFO Controlled for CEO
annualized long-short returns	4.36%	2.75%	4.05%	1.59%
t-statistic	4.29	2.22	4.01	1.27

Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

Is Sentiment Discordance between CEO and CFO Meaningful?

One plausible explanation of the similarities in the economic performance of sentiment-based signals between the CEOs and the CFOs is the pre-call coordination between the CEO and the CFO to present a unified front. Despite the best coordination, there may be a (unintentional) divergence during a call especially during the Q&A.

Is sentiment discordance between the CEO and the CFO of a firm on a call meaningful? Our ex-ante hypothesis is that the CFO knows the financials most intimately. When the CFO of a firm exhibits more (less) positivity, the extra positivity gives additional (less) credence to the CEO's sentiment. Our results suggest that firms whose CFO is more negative than the CEO (on a percent change basis) historically underperform (row 7 in appendix A.21).

4.4 Sell-Side Analysts and Sentiment

In this section, we explore the aggregate sentiment of sell-side analysts from their questions to assess its historical predictability and to explore the interaction between analyst sentiment and analyst revision. The analysts are identified in the earnings call data set via meta-tags which connect earnings call transcripts to S&P Global Market Intelligence's Estimates data set which contains analyst-level estimates.

Our results indicate that relative to analyst sentiment change and analyst sentiment trend, analyst sentiment level performs the best with an annualized long-short return spread of 424 bps per annum. The analyst sentiment change and the analyst sentiment trend show more attenuated results. The attenuation may be attributed to two things. First, different analysts are called on for each call so the aggregate measure may no longer be comparable. Second, the analyst sentiment change or trend as a signal is historically no longer predictive when it is measured as far back as YoY or as a change from two years ago.

Exhibit 10: Analysts - Sentiment
Russell 3000 May 2010 – December 2017

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Aggregate Analyst Positivity	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Positivity	D	201005	475	0.012	70.7%	1.51%	0.81	64.1%	4.24%	1.37	70.7%
[2]	p-value	NaN	NaN	NaN	0.000	0.000	0.027	NaN	0.005	0.000	NaN	0.000
[3]	YoY Positivity Change	D	201005	422	0.005	59.8%	1.05%	0.58	57.6%	2.51%	0.95	59.8%
[4]	p-value	NaN	NaN	NaN	0.023	0.047	0.114	NaN	0.117	0.010	NaN	0.047
[5]	Positivity Trend	D	201005	409	0.005	62.0%	0.47%	0.24	54.3%	1.43%	0.56	58.7%
[6]	p-value	NaN	NaN	NaN	0.037	0.016	0.502	NaN	0.348	0.126	NaN	0.076

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

Interaction between Analyst Revision and Aggregate Analyst Sentiment

From the exhibit above, one question that comes to mind is what is the interaction between aggregate analyst sentiment and analyst revision (i.e., 3-month change in EPS FY1 consensus)? The correlation between their monthly long-short return estimates from cross-sectional regressions is about 0.48 in our sample period, which suggests fairly strong positive correlation between the two strategies (and intuitively so).

Is aggregate analyst sentiment on earnings calls just an embodiment of analyst revision or vice versa? We assess the interaction between the two by controlling one relative to the other using the Fama-Macbeth framework. Our results suggest that neither signal subsumes the other. In fact, both signals historically seem to have predictive power jointly (Exhibit 11).

Exhibit 11: Aggregate Analyst Sentiment versus Analyst Revision 3-Month EPS FY1
Russell 3000 May 2010 – December 2017

	Analyst Aggregate Sentiment	Analyst Revision 3-month FY1 EPS	Analyst Aggregate Sentiment Controlled for Analyst Revision	Analyst Revision 3-month FY1 EPS Controlled for Aggregate Sentiment
annualized long-short returns	4.08%	5.17%	3.26%	5.78%
t-statistic	4.06	3.28	3.65	3.56

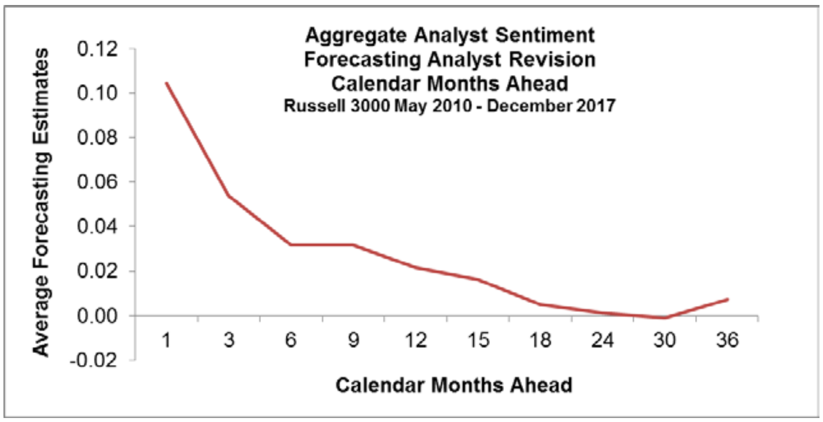
Note: The estimated returns may be slightly different from the results in the earlier section because we are using two different frameworks (i.e., quintile return spread vs Fama-Macbeth). The estimated results are very close and in fact serve as a robustness check for each other. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

Does Aggregate Analyst Sentiment Forecast Analyst Revision?

Another question that comes to mind is whether stock-level analyst sentiment is capable of forecasting future stock-level analyst revision. We regress the 1-, 3-, 6-, 9-, 12- 15-, 18- 24, 30-, and 36-forward month stock-level analyst revision signal ranks on the current month's stock-level analyst sentiment signal ranks. Our results indicate that there is some indication that current analyst sentiment ranks are historically predictive of future analyst revision ranks up to 18 months out. The forecasting power is the strongest one-month forward and from there it tails off (Exhibit 12).

Exhibit 12: Aggregate Analyst Sentiment Forecasting Future Analyst Revision
Russell 3000 May 2010 – December 2017

	Number of Calendar Months Forward									
	1	3	6	9	12	15	18	24	30	36
Estimate	0.104	0.054	0.032	0.032	0.022	0.016	0.005	0.001	-0.001	0.007
p -value	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.66	0.70	0.04



Source: S&P Global Market Intelligence Quantamental Research, as of 02/01/2018.

5. Controlling for Commonly Used Alpha and Risk Signals

Up to this point, we have showed historical predictive results for each of the standalone strategies that use the content from earnings call transcripts. The predictability may, in part or in all, be driven by commonly used alpha and/or risk strategies. To validate our earnings call-related signals have additive predictive power historically, we examine returns with controls on the following metrics. We start by exploring the (underlying) characteristics of the sentiment- and behavioral-based signals along the following eight dimensions, which have historically been shown to predict forward stock returns as well:

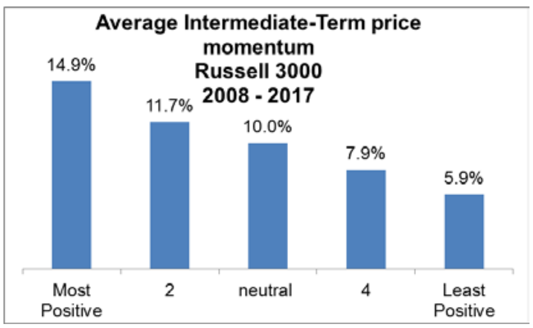
- Beta – CAPM beta 60 months
- Market capitalization – natural log market cap
- Valuation – book-to-market
- Price momentum – 12-month return excluding the most recent month's
- Asset growth – one-year in asset growth

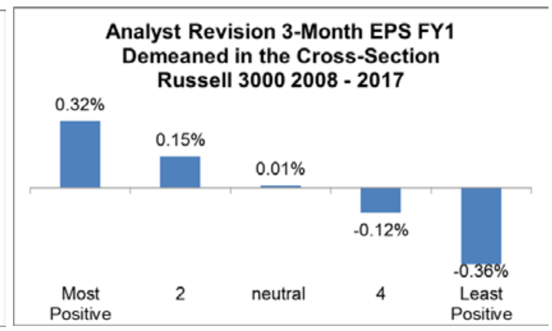
- Gross Profitability – gross profit scaled by total assets
- Analyst Revision – 3-month revision in analyst consensus EPS FY1 estimate
- Earnings Surprise – Standardized Unexpected earnings surprise

Using the positivity signal as an example, our analysis shows that the positivity signal has strong positive tilts (i.e., correlations) to price momentum, asset growth, analyst revision and earnings surprise dimensions. In other words, the 20% of stocks that exhibit the most (least) positivity also exhibit the best (worst) price momentum in the past 12-months, exhibit the lowest (highest) asset growth, exhibit the highest (lowest) analyst revision in the past 3-months and beat their consensus EPS estimates by the most (least). See Exhibit 13 and rest of the characteristics are in Exhibit A.9.

Exhibit 13: Positive Tilts

Russell 3000 January 2008 – December 2017



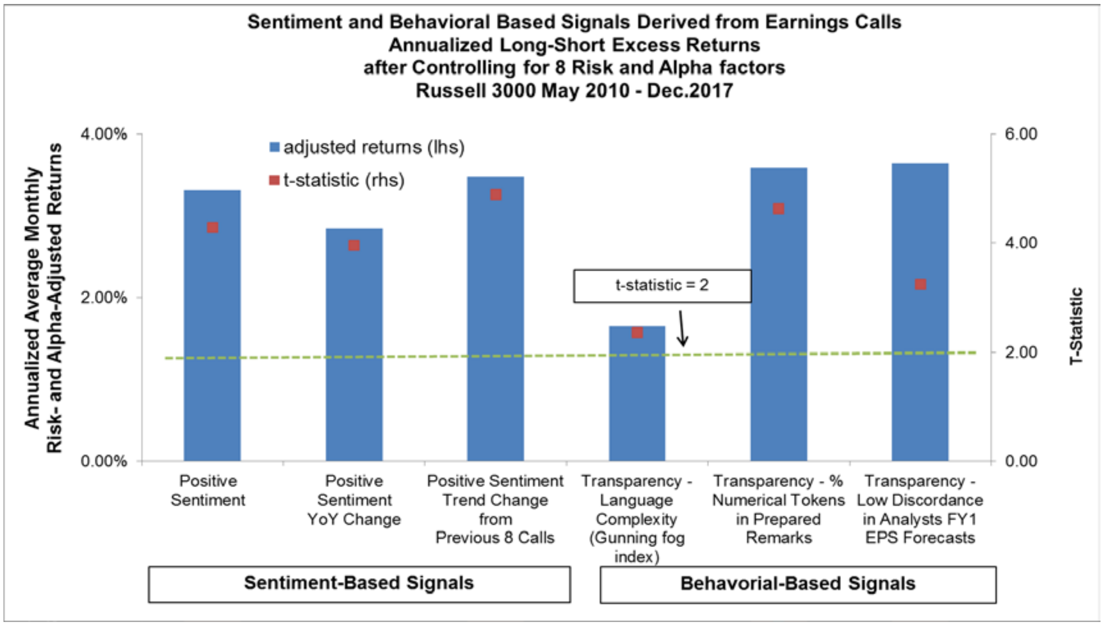


Source: S&P Global Market Intelligence Quantamental Research, as of 02/01/2018.

In light of these results, we need to neutralize the positive correlations such that the standalone results in Section 4 are not just capturing the performance of well-known risk and alpha signals. In other words, we want to ascertain whether sentiment- and behavioral-based signals historically provide additive predictive power above and beyond the eight underlying characteristics that are also historically common drivers of stock returns.

In Exhibit 14, we use the Fama-Macbeth framework to control for all eight of the risk and alpha signals. Our results indicate that sentiment- and behavioral-based signals still provide excess returns after the adjustments ranging from 170 bps to 375 bps per year with statistical significance at least at the 5% level. This suggests that the sentiment- and behavioral-based signals from Section 4 have historically additive predictive power above and beyond the eight commonly used alpha and risk signals.

Exhibit 14: Sentiment- and Behavioral-Based Signals
Controlled for Eight Commonly Used Risk and Alpha Signals
Russell 3000 May 2010 – December 2017



Note: Results after controlling for beta, size, value, price momentum, asset growth, gross profitability, analyst revision and earnings surprise – A.1 Factor Definitions. Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

6. Correlations

In this section, we show correlations of long-short quintile return spreads of the six standalone stock selection strategies from the previous section - Exhibit 15. Our analysis suggests that sentiment level is moderately positively correlated (i.e., <= 0.50) with sentiment change and sentiment trend. Sentiment change and trend are strongly positively correlated among all the pairs at 0.71.

Behavioral-based signals are generally less correlated among each other where the pairwise correlation between the language complexity signal and the analyst conviction signal is the lowest among all pairs at 0.08 and the pairwise correlation between the objectivity signal and the analyst conviction signal is the highest in this category at 0.53.

The most noteworthy result is that the low and even negative correlations between the sentiment- and behavioral-based signals (highlighted in the red box) which means that a composite signal that blends the signals from the two categories should historically yield a more predictive overall signal at a lower volatility.

Exhibit 15: Correlations of Long-Short Quintile Return Spreads of Sentiment- and Behavioral-Based Signals

Russell 3000 May 2010 – December 2017

		[1]	[2]	[3]	[4]	[5]	[6]
[1]	Positive Sentiment		0.43	0.49	0.23	-0.06	0.17
[2]	Positive Sentiment YoY Change			0.71	-0.07	-0.14	-0.09
[3]	Positive Sentiment Trend Change from Previous 8 Calls				-0.09	-0.19	-0.09
[4]	Language Complexity - Gunning fog index					0.28	0.08
[5]	Objectivity - % Numerical Tokens in Prepared Remarks						0.53
[6]	Transparency - Analyst Conviction Low Dispersion in FY1 EPS Forecasts						

Source: S&P Global Market Intelligence Quantamental Research, as of 02/01/2018.

7. Data & Methodology

The transcripts data is a new addition to the S&P Global Market Intelligence's Xpressfeed product in September 2017. The historical coverage in the Russell 3000 universe starts in calendar Q1 2008 (Exhibit A.22). Among its key features, the data set captures the different segmentations of earnings calls by sections (e.g., prepared remarks section vs. Q&A section), by speaker types (e.g., managers, sell-side analysts, shareholders etc.) and by professionals (e.g., Tim Cook) where the individual professional identifiers serve as a unique key that connects the transcripts data set with the S&P Global Market Intelligence's Professionals and Estimates data sets.

We impose a lag of three trading days to sufficiently account for the latency between an earnings call and its transcription. In the past five years, 99% of all earnings call transcripts are transcribed and hit the database within 24 hours of an earnings call.

Within the Russell 3000 universe, there is an average of 2400+ distinct firms since 2008 that have earnings call transcripts. The main reason for a missing earnings call transcript is that a firm does not hold earnings calls (e.g., Berkshire Hathaway).

8. Conclusion

S&P Global Market Intelligence's earnings call transcripts data is a primary source, unstructured data set that may offer a differentiated source of alpha. Our analysis suggests that sentiment- and behavioral-based signals using the content from earnings calls have historically demonstrated additive stock selection power above and beyond traditional strategies such as value, momentum, quality, analyst revision and earnings surprise in the Russell 3000 universe since 2008. The sentiment- and behavioral-based categories of signals are lowly and even negatively correlated. A composite strategy using the signals from the two categories may offer investors additional benefits via diversification.

Our analysis also suggests that the sentiment of the CEO is the most important among the sentiment of all C-Suite executives. The aggregate analyst sentiment signal and the 3-month analyst revision FY1 EPS signal are complementarily in nature and when used in conjunction, the composite signal shows a higher predictability of forward stock returns.

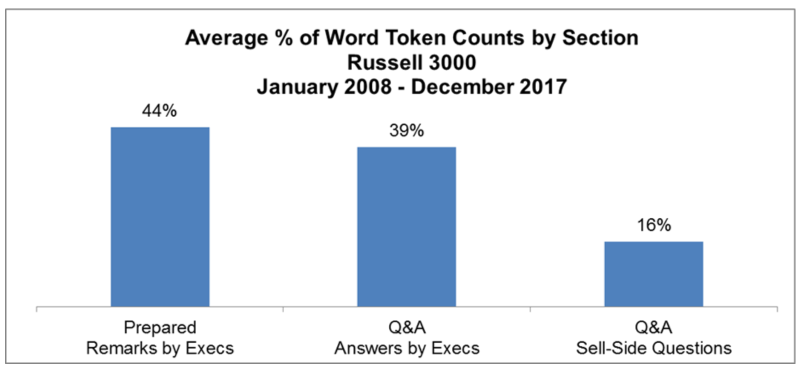
Appendix

A.1 Factor Definitions

Signal	Description
Beta	CAPM beta 60 months
Market Capitalization	natural log market cap
Valuation	book-to-market
Price Momentum	price momentum 12-month return exclude the most recent month's
Asset Growth	one-year percent change in total asset growth
Gross Profitability	ratio of gross profit to total assets
Analyst Revision	3-month revision in analyst consensus EPS FY1 estimate
Earnings Surprise	difference between actual EPS less average consensus EPS divided by prior day's closing price

A.2 Decomposition of Words in Earnings Calls

Executives speak about 83% of all words on earnings calls. Out of which, 44% are in the prepared remarks section. Analysts speak 16% of all words in the form of questions. The remaining about 1.5% of words is spoken by buy-side and other attendees.



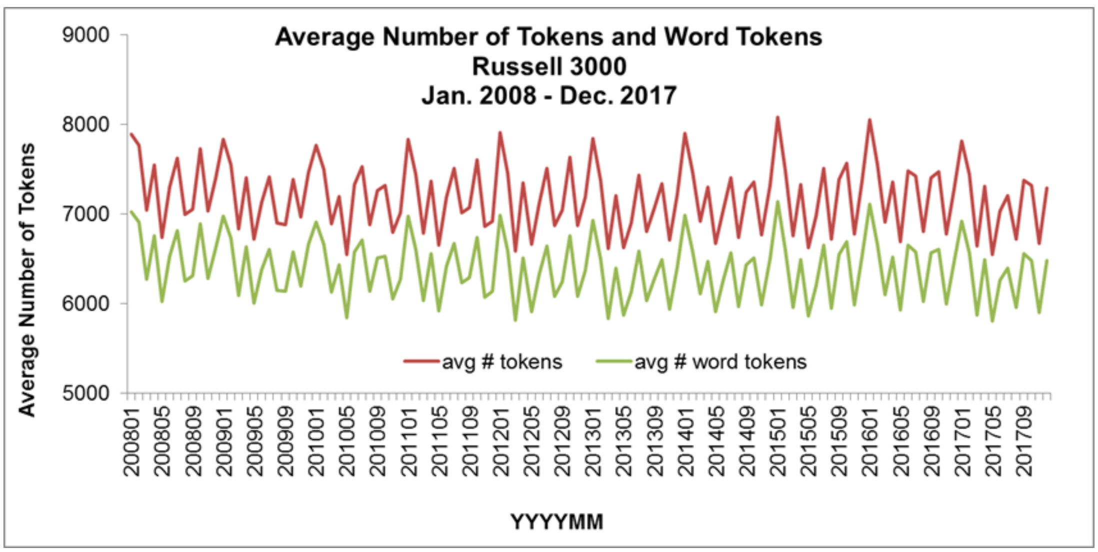
Source: S&P Global Market Intelligence Quantamental Research, as of 02/01/2018.

A.3 Historical Count of Tokens

Tokens (the red line) include words, numbers and acronyms and the green line is only word tokens.

The average speaking rate at a comfortable pace by a professional speaker such as a radio host or an audiobook narrator is about 150 words per minute (wpm).[13] The average number of tokens (i.e., words and numbers) per call historically in the Russell 3000 universe is about 7,200 (see the red line in Exhibit 2), which translates to about 48 minutes assuming the 150 wpm rate. [14,15]

There is a seasonal spike in the average number of tokens (i.e., words and numbers) for calls that took place between January and March of every year suggesting that the average call length in this calendar quarter tends to be longer than the average call length of calls that take place in the other three calendar quarters. The seasonal spike is due to the fact that the fiscal year end for about 60% of U.S. firms coincides with the calendar year end where executives review the results for the entire fiscal year instead.

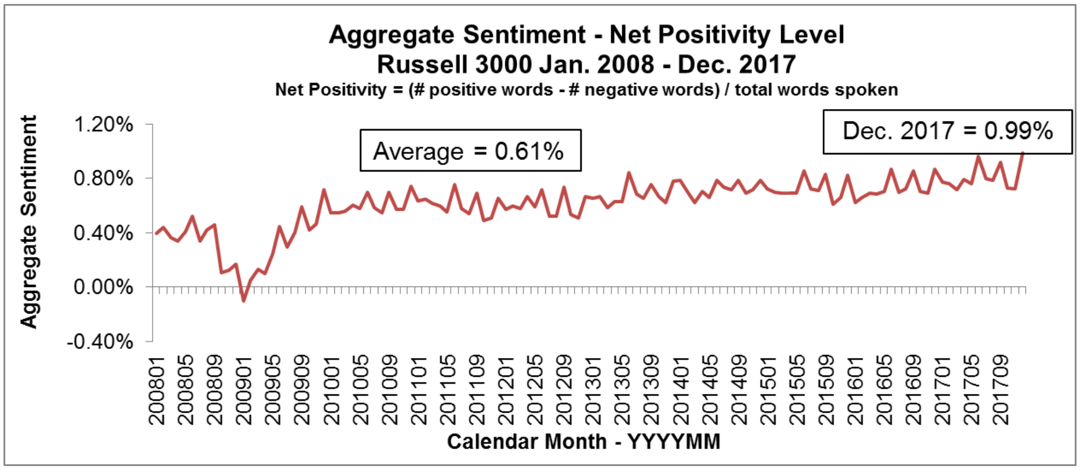


Source: S&P Global Market Intelligence Quantamental Research, as of 02/01/2018.

[13] Bansal, S. (2018, Jan. 20). Average Speaking Rate and Words per Minute [Web log post]. Retrieved Aug. 30, 2018, from https://virtualspeech.com/blog/average-speaking-rate-words-per-minute
[14] The implicit assumption is that executives are well-spoken and are able to comfortably go through about 150 wpm.
[15] When we examine the average duration of calls via audio files, the average length is about 51 minutes historically.

A.4 Aggregate Sentiment

The net positivity metric is used as a proxy for sentiment where net positivity is defined as follows: (# positive words - # negative words) / total words using Loughran & McDonald's word lists.



Source: S&P Global Market Intelligence Quantamental Research, as of 02/01/2018.

A.5 Construction and Intuition of Sentiment-Based Signals

Signal	Construction	Sort Order	Intuition
Sentiment Level	Percent of Loughran & McDonald's sentiment words in a call	D/A	Positivity (or the absence of negativity) reflects bright prospects ahead. See the four base measures of sentiment (see Exhibit 1 for definitions).
Change in Sentiment Level	$Sig_{i,t}$ = ($Sig_{i,t}$ – $Sig_{i,t-4}$) / Abs($Sig_{i,t-4}$) where t is in calendar months and i is for stock i	D	It is the change in the level that is more informative than the level itself
Change in Sentiment Trend	$Sig_{(i,t)}$ = ($Sig_{(i,t)}$ – SMA) / abs(SMA) where SMA = average($Sig_{i,t-1,\ t-8}$) and t is in calendar months and i is for stock i and $Sig_{i,t-1,\ t-8}$ needs to have a minimum of six calls in the past 24 months	D	Easier to identify inflection points and accelerations

Source: S&P Global Market Intelligence Quantamental Research, as of 02/01/2018.

A.6 Meaning of Columns in Tables Containing Empirical Results

Signal Name, Sort Order, Start Date, Firm Count

- Column 1: the sort order of the signal where -1 is descending and 1 is ascending
- Column 2: the date back-tests commenced for a signal
- Column 3 - the average number of firms in a quintile bucket in our sample period

Signal Strength Metrics

- Column 4 - the average monthly information coefficient (i.e., Spearman correlation) that is used to assess a signal's historical predictive strength
- Column 5: the monthly hit rate for column 4 - the percent of the months where the IC > 0

Active Long Metrics

- Column 6: the annualized average monthly market-adjusted return of the long portfolio
- Column 7: annualized information ratio of column 6
- Column 8: the monthly hit rate for column 6 where the market-adjusted return of the long-side > 0

Long-Short Metrics

- Column 9: the annualized long-short returns
- Column 10: annualized information ratio of column 9
- Column 11: the monthly hit rate for column 9 where the monthly long-short return > 0

A.7 Loughran & McDonald

There are many ways to define sentiment. We use a bag-of-words approach where the sentiment word lists are from the Loughran and McDonald (2011) financial dictionary. Their dictionary has become the de facto financial dictionary for NLP analysis due to its **accessibility**, its **comprehensiveness**, its **financial-specific context**, its **lack of dependency on the transitory nature of its words** and, lastly and perhaps most importantly, its **unambiguous and singularly connoted words**. Details below.

- **Accessibility** – their word lists are readily accessible because they are freely posted online.

- **Comprehensiveness** – the dictionary is comprehensive such that it is difficult for managers to game the system (i.e., circumvent certain words that have empirically been shown to lead to future stock underperformance) because they start with every conceivable English word with all inflections of a word, totaling 80,000+ distinct words in the master word list.

- **Financial-specific context** - they filter their initial master word list down to their sentiment word lists by examining 10-K filings between 1994 and 2008 inclusively.

- **Permanence of words** - their master and sentiment word lists are less transitory because they start with the most comprehensive list of English words possible and, more importantly, the master word list doesn't rely on transitory terms such as iphone.

- **Unambiguous and Singularly Connoted Words** - they arrive at their sentiment word lists containing unambiguous and singularly connoted words by looking at the most frequently occurring words in the 10-Ks from the master word list. From there, they went word-by-word and assessed each of the word's meaning in a business context. At the end of their process, the words that ended up in their word lists are less ambiguous in their meaning with singular connotation.

Their three most important lists of words for our use cases are the master word list, positive and negative sentiment word lists with distinct word counts of 80,000+, 350+ and 2300+, respectively. Examples of positive words are able, abundance, acclaimed, accomplish and so forth. Examples of negative words are abandon, abdicate, aberrant, abetting and so forth.

A.8 Details and Assumptions on Sentiment-Based Signal Construction

Sentiment-based signals are constructed using the frequency of appearance of words on Loughran & McDonald's master, positive and negative word lists. Before aggregating the frequency of positive words, the preprocessing of each word includes the following:

- Tokenize words, sentences, numerical values, punctuations
- Made all word tokens lower case
- Spelled out all contractions (e.g., aren't → are not)
- There is no lemmatization since Loughran & McDonald's master word list has all inflections of an English word
- We remove all text blocks attributed to the operator of a call
- Words good and great are in LM's positive word list, so we track and exclude from tally the following phrases towards a positive count
  - Good morning (afternoon, evening)
  - Good and great question(s)
- Negation
  - Positive negation such as 'we didn't have a good quarter' isn't counted as a positive instance
  - The negation list includes: no, not, none, neither, never, nobody
  - Negative negation such as 'we didn't have a bad quarter isn't treated because we believe this case is very rare and when executives have good news they will deliver it clearly and simply

A.9 Sentiment Characteristics

The 20% of stocks that have the most (least) positive sentiment level exhibit

- the largest market-capitalizations
- the highest (lowest) intermediate-term price momentum
- the lowest (highest) asset growth YoY
- the best (worst) 3-month analyst revision EPS FY1
- the largest (lowest) earnings surprise

Russell 3000 January 2008 – December 2017

avg(avg)	Most Positive	2	neutral	4	Least Positive
beta	1.31	1.34	1.40	1.33	1.26
cap ($ millions)	10619	8201	7209	5581	4100
book-to-market	0.54	0.56	0.56	0.58	0.61
price mom	14.9%	11.7%	10.0%	7.9%	5.9%
asset growth	9.73%	12.99%	13.63%	15.42%	16.17%
gross profitability	32.0%	30.2%	30.2%	29.7%	30.6%
analyst revision	0.32%	0.15%	0.01%	-0.12%	-0.36%
suec	0.39	0.22	0.02	-0.19	-0.44

Source: S&P Global Market Intelligence Quantamental Research, as of 02/01/2018.

A.10 Entire Earnings Call - Sentiment Level – Entire Earnings Call

The exhibit has results for the four different flavors of sentiment since May 2008:

- Positivity = # positive words / # total words
- Negativity = # negative words / # total words
- Net Positivity = (# positive words - # negative words) / # total words
- Positivity-to-Negativity = (# positive words / # negative words)

Russell 3000 May 2008 – December 2017

	Russell 3000 Universe	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
	Sentiment Level	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Positivity	D	200805	483	0.013	66.4%	1.81%	0.72	61.2%	2.52%	0.59	62.9%
[2]	p-value	NaN	NaN	NaN	0.000	0.000	0.028	NaN	0.012	0.070	NaN	0.004
[3]	Negativity	A	200805	483	0.010	61.2%	0.13%	0.04	53.4%	1.82%	0.30	57.8%
[4]	p-value	NaN	NaN	NaN	0.020	0.012	0.895	NaN	0.403	0.346	NaN	0.077
[5]	Net Positivity	D	200805	483	0.015	69.8%	1.57%	0.49	66.4%	3.10%	0.49	68.1%
[6]	p-value	NaN	NaN	NaN	0.000	0.000	0.133	NaN	0.000	0.133	NaN	0.000
[7]	Positivity-to-Negativity	D	200805	483	0.015	67.2%	0.99%	0.24	66.4%	2.85%	0.46	66.4%
[8]	p-value	NaN	NaN	NaN	0.001	0.000	0.465	NaN	0.000	0.154	NaN	0.000

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

A.11 Change in YoY Sentiment level – Entire Earnings Call

Russell 3000 March 2009 – December 2017

	Russell 3000 Universe	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
	YoY Change Sentiment Level	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Positivity	D	200903	437	0.008	60%	1.47%	0.64	60.4%	2.41%	0.77	57.5%
[2]	p-value	NaN	NaN	NaN	0.001	0.025	0.061	NaN	0.025	0.024	NaN	0.098
[3]	Negativity	A	200903	437	0.010	70%	1.36%	0.60	59.4%	2.64%	0.78	67.0%
[4]	p-value	NaN	NaN	NaN	0.001	0.000	0.077	NaN	0.041	0.022	NaN	0.000
[5]	Net Positivity	D	200903	435	0.011	65%	1.20%	0.56	59.4%	1.93%	0.46	69.8%
[6]	p-value	NaN	NaN	NaN	0.000	0.001	0.101	NaN	0.041	0.176	NaN	0.000
[7]	Positivity-to-Negativity	D	200903	437	0.012	66%	2.25%	1.00	64.2%	3.19%	0.89	74.5%
[8]	p-value	NaN	NaN	NaN	0.000	0.001	0.004	NaN	0.002	0.009	NaN	0.000

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

A.12 Change in Sentiment Trend – Entire Earnings Call

Russell 3000 May 2010 – December 2017

	Russell 3000 Universe	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
	Sentiment Trend Look-Back 8 Previous Calls	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Positive	D	201005	425	0.011	67.4%	2.48%	1.27	60.9%	3.96%	1.48	65.2%
[2]	p-value	NaN	NaN	NaN	0.000	0.001	0.001	NaN	0.028	0.000	NaN	0.002
[3]	Negative	A	201005	425	0.014	68.5%	2.63%	1.21	69.6%	4.63%	1.51	67.4%
[4]	p-value	NaN	NaN	NaN	0.000	0.000	0.001	NaN	0.000	0.000	NaN	0.001
[5]	Net Positivity	D	201005	425	0.014	67.4%	1.93%	0.87	60.9%	4.55%	1.33	65.2%
[6]	p-value	NaN	NaN	NaN	0.000	0.001	0.017	NaN	0.028	0.000	NaN	0.002
[7]	Positive-to-Negative	D	201005	425	0.017	69.6%	3.40%	1.51	66.3%	5.73%	1.79	70.7%
[8]	p-value	NaN	NaN	NaN	0.000	0.000	0.000	NaN	0.001	0.000	NaN	0.000

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

A.13 Discordance in Sentiment between the Prepared Remarks and the Responses in the Q&A

This exhibit has results that are based on the sentiment difference between the responses during the Q&A and the prepared remarks.

Russell 3000 May 2010 – December 2017

	Russell 3000 Universe	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
	(Q&A Sentiment - Prepared Remarks Sentiment)	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Positivity	D	201005	479	-0.001	48.9%	0.40%	0.25	53.3%	0.18%	0.08	54.3%
[2]	p-value	NaN	NaN	NaN	0.809	0.755	0.496	NaN	0.466	0.829	NaN	0.348
[3]	Negativity	A	201005	479	-0.012	32.6%	-1.93%	-0.82	42.4%	-2.06%	-0.60	44.6%
[4]	p-value	NaN	NaN	NaN	0.002	0.001	0.025	NaN	0.117	0.102	NaN	0.251
[5]	Net Positivity	D	201005	479	-0.007	39.1%	-0.51%	-0.29	42.4%	-0.96%	-0.35	43.5%
[6]	p-value	NaN	NaN	NaN	0.021	0.028	0.424	NaN	0.117	0.341	NaN	0.175

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

A.14 Discordance in Sentiment between the Prepared Remarks and the Responses in the Q&A (Continued)

This exhibit has results that are based on the sentiment percent difference between the responses during the Q&A and the prepared remarks.

Russell 3000 March 2009 – December 2017

	Russell 3000 Universe	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
	(Q&A Sentiment - Prepared Remarks Sentiment) / Prepared Remarks Sentiment	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Positivity	D	201005	478	0.004	58.7%	0.23%	0.14	50.0%	1.64%	0.70	57.6%
[2]	p-value	NaN	NaN	NaN	0.094	0.076	0.707	NaN	0.917	0.055	NaN	0.117
[3]	Negativity	A	201005	479	-0.012	30.4%	-1.27%	-0.73	39.1%	-1.38%	-0.43	41.3%
[4]	p-value	NaN	NaN	NaN	0.001	0.000	0.047	NaN	0.028	0.232	NaN	0.076
[5]	Net Positivity	D	201005	478	0.000	48.9%	-1.75%	-0.82	42.4%	0.17%	0.07	52.2%
[6]	p-value	NaN	NaN	NaN	0.929	0.755	0.026	NaN	0.117	0.848	NaN	0.602

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

A.15 Empirical Results for Behavioral-Based Signals

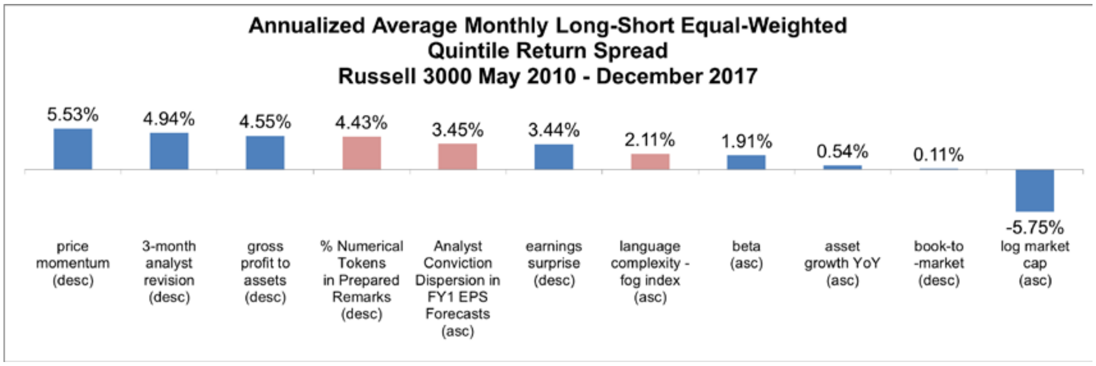
Russell 3000 May 2008 – December 2017

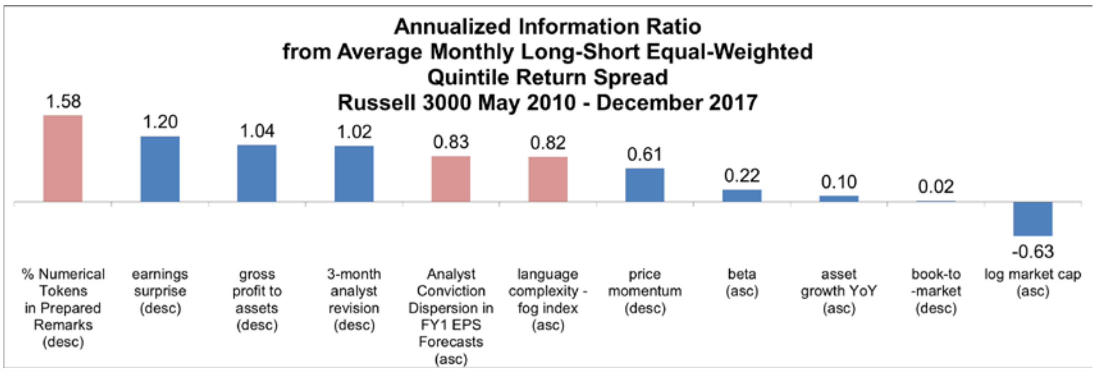
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Behavioral-Based Signals	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Language Complexity - Gunning fog index	A	200805	483	0.009	61.2%	0.82%	0.40	54.3%	2.39%	0.78	57.8%
[2]	p-value	NaN	NaN	NaN	0.000	0.012	0.221	NaN	0.307	0.017	NaN	0.077
[3]	Concreteness - % Numerical Tokens in Prepared Remarks	D	200805	483	0.013	70.7%	1.76%	0.99	58.6%	4.28%	1.28	66.4%
[4]	p-value	NaN	NaN	NaN	0.000	0.000	0.003	NaN	0.051	0.000	NaN	0.000
[5]	Transparency - Analyst Conviction Dispersion in FY1 EPS Forecasts	A	201005	280	0.011	65.2%	-0.38%	-0.14	44.6%	3.45%	0.83	55.4%
[6]	p-value	NaN	NaN	NaN	0.022	0.002	0.706	NaN	0.251	0.023	NaN	0.251

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

A.16 Economic Performance and Information Ratio of Behavioral-Based Signals

Russell 3000 Universe; May 2010 – December 2017





Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

A.17 Executives with Chief in Their Titles from CIQ Professionals Data Set

CEO Bucket = {CEO, Co-CEO}

CFO Bucket = {CFO, co-CFO, Chief Accounting Officer}

Other Executives = {Executives in the table below who are not in the CEO and CFO buckets}

Professional Type ID	Office Title
1	Chief Executive Officer
2	Co-Chief Executive Officer
6	Chief Financial Officer
7	Chief Operating Officer
11	Chief Investment Officer
12	Chief Accounting Officer
15	Chief Technology Officer
16	Chief Information Officer
21	Chief Administrative Officer
23	Chief Legal Officer
77	Chief Scientific Officer
450	Co-Chief Investment Officer
451	Co-Chief Financial Officer
452	Co-Chief Operating Officer
463	Chief Compliance Officer

A.18 Economic Performance of Positive Sentiment of Non-CEO, -CFO Executives Who Appear on Earnings Calls; Russell 3000 Universe; May 2012 – December 2017

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	non-CEO, -CFO Sentiment	Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Positivity	D	201205	119	0.008	57.4%	0.34%	0.11	51.5%	1.54%	0.36	52.9%
[2]	p-value	NaN	NaN	NaN	0.118	0.182	0.798	NaN	0.716	0.397	NaN	0.545
[3]	YoY Positivity Change	D	201205	80	0.015	63.2%	0.06%	0.02	44.1%	3.18%	0.67	60.3%
[4]	p-value	NaN	NaN	NaN	0.004	0.021	0.970	NaN	0.275	0.117	NaN	0.068
[5]	Positivity Trend	D	201205	71	0.004	51.5%	1.11%	0.23	51.5%	1.54%	0.29	51.5%
[6]	p-value	NaN	NaN	NaN	0.576	0.716	0.588	NaN	0.716	0.499	NaN	0.716

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

A.19 Difference in Economic Performance between the Positive Sentiment of CEOs and CFOs; Russell 3000 May 2010 – December 2017

	Positivity	Net Positivity
Annualized Average Difference in Long-Short Returns	-0.29%	-1.12%
p-value	0.85	0.56

Source: S&P Global Market Intelligence Quantamental Research, as of 02/01/2018.

A.20 Positive Sentiment YoY Change and Positive Sentiment Trend for CEOs and CFOs Russell 3000 Universe; May 2010 – December 2017

Positive Sentiment Change YoY	CEO Standalone	CFO Standalone	CEO controlled for CFO	CFO Controlled for CEO
annualized long-short returns	2.14%	1.89%	2.00%	1.51%
t-statistic	2.53	2.12	2.39	1.66

Positive Sentiment Change in Trend	CEO Standalone	CFO Standalone	CEO controlled for CFO	CFO Controlled for CEO
annualized long-short returns	2.24%	2.17%	2.34%	1.66%
t-statistic	2.50	2.51	2.49	1.91

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

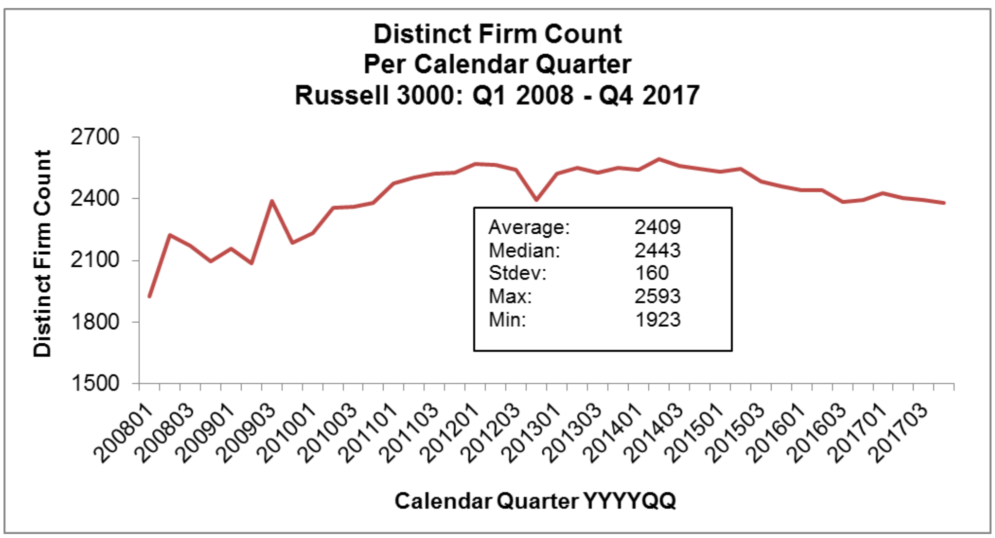
A.21 Sentiment Discordance between the CEO and the CFO

Russell 3000 Universe; May 2010 – December 2017

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
		Signal Sort Order	Strategy Start Date	Average Firm Count in Each Quintile Bin	Average Monthly Spearman Correlation	Hit Rate Monthly Spearman Correlation	Annualized Average Monthly Long - Market	Annualized Monthly IR (Long - Market)	Hit Rate Average Monthly Long - Market	Annualized Average Monthly Long - Short	Annualized Monthly IR (Long - Short)	Hit Rate Average Monthly Long - Short
[1]	Positivity Difference CFO - CEO	D	201005	433	0.002	53.3%	0.93%	0.47	56.5%	-4.55E-04	-0.02	41.3%
[2]	p-value	NaN	NaN	NaN	0.474	0.466	0.198	NaN	0.175	0.962	NaN	0.076
[3]	Positivity % Change (CFO - CEO) / CEO	D	201005	433	0.007	57.6%	0.52%	0.28	51.1%	1.68%	0.58	59.8%
[4]	p-value	NaN	NaN	NaN	0.019	0.117	0.440	NaN	0.755	0.109	NaN	0.047
[5]	Net Positivity Difference CFO - CEO	D	201005	433	0.005	63.0%	0.86%	0.49	57.6%	0.33%	0.12	54.3%
[6]	p-value	NaN	NaN	NaN	0.060	0.009	0.178	NaN	0.117	0.734	NaN	0.348
[7]	Net Positivity % Change (CFO - CEO) / CEO	D	201005	432	0.012	66.3%	-0.01%	-0.01	53.3%	2.66%	0.87	69.6%
[8]	p-value	NaN	NaN	NaN	0.000	0.001	0.983	NaN	0.466	0.018	NaN	0.000

Note: Values that are shaded in green (red) are statistically significant at least at the 10% level and are consistent (inconsistent) with our ex-ante hypothesis. Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 02/01/2018.

A.22 Distinct Firm Count by Calendar Quarter



Source: S&P Global Market Intelligence Quantamental Research, data as of 02/01/2018.

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Our Recent Research

July 2018: A Case of 'Wag the Dog'? - ETFs and Stock-Level Liquidity
Highlights include:

- We present an ETF price impact model, which posits single-day impact of up to 370 bps / day on an individual security and up to 250 bps / day on the index itself. Analyses indicate the effect is transitory and reverses over a period of 3-5 trading days.
- The Feb 2018 market correction was accompanied by a $25B outflow of assets from ticker SPY, the SSGA S&P 500 Trust ETF. Modeling suggests that as much as one-third of the pullback was due to price pressure from ETF trading and that securities more sensitive to ETF flow underperformed.
- Sensitivity to ETF flow is used to build a risk model, which generates improved performance in a historical optimization. We offer a method for estimating ETF sensitivity for funds, using the S&P Global Ownership dataset.

June 2018: The (Gross Profitability) Trend is Your Friend
Trend strategies based on changes in stock price or earnings are widely used by investors. In this report, we examine the performance of a trend strategy derived from gross profitability ("GP"). Gross profitability trend ("GPtrend"), was proposed by Akbas et al. who argued that the trajectory of a firm's profitability is just as important as the level (GP). We define GPtrend as the year-on-year difference in either quarterly or trailing twelve month GP, where GP is calculated as revenue minus cost of goods sold, divided by total assets. Our back-tests confirm that GPtrend has historically been an effective stock selection signal globally, with the added benefit of low to moderate correlation with commonly used investment strategies.

May 2018: Buying the Dip: Did Your Portfolio Holding Go on Sale?
'Buy the Dip' ("BTD"), the concept of buying shares after a steep decline in stock price or market index, is both a Wall Street maxim, and a widely used investment strategy. Investors pursuing a BTD strategy are essentially buying shares at a "discounted" price, with the opportunity to reap a large pay-off if the price drop is temporary and the stock subsequently rebounds. BTD strategies are especially popular during bull markets, when a market rally can be punctuated by multiple pullbacks in equity prices as stock prices march upwards.

March 2018: In The Money: What Really Motivates Executive Performance?
CEO compensation has soared over the past four decades, aided by consultants, compensation committees, the CEOs themselves, and an extended bull market (1982-1999). "Pay for performance" has become dogma and large equity grants de rigueur. But there is a cost to such largesse. Figure 1 shows that realized pay1 for a company's top five executives can approach 6%-11% of earnings before interest and taxes (EBIT), on the index level, for small and mid-cap firms. What types of compensation motivate top executives to boost shareholder returns? And what are the fundamental characteristics of companies in which executives are motivated to boost stock performance?

February 2018: **The Art of (no) Deal: Identifying the Drivers of Cancelled M&A Deals**
Terminated deals impact capital market participants in various ways. Predicting deals that are likely to be canceled is of interest to both M&A advisers and equity investors. This report identifies several drivers of cancelled deals, including size, deal proportionality, perceived price discount, CEO age, and regulatory risk, and concludes with a model built from four of these drivers.

January 2018: **U.S Stock Selection Model Performance Review**
Starting with the U.S. Election in November 2016, the S&P 500 Index has registered 14 consecutive months of positive returns. Only once has the S&P 500 had a longer run of positive returns since 1959. Coincident with strong equity returns, U.S. stocks began to trade on the basis of their own idiosyncratic factors, as opposed to sector or common factor risk. All 4 of our U.S strategy models returned positive long-only returns in 2017. This report reviews the performance of all 4 models during the year.

September 2017: **Natural Language Processing - Part I: Primer**
Given the growing interest in NLP among investors, we are publishing this primer to demystify many aspects of NLP and provide three illustrations, with accompanying Python code, of how NLP can be used to quantify the sentiment of earnings calls. The paper is laid out into four sections:

- **What is NLP:** We demystify common NLP terms and provide an overview of general steps in NLP.
- **Why is NLP Important:** Forty zettabytes (10^21 bytes) of data are projected to be on the internet by 2020, out of which more than eighty percent of the data are unstructured in nature, requiring NLP to process and understand
- **How can NLP help me:** We derive insights from earnings call transcripts measuring industry-level trends or language complexity.
- **Where do I start:** Code for each use is enclosed, enabling users to replicate the sentiment analysis

July 2017: **Natural Language Processing Literature Survey**

June 2017: **Research Brief: Four Important Things to Know About Banks in a Rising Rate Environment**

April 2017: **Banking on Alpha: Uncovering Investing Signals Using SNL Bank Data**

March 2017: **Capital Market Implications of Spinoffs**

January 2017: **U.S. Stock Selection Model Performance Review 2016**

November 2016: **Electrify Stock Returns in U.S. Utilities**

October 2016: **A League of their Own: Batting for Returns in the REIT Industry - Part 2**

September 2016: **A League of their Own: Batting for Returns in the REIT Industry - Part 1**

August 2016: Mergers & Acquisitions: The Good, the Bad and the Ugly (and how to tell them apart)

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January 2016: What Does Earnings Guidance Tell Us? – Listen When Management Announces Good News

December 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 6

November 2015: Late to File - The Costs of Delayed 10-Q and 10-K Company Filings

October 2015: Global Country Allocation Strategies

September 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 5

September 2015: Research Brief: Building Smart Beta Portfolios

September 2015: Research Brief – Airline Industry Factors

August 2015: Point-In-Time vs. Lagged Fundamentals – This time i(t')s different?

August 2015: Introducing S&P Capital IQ Stock Selection Model for the Japanese Market

July 2015: Research Brief – Liquidity Fragility

June 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 4

May 2015: Investing in a World with Increasing Investor Activism

April 2015: Drilling for Alpha in the Oil and Gas Industry – Insights from Industry Specific Data & Company Financials

March 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 3

February 2015: U.S. Stock Selection Model Performance Review - The most effective investment strategies in 2014

January 2015: Research Brief: Global Pension Plans - Are Fully Funded Plans a Relic of the Past?

January 2015: Profitability: Growth-Like Strategy, Value-Like Returns - Profiting from Companies with Large Economic Moats
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October 2014: Lenders Lead, Owners Follow - The Relationship between Credit Indicators and Equity Returns

August 2014: Equity Market Pulse – Quarterly Equity Market Insights Issue 1

July 2014: Factor Insight: Reducing the Downside of a Trend Following Strategy

May 2014: Introducing S&P Capital IQ's Fundamental China A-Share Equity Risk Model

April 2014: Riding the Coattails of Activist Investors Yields Short and Long Term Outperformance

March 2014: Insights from Academic Literature: Corporate Character, Trading Insights, & New Data Sources

February 2014: Obtaining an Edge in Emerging Markets

February 2014: U.S. Stock Selection Model Performance Review

January 2014: Buying Outperformance: Do share repurchase announcements lead to higher returns?

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