McKinley Capital Management, LLC

Getting Sentimental: *Conference Call Sentiment and Stock Returns*

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Quantitative investing is, as the name suggests, all about numbers. Successful quantitative strategies have always had a voracious appetite for numerical data, happily devouring terabytes of ones and zeros without breaking a sweat. But there is a limit to how much of the world's information is naturally encoded in numbers. After all, most of human experience is expressed in written and spoken language, not sterile numbers. For a long time this imprecise world of emotions was off-limits to quantitative investors. But now advances in natural language processing and machine learning have given quants the tools they need to extract information from unstructured, text-based data sets.

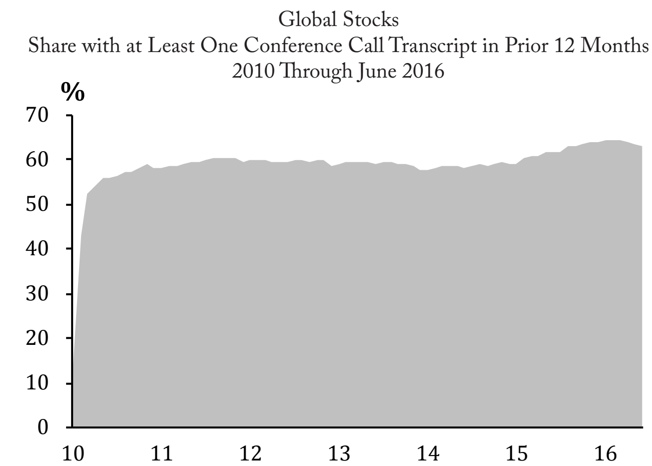
In this research we study whether the sentiment expressed in company conference calls, like the now-ubiquitous quarterly earnings call, can predict the cross-section of future stock returns. Conference calls are a direct interface between the C-suite of a listed company, its shareholders, and the sell-side analysts covering the company. As such, conference calls present a unique opportunity to put context around the cold, hard numbers presented in a company's financial statements. Our basic question is whether there is useful information in the language used in conference calls that goes above and beyond what one can glean from the numbers alone.

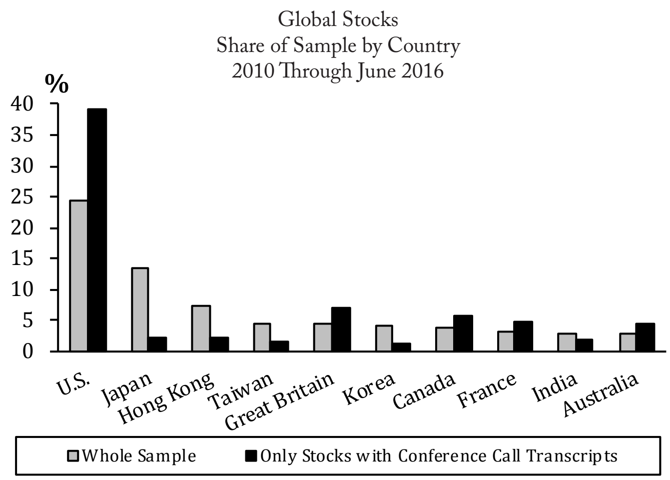
Listen Up: Extracting Sentiment from Conference Calls

The data set for our study is a large archive of conference call transcripts collected by FactSet, a data vendor. The database includes the transcribed proceedings of over 50,000 conference calls for global companies, beginning at the start of 2010 and finishing at the end of June 2016. Around 85% of the calls are quarterly or semi-annual earnings calls. An unique feature of the database is that the transcripts are in XML format, which makes it possible to separate out different parts of the call. For example, it is possible to extract the prepared remarks by the company's CEO from the analyst Q&A session that usually follows.

Exhibit 1 (over) shows the share of stocks in the McKinley Capital global stock universe that have conference call data over time, as well as the coverage by country. About 60% of companies in the universe have conference call data and, as we would expect, the coverage is skewed toward companies domiciled in English-speaking locales.

Exhibit 1: Conference Call Transcript Coverage of the McKinley Capital Global Stock Universe





Source: McKinley Capital, FactSet Research Systems.

The first question is how to quantify the information contained in each call. One plausible approach is to try to measure the sentiment expressed unconsciously by each speaker on the call. To do that we deploy the dictionary developed in Loughran and McDonald [2011]. In their research the authors classified words in the English language in those with positive, negative, and neutral connotations. An important feature of their dictionary is that the classifications are based on a *financial* context, for example the word "restatement" is generally more negative when used in finance-speak than when used in general English. Following their lead, we define the sentiment for a body of text to be the count of positive words less the count of negative words scaled by the total number of words.

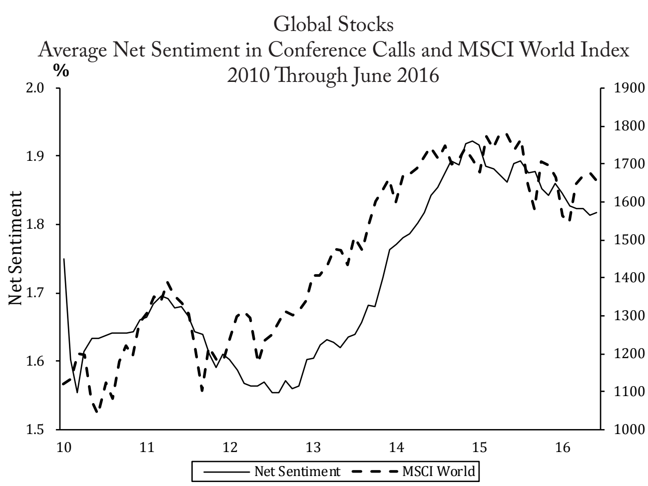
Armed with this metric we can compute the aggregate sentiment of all the conference calls over time and also the sentiment of the management discussion and analyst Q&A sections separately, see Exhibit 2.

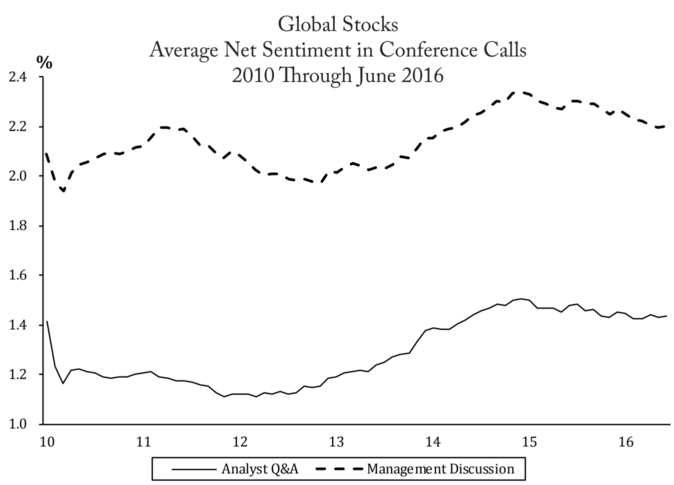
There are two noteworthy results. First, aggregate conference call sentiment tends to track the MSCI World Index, a promising result because it suggests a link between the tone used by participants on the conference calls and *market* sentiment. Second, the prepared remarks by company managers are consistently more positive than the analyst Q&A that follows, a result that will not come as a huge surprise to anyone who has listened to the carefully-vetted opening monologues that companies prepare these days.

Unstructured Alpha

To test whether conference call sentiment predicts future stock returns we first aggregate sentiment at the company level.

Exhibit 2: Aggregate Conference Call Sentiment





Source: McKinley Capital, FactSet Research Systems.

To do that for a given company at a given point in time we collect all the conference call transcripts for that firm over the prior 12 months and compute the average sentiment across all the calls for the management discussion sections and analyst Q&A sessions separately. We also compute a difference-in-sentiment factor, which is the sentiment in the analyst Q&A session less that of the management discussion.

Exhibit 3 shows the time-series of the monthly rank information coefficients (IC) over time and also the average over the whole sample. An information coefficient is a simple way to measure the predictive power of a stock-selection factor and is defined as the cross-sectional correlation between stocks ranked on the factor at time *t* and the ranking of stocks by their subsequent return from time *t* to *t*+1. A positive correlation indicates that stocks which scored highly on the factor, in this case stocks with highly positive conference call sentiment, went on to deliver the largest returns in the following month.

also studied the performance of realistic, optimized portfolios based on the sentiment factors. The mean-variance (MV) portfolio construction can be summarized as:

$$\text{minimize } w^T C w - \lambda \mu^T w \qquad (1)$$

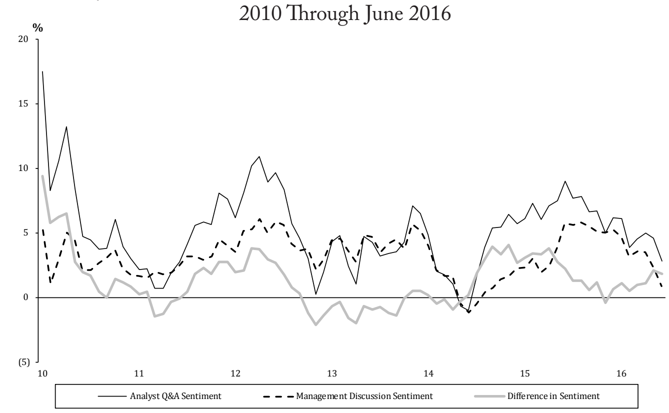
where μ is the expected return vector, C is the variance-covariance matrix, w is the portfolios weights, and λ is the risk-return tradeoff parameter. The estimation of C is usually done by a multifactor model, in which the individual stock return R_j of security *j*, at time *t*, dropping the subscript *t* for time, may be written like this:

$$R_j = \sum_{k=1}^{K} \beta_{jk} \tilde{f}_k + \tilde{e}_J \qquad (2)$$

The non-factor, or asset-specific return on security *j*, $\tilde{e}_j$ is the residual risk of the security after removing the estimated impacts of the *K* factors. The term f_k is the rate of return on factor *k*. The factor model simplifies the *C* as the sum of

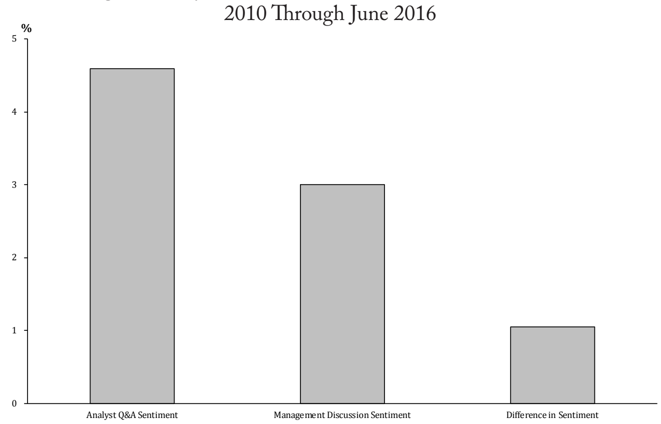
Exhibit 3: Information Coefficients for Conference Call Sentiment Factors

Global Stocks
Monthly Information Coefficient for Conference Call Sentiment Factors[1]
2010 Through June 2016



[1] Data smoothed on a trailing 12-month basis.

Global Stocks
Average Monthly Information Coefficient for Sentiment Factors
2010 Through June 2016



Source: McKinley Capital, FactSet Research Systems.

Based on the simple IC metric, sentiment derived from the analyst Q&A session of the calls has the strongest predictive power for month-ahead stock returns: the time-series is consistently positive and the average IC over the sample is around +4.5%, a high number by the standards of ICs. The IC for management discussion sentiment is lower but still positive, a finding that is somewhat intuitive given CEOs rarely depart from their attorney-vetted remarks these days. Interestingly the difference in sentiment seems to have little predictive power. Our hypothesis was that a big divergence in sentiment between the company's management and the analysts covering it might tell us something, but that was not borne our in the data.

Because ICs are a very crude measure of predictive power, we

systematic risk covariance and diagonal specific variances,

$$C = \beta C_{f,f} \beta' + \Sigma \qquad (3)$$

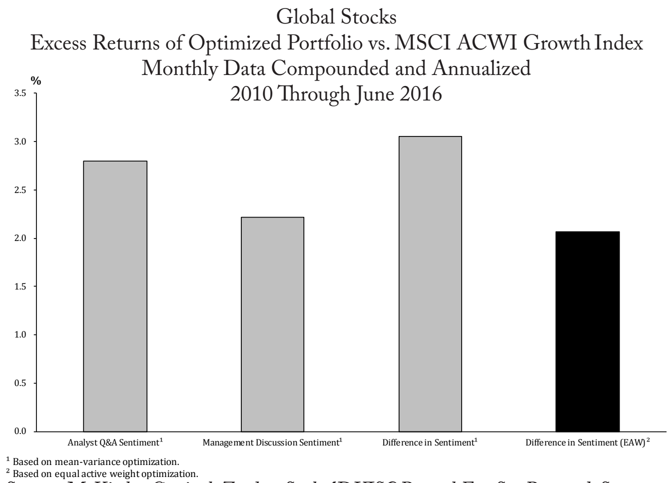
The portfolio risk is accordingly decomposed into systematic risk and specific risk

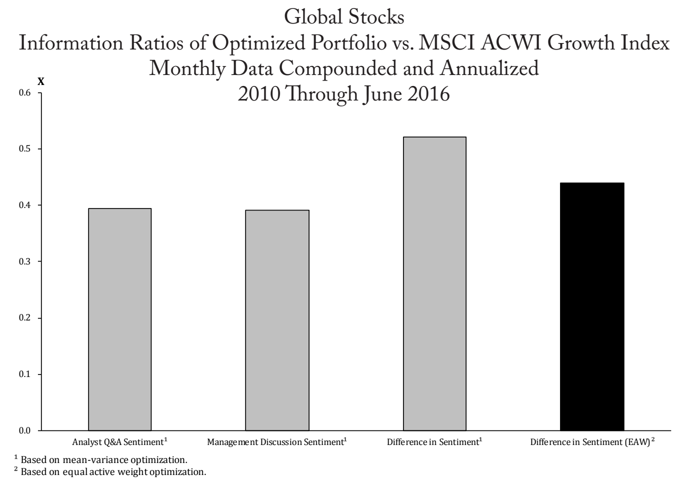
$$\sigma_p^2 = w' \beta C_{f,f} \beta' w + w' \Sigma w$$
$$= \sigma_{\beta P}^2 + \sigma_{SP}^2 \qquad (4)$$

If the investor is more concerned about tracking a particular benchmark, mean-variance optimization (1) can be reformulated as mean-variance tracking error at risk (MVTaR) optimization:

$$\text{minimize } (w-w_b)^T C (w-w_b) - \lambda \mu^T (w-w_b) \qquad (5)$$

Exhibit 4: Real-World Portfolio Performance for Conference Call Sentiment Factors





Source: McKinley Capital, Zephyr StyleADVISOR, and FactSet Research Systems.

where w_b is the weight vector of benchmark. One can also add equal active weighting constraints (EAW):

$$|w_j - w_{(b)j}| \leq x, \text{ for all } j \tag{6}$$

The MVTaR with constraints (6) will be noted as EAWTaR. The total tracking error can be decomposed into systematic tracking error and specific tracking error:

$$\begin{aligned}\sigma^2_{pTE} &= (w-w_b)'\beta C_{f,f}\beta'(w-w_b)+(w-w_b)'\Sigma(w-w_b)\\ &= \sigma^2_{\beta PTE}+\sigma^2_{SPTE}\end{aligned} \tag{7}$$

Guerard, Markowitz, and Xu [2015] tested several optimization techniques: (1) total risk minimization with no reference to systematic risk, denoted MVM59, which uses mean-variance analysis with a fixed maximum weight (4%) with the same optimization conditions; (2) mean-variance analysis with tracking error at risk, denoted MVTaR; and (3) an equal active weighting tracking error at risk with a maximum deviation of two percent, denoted EAW2TaR. The EAW2TaR optimization technique weights the systematic risk at three times the importance of specific risk and EAW2TaR where x in constraints equation (7) is set to be 2. MVM59, MVTaR, and EAW2TaR have proved to be effective techniques in real-world portfolio construction and management. We seek to maximize the geometric mean of the portfolios, consistent with Latane [1959] and Markowitz [1959][1]. We refer to the creation of portfolios with a multifactor model and the generation of the efficient frontier as a Level II test of portfolio construction.

Exhibit 4 shows the results for the sentiment factors using the EAW2TaR methodology. The risk model deployed was the Axioma Statistical Risk Model, composed of 15 factors from a Principal Components Analysis (PCA) estimation, see Guerard, Markowitz, and Xu [2015] for more details. The portfolios delivered excess returns over the MSCI All Country World Index of +2-3% per annum. The information ratios for the signals both have a value of 0.4. Both numbers are economically significant in a real-world active management setting.

We conducted attribution analysis on the optimized portfolios to assess the contributions made by stock-selection and factor exposures to active risk and returns. Exhibit 5 (over) shows the results for the Analyst Q&A factor, based on a mean-variance optimization. The left-hand chart decomposes the active return into the specific portion, due to stock-selection ability, and the portion due to factor and style exposures. The specific return is positive and significant at the 5% level while all other contributions are insignificant. That suggests most of the observed alpha in the signal is being produced by picking the right stocks, and not as the byproduct of embedded factor exposures. The right-hand chart shows the same decomposition for the active risk of the portfolio.

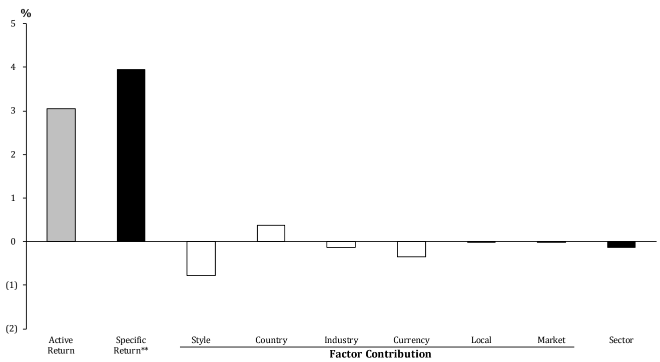
Contains MSG: Sentiment as a Flavor-Enhancer

The evidence so far suggests that conference call sentiment, particularly when derived from the analyst Q&A session, has some predictive power for future stock returns. In this section we study the interaction between conference call sentiment and a proprietary earnings forecasting factor called CTEFROIC that is deployed at McKinley Capital. CTEFROIC combines forecast earnings yield, one-month earnings revisions, breadth, and direction of revisions into a single factor that has delivered strong alpha as a stock-selection signal in live, out-of-sample

[1] Guerard, Markowitz, and Xu [2015] referred to the creation of portfolios with a multifactor model and the generation of the efficient frontier as a Level II test of portfolio construction.

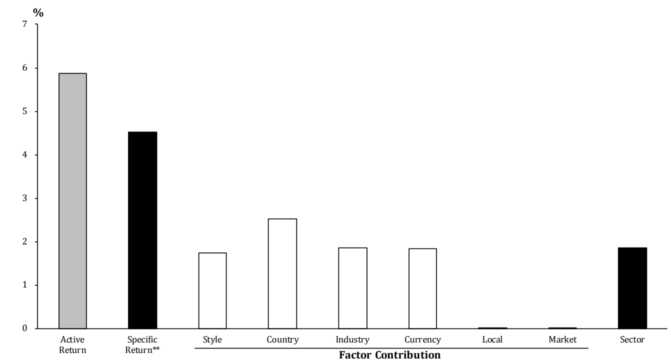
Exhibit 5: Attribution Analysis for Real-World Portfolios Based on Difference in Sentiment Factor

Global Stocks Active Return Attribution Analysis
of Optimized Portfolio Based on Analyst Q&A Sentiment[1]
2010 Through June 2016



[1] Mean-variance optimization; benchmark is MSCI All Country World Growth Index.

Global Stocks Active Risk Attribution Analysis
of Optimized Portfolio Based on Analyst Q&A Sentiment[1]
2010 Through June 2016



[1] Mean-variance optimization; benchmark is MSCI All Country World Growth Index.

Source: McKinley Capital, Axioma.

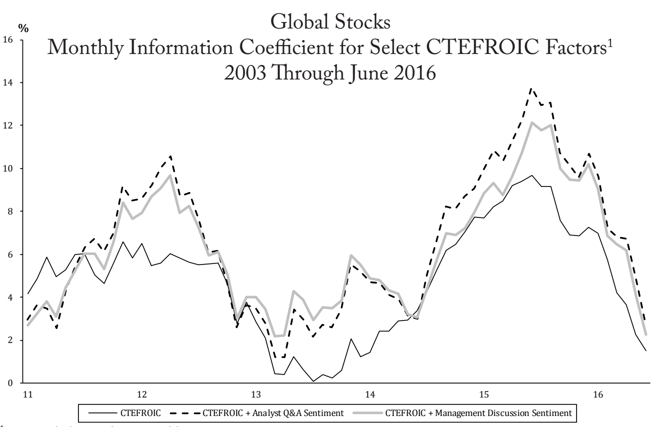
performance (see Guerard et al. [1997] for more details). Thus a factor that can enhance CTEFROIC has cleared a high hurdle rate.

The left hand side of Exhibit 6 shows there is a low correlation of ICs between CTEFROIC and the two conference call sentiment factors. That suggests it may be possible to glean some diversification benefit by combining signals. Indeed that proved to be the case. The right-hand side of Exhibit 6 shows the time-series of monthly ICs for CTEFROIC as a stand-alone signal as well as 50/50 combinations of CTEFROIC with each sentiment factor. Over time the combination of CTEFROIC and the analyst Q&A sentiment factor is consistently better than CTEFROIC on its own.

The improvement in predictive power over the whole sample is depicted in Exhibit 7 (over). The left-hand chart shows the average IC for CTEFROIC increases by +35-45% when combined with the sentiment signals in a 50/50 blend. Note that in this analysis stocks that do not have a sentiment score (around 40% of the sample, as per Exhibit 1) are omitted. This potentially makes the comparison between CTEFROIC and the sentiment factors unfair, since the performance of the latter is measured over a smaller universe. Therefore we repeated the same exercise in the right-hand chart, except this time we gave any stock with missing sentiment data the median score of the universe. The result is qualitatively the same, but the improvement in average IC does come down to about +25%.

Exhibit 6: Analysis of Sentiment Combined with CTEFROIC

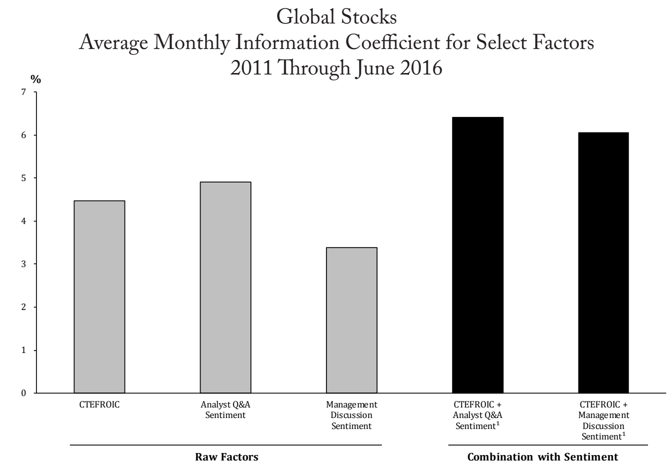
	CTEFROIC	Analyst Q&A Sentiment	Management Discussion Sentiment
CTEFROIC	100%		
Analyst Q&A Sentiment	6	100%	
Management Discussion Sentiment	7	83	100%

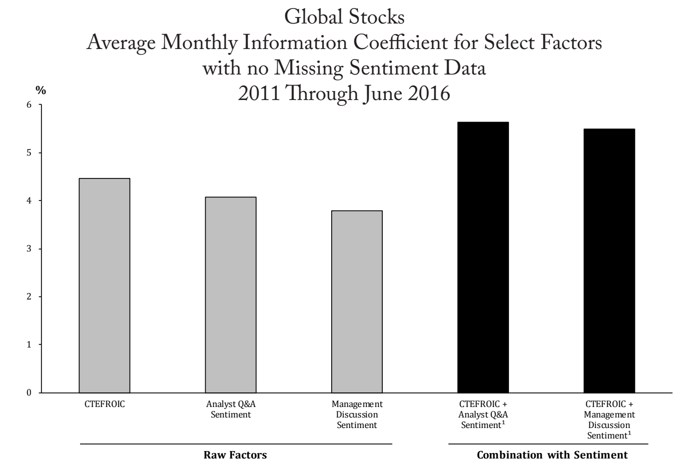


[1] Data smoothed on a trailing 12-month basis.

Source: Compustat, DataExplorers, Russell, Thomson Reuters, Deutsche Bank.

Exhibit 7: Enhancement in CTEFROIC Information Coefficient with Sentiment





[1] The differences in ICs between CTEFROIC and CTEFROIC blended with sentiment are statistically significant at the 5% level.

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Source: McKinley Capital, FactSet Research Systems.

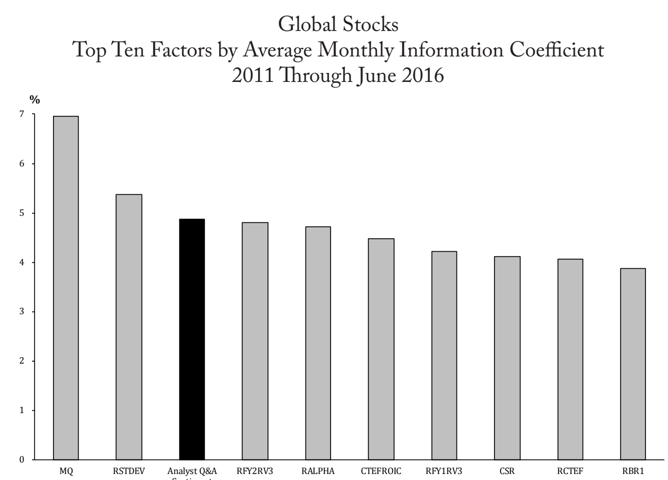
The Rise of the Machines: Sentiment and Machine Learning Models

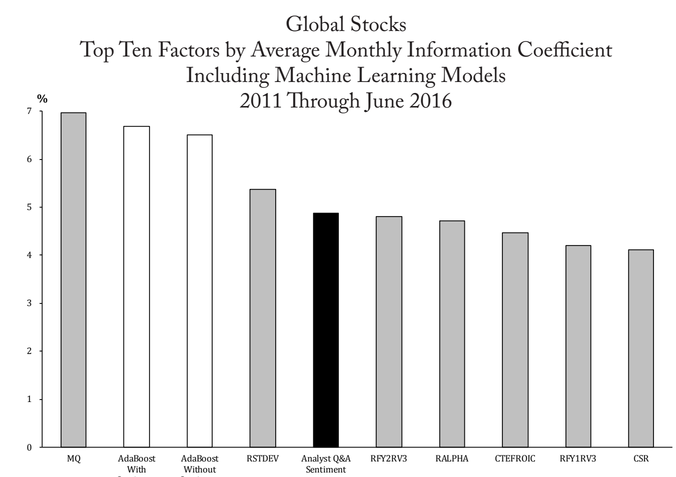
The fact conference call sentiment can enhance CTEFROIC is promising, because that factor has been powerful in live performance. However, an even higher hurdle is to benchmark the sentiment factors against a broad universe of factors known to predict future stock returns. To that end we collected 41 different factors, representing a comprehensive survey of the factors used by practitioners. Included are all the usual suspects like price momentum, earnings revisions, valuation ratios, earnings quality metrics, along with a number of proprietary factors developed at McKinley Capital. The first chart in Exhibit 8 shows the top ten factors over the sample period, when ranked by average IC. It turns out the analyst Q&A sentiment factor finishes third out of the pool of 41 factors.

That is a promising start, but to harvest that alpha we would have had to know ex-ante that analyst Q&A sentiment would end up being a good factor, i.e., back in 2010 we would have had to somehow know that we should bet on that factor instead of the 41 other factors. Thus an even stricter test is whether a factor-selection algorithm would have identified the sentiment factor as useful *back at each point in time*, knowing only what one knew back then. The right-hand chart in Exhibit 8 uses the AdaBoost machine learning algorithm as a factor-selection tool.

At each point in time the model is trained on the prior 12 months of factor performance. The idea is the machine should "learn" which factors are useful, based only on the information

Exhibit 8: Sentiment Factors Benchmarked Against a Broad Universe of Factors





Source: McKinley Capital, FactSet Research Systems.

known at the time. If there was enough information back through time to suggest the sentiment factor would be a useful factor going forward, then the machine would select it and use it to improve performance.

The white bars in the chart show that when the AdaBoost model was allowed to draw from a pool of factors that included sentiment, it did indeed use it to further enhance performance. In other words, the analyst Q&A sentiment factor showed enough performance even early in the sample to convince a machine learning algorithm that it should use the factor going forward.

Conclusion: A Promising New Alpha Source

Unstructured, text-based data from conference call transcripts appears to contain useful information for forecasting the future returns of global stocks. Specifically, sentiment extracted from the language used in the analyst Q&A session that usually concludes an earnings call has positive predictive power for month-ahead stock returns. In addition to stand-alone alpha, we found evidence that conference call sentiment can be used to enhance a proprietary earnings forecasting factor. Furthermore the factor's performance consistency was high enough to allow a machine learning model to identify the factor's potential ex-ante.

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References

Gillam, R.G., Guerard, J.B., Jr., and R. Cahan, 2015. "News Volume Information: Beyond Earnings Forecasting in a Global Stock Selection Model", *International Journal of Forecasting*, Vol. 31, pp. 575-581.

Guerard, J.B., Jr., Gultekin, M., and B.K. Stone, 1997. "The Role of Fundamental Data and Analysts' Earnings Breadth, Forecasts, and Revisions in the Creation of Efficient Portfolios." In *Research and Finance* 15, Edited by A. Chen.

Guerard, J.B., Jr., R.T. Rachev, and B. Shao, 2013. "Efficient Global Portfolios: Big Data and Investment Universes", *IBM Journal of Research and Development* 57, No. 5, Paper 11, 1-11.

Guerard, J.B., Jr., H.M. Markowitz, and G. Xu, 2015. "Earnings Forecasting in a Global Stock Selection Model and Efficient Portfolio Construction and Management", *International Journal of Forecasting*, Vol. 31, pp. 550-560.

Loughran, T., and B. McDonald, 2011. "When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks." *Journal of Finance*, Vol. 66, pp. 35-65.

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