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AI for Stock Selection – the ESG Connection

- We introduce a novel AI-based technique for rating company ESG quality. Our method employs a unique Natural Language Processing (NLP) approach to analyse earnings call transcripts, uncovering ESG-relevant narratives and extracting ESG signals we can use to guide stock selection.
- Our NLP algorithm, which blends traditional machine learning and cutting edge deep learning, identifies company ESG characteristics in ways that relate meaningfully to company financial performance. To achieve this, we take advantage of the Sustainability Accounting Standards Board's (SASB) framework for identifying ESG features that combine financial materiality and sustainability materiality.
- We demonstrate the benefit of our NLP-derived ESG signal for stock selection by constructing long-only and long-short portfolios that favor companies with better ESG qualities. These portfolios produce excellent returns in out-of-sample back-tests.
- To confirm that our NLP ESG signal corresponds to generally accepted company ESG characteristics, we show portfolios consisting of top NLP ESG-ranked stocks have superior overall ESG quality as measured by the consensus-based portfolio ESG rating introduced in our previous report, "A Measured Approach to ESG Investing". Good ESG quality can indeed produce good investment returns.

Companies host earnings calls to report financial results to investors and shareholders, and these calls importantly provide more than just financial information. They offer prepared language by the company and carefully worded responses to analysts' questions. There is often a hidden narrative that can be easily missed.

In this report, we show how we use Natural Language Processing (NLP) Artificial Intelligence to interpret the language of earnings calls in the context of ESG. We then use this understanding to generate an ESG score for the company and to guide stock selection.

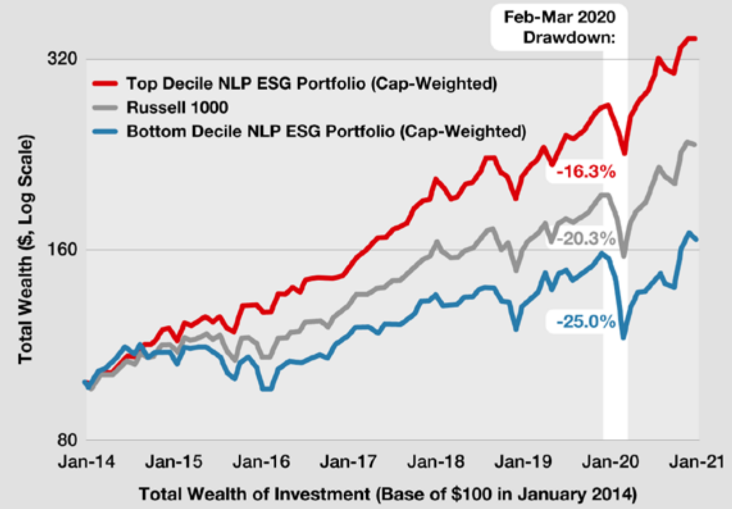
Systematic strategies using this approach have worked very well in our seven-year out-of-sample back-tests, and have performed especially well over the past few years – a period during which systematic stock selection strategies have performed miserably.

STOCK SELECTION BASED ON ESG NARRATIVES

First, we'll show what is achieved for stock selection. In Fig. 1, we show the cumulative wealth for three long-only portfolios: The top NLP ESG-ranked decile of Russell 1000 stocks, the Russell 1000 index, and the bottom NLP ESG-ranked decile of Russell 1000 stocks.

We trained our NLP algorithms on text from earnings call transcripts from 2007 through the end of 2013, so the results plotted in Fig. 1 are out of sample. It shows that the top NLP ESG-ranked Russell 1000 stocks produced superior returns and risk-adjusted returns compare to the Russell 1000 index.

The bottom-ranked ESG stocks, by contrast, generate inferior returns and risk-adjusted returns compared to the Russell 1000 index. The drawdown in the Covid-19 market collapse of February-March 2020 highlights an important feature of this ESG ranking. The drawdown of the Russell 1000 was -20.3% in the collapse, significantly better than the -25.0% drawdown for the bottom-ranked ESG stocks but worse than the -16.3% drawdown for the top-ranked ESG stocks.



	Top Decile Portfolio	Bottom Decile Portfolio	Russell 1000
2020 – Jan 2021 Return	28.4%	5.2%	20.0%
2018 – Jan 2021 Annualized Return	20.9%	7.4%	14.1%
Vol	18.2%	20.7%	19.1%
Return/Vol	1.1	0.4	0.7
2014 – Jan 2021 Annualized Return	19.1%	7.4%	12.7%
Vol	14.0%	15.9%	14.5%
Return/Vol	1.4	0.5	0.9

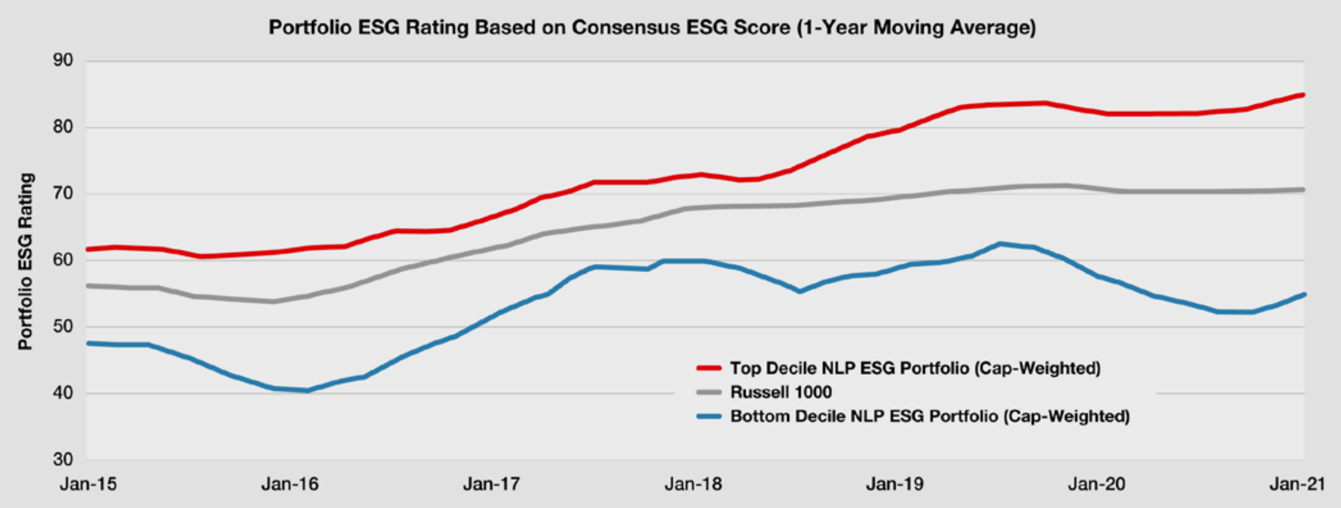
Note: The chart shows the performance of the top and bottom decile NLP ESG portfolios of Russell 1000 stocks, and the Russell 1000 index. The table shows return and volatility of the top and bottom decile NLP ESG portfolios of Russell 1000 stocks, as well as the Russell 1000 index. Portfolios are cap-weighted and rebalanced monthly. Period is from January 2014 through January 2021.

Source: Compustat, Factset, Russell, Nomura.

Fig. 1: Performance of Long-Only Portfolios Based on NLP ESG

But a question remains: How do we know the top NLP ESG portfolio in Fig. 1 really has better ESG quality than the Russell 1000 benchmark and the bottom NLP ESG portfolio? In our previous report, "**A Measured Approach to ESG Investing**," we described why a portfolio ESG rating should not be measured by aggregating company-level ESG ratings from any single provider. Instead, we use consensus company-level ESG ratings across a wide range of providers to calculate an aggregate portfolio ESG rating.

Fig. 2 shows the consensus-based ESG ratings for the portfolios in the long-only strategies displayed in Fig. 1. The top NLP ESG-ranked portfolio (red line) achieves a clearly higher consensus-based portfolio ESG rating than the Russell 1000 benchmark (gray line), which in turn has consistently higher consensus-based ESG rating than the bottom NLP ESG-ranked portfolio (blue line). Thus, the top decile NLP ESG-ranked portfolio achieves both superior performance (Fig. 1) and better ESG quality (Fig. 2).



Note: Shows the 1-year moving average of portfolio ESG ratings for the cap-weighted top and bottom decile NLP ESG portfolios, and the Russell 1000 Index. The portfolio ESG rating is calculated as the weighted average (according to companies' weights in the portfolio) of individual companies' percentile ranks of consensus ESG rating within their industry groups. Period is from January 2015 through January 2021.

Source: Compustat, Factset, Russell, GICS, OWL Analytics, Nomura.

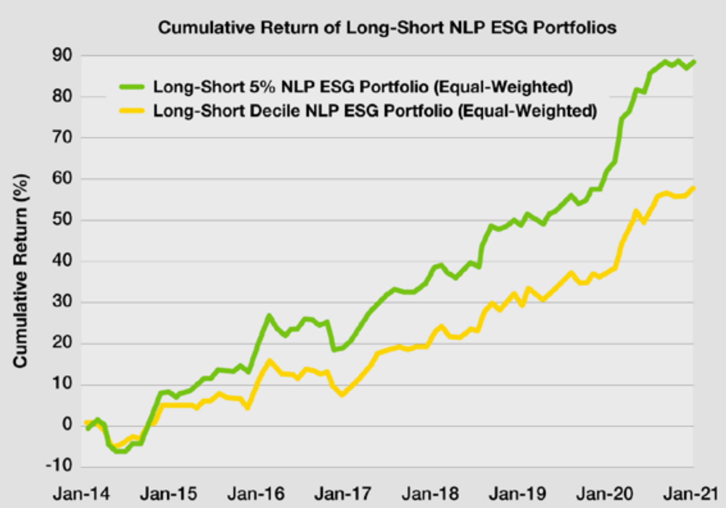
Fig. 2: Top (Cap-Weighted) NLP ESG Portfolio Shows ESG Advantage

Now, given the performance contrast between the top and bottom NLP ESG-ranked stocks evident in Fig. 1, a long-short strategy makes sense (long the top NLP ESG-ranked stocks and short the bottom NLP ESG-ranked stocks).

The yellow line in Fig. 3 represents the same top and bottom NLP ESG-ranked decile of stocks used earlier, but combined into a single long-short portfolio. These portfolios are rebalanced monthly, as in Fig. 1, but they are equal-weighted rather than cap-weighted to reduce portfolio concentration.

The reduced concentration achieved by equal-weighting the portfolio enables us to build an even more ESG-focused long-short portfolio based on the top and bottom 5% NLP ESG ranked Russell 1000 stocks (i.e., top 50 stocks vs. bottom 50 stocks). This produces even better returns than the long-short NLP ESG decile portfolio.

Fig. 3 shows cumulative spread returns for both the long-short NLP ESG decile portfolio (yellow line) and 5% portfolio (green line). The performance summarized in the table is stellar, especially for the 5% long-short strategy.



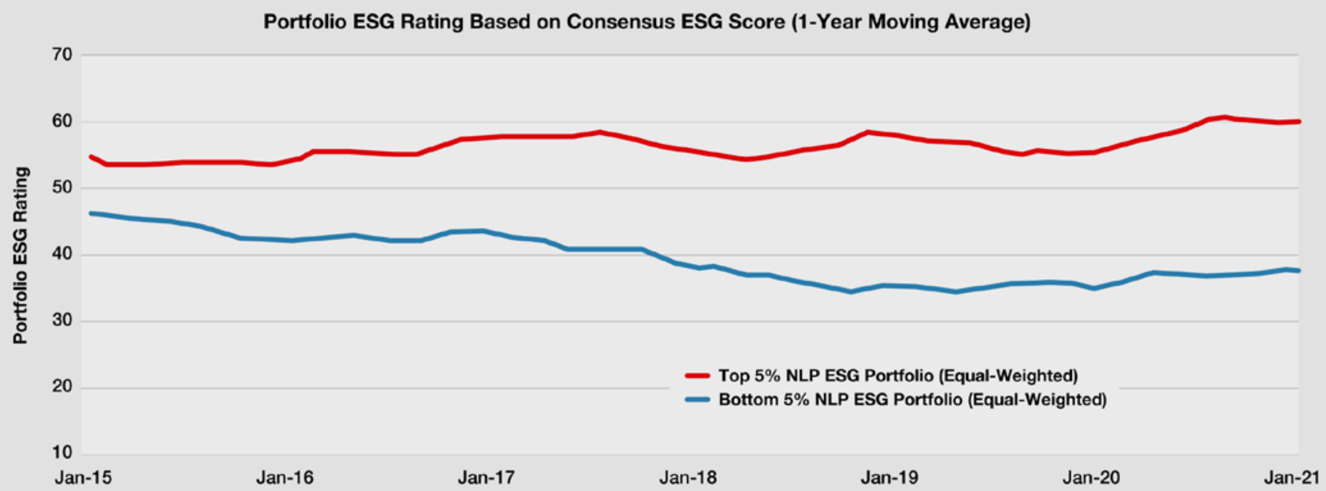
	Long-Short 5% Portfolio	Long-Short Decile Portfolio
2020 – Jan 2021 Return	31.1%	21.9%
Hit Rate	*77%*	*77%*
2018 – Jan 2021 Annualized Return	17.4%	12.5%
Vol	8.7%	7.7%
Return/Vol	2.0	1.6
Hit Rate	*70%*	*65%*
2014 – Jan 2021 Annualized Return	12.6%	8.2%
Vol	8.4%	7.0%
Return/Vol	1.5	1.2
Hit Rate	*69%*	*62%*

Note: The chart shows cumulative (arithmetic sum) long-short spread return of the equal-weighted 5% and decile NLP ESG portfolios. The table shows the performance statistics. Universe is the Russell 1000. Long-short portfolios are rebalanced monthly. Period is from January 2014 through January 2021.

Source: Compustat, Factset, Russell, Nomura.

Fig. 3: Performance of Long-Short Portfolios Based on NLP ESG

Similarly to Figs. 1 & 2, the portfolio ESG ratings of the equal-weighted top and bottom 5% NLP ESG-ranked portfolios used to generate the results in Fig. 3 are shown in Fig. 4. These ratings are also calculated using company-level consensus ESG ratings, which do not include our proprietary NLP ESG ratings that we used to construct the portfolios. The equal-weighted top 5% NLP ESG portfolio shows an ESG advantage over the equal-weighted bottom 5% NLP ESG portfolio.



Note: Shows the 1-year moving average of portfolio ESG ratings for the equal-weighted top and bottom 5% NLP ESG baskets. Period is from January 2015 through January 2021.

Source: Compustat, Factset, Russell, GICS, OWL Analytics, Nomura.

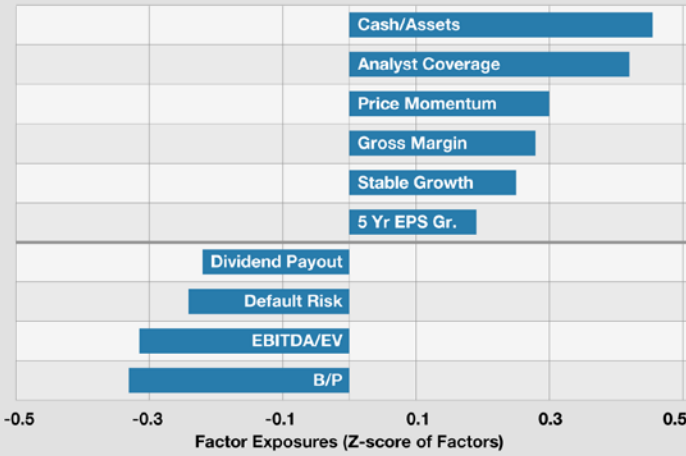
Fig. 4: Top (Equal-Weighted) NLP ESG Portfolio Shows ESG Advantage

WHAT DROVE THE NLP ESG STRATEGY'S SUCCESS?

The long-short performance shown in Fig. 3 is impressive, especially given the generally terrible performance of long-short quant equity strategies in 2018-2020. We attribute some measure of this success to the fact that good ESG quality dynamically nudged the NLP ESG portfolios into beneficial factor exposures.

These factor exposures are not static but, as an example, Fig. 5 (on the bar chart and in the first column of the table) shows the ten largest factor exposures (by magnitude) for the equal-weighted long-short decile NLP ESG portfolio in 2020. The table in Fig. 5 also shows the cumulative factor returns for the Covid market collapse of February-March 2020 in the center column and factor returns for 2020 in the rightmost column. The long-short portfolio had beneficial factor exposures during the 2020 Covid market collapse, as well as for 2020 in general. Among other things, the portfolio had positive exposure to price momentum, gross margin, and growth (stable earnings growth and 5-year EPS growth) and had negative exposure to value (B/P and EBITDA/EV). The highest factor exposure was to cash/assets, which proved protective during the Covid market meltdown and produced excellent returns over 2020.

Most Exposed Factors of L-S Decile Portfolio based on NLP ESG in 2020



	Factor Exposure	Feb-Mar 2020 Return (%)	2020 Return (%)
Cash/Assets	0.46	16.4	50.8
Analyst Coverage	0.42	-6.0	30.8
Price Momentum	0.30	17.5	-12.5
Gross Margin	0.28	15.3	21.9
Stable Growth	0.25	15.2	20.1
5 Year EPS Growth	0.19	17.3	27.2
Dividend Payout	-0.22	-1.6	-15.8
Default Risk	-0.24	-22.7	17.1
EBITDA/EV	-0.32	-25.1	-53.6
B/P	-0.33	-24.7	-9.1

Note: Bar chart shows the ten most exposed factors (by magnitude) of the equal-weighted long-short decile portfolio based on NLP ESG for 2020. Factor exposures are calculated as the weighted z-score of factors of the long NLP ESG basket minus the weighted z-score of factors of the short basket. The table shows exposure of the ten most exposed factors (first column). It also shows the equal-weighted long-short decile spread returns of those ten factors for Febraury-March 2020 (second column) and 2020 (third column). Universe is the Russell 1000 and portfolios/factors are rebalanced monthly.

Source: Compustat, Factset, Russell, I/B/E/S, Nomura.

Fig. 5: Factor Exposure of Long-Short NLP ESG Portfolio Benefited in 2020

USING NLP TO GENERATE ESG RATINGS

As with many things, context is key, and deriving meaning from a text requires framing that text within a certain context. Analyzing the text of earnings calls for ESG content provides a useful way of evaluating the ESG features of companies and enables us to systematically rank companies for ESG quality according to the implicit content of their public statements.

To ensure that our algorithm identifies company ESG quality in a way that relates meaningfully to company financial performance, we adopt the Sustainability Accounting Standards Board's (SASB) framework for identifying ESG features, since that framework systematically links ESG features to company financial performance.

Note: Shows 5 ESG dimensions and 26 ESG categories of the SASB sustainability framework.

Source: SASB (https://www.sasb.org/), Nomura.

Fig. 6: The SASB Sustainability Framework: Domensions and Categories

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The SASB framework emphasizes what it calls double materiality – financial materiality and sustainability materiality. Fig. 6 shows the SASB framework. The framework comprises five major dimensions (Environment, Social Capital, Human Capital, Business Model & Innovation, and Leadership & Governance), each of which are related to some company financial features or business practices.

From these five major dimensions of sustainability, SASB derives 26 ESG categories (see Fig. 6). Our NLP then matches sentences in the aforementioned earnings call transcripts to one of the 26 categories. A company's ESG score is calculated as the number of positive ESG sentences minus the number of negative ESG sentences, divided by the total number of ESG-related sentences in the transcript.

We'll consider a few examples that illustrate the point.

Below we outline example ESG sentences from a few companies that were the largest alpha contributors in 2020 from the long side (high NLP ESG-ranked companies) and the short side (low NLP ESG-ranked companies) of the results shown in Fig. 3.

EXAMPLES OF ESG SENTENCES IDENTIFIED BY NLP (FROM LONG SIDE)

Critical Incident Risk Management Category Positive (within Leadership and Governance Dimension):

"It certainly appears to have some level of -- some small level of incrementality, but really it's most important for us as what I'll call an insurance policy when or if we have stores that are unable to operate, keeping them open and able to operate in that buy online pick up in store manner, especially in our off-mall locations is a very nice safety net to now have as a capability."

Supply Chain Management Category Positive (within Business Model & Innovation Dimension):

"We feel very fortunate that our supply chain has been able to weather the pandemic and has figured out how to operate both in a very safe way, but also increased capacity and output relative to our sales increase."

"And the good news is that we have supply chain partners, manufacturing partners that we have long-standing relationships and a very clear mind about how to move quickly and with agility and the best we can."

Employee Health & Safety Category Positive (within Human Capital Dimension):

"We require that our associates wear masks either that we provide or that they bring from home"

"We also ask that in many cases they wear gloves."

"Our priorities are the same, as Andrew articulated, and would be the case I think for any retailer which is first and foremost is how we keep associates and customers safe."

EXAMPLES OF ESG SENTENCES IDENTIFIED BY NLP (FROM SHORT SIDE)

Business Model Resilience Category Negative (within Business Model & Innovation Dimension):

"The impact of COVID-19 on the global macro economy has created an unprecedented destruction of demand as well as lack of forward visibility for many of the transportation fuels, lubricants and specialty products and the associated transportation and terminal services that we provide."

Systemic Risk Management Category Negative (within Leadership & Governance Dimension):

"We saw seasonal weakness in late December and early January, and this was compounded by the timing of the Chinese New Year."

Management of Legal and Regulatory Environment Category Negative (within Leadership & Governance Dimension):

"Some are real, some are perceived, some are more to do with awareness in terms of the policies, but obviously there are logistical challenges relating to the testing, the COVID testing as well as the visa application."

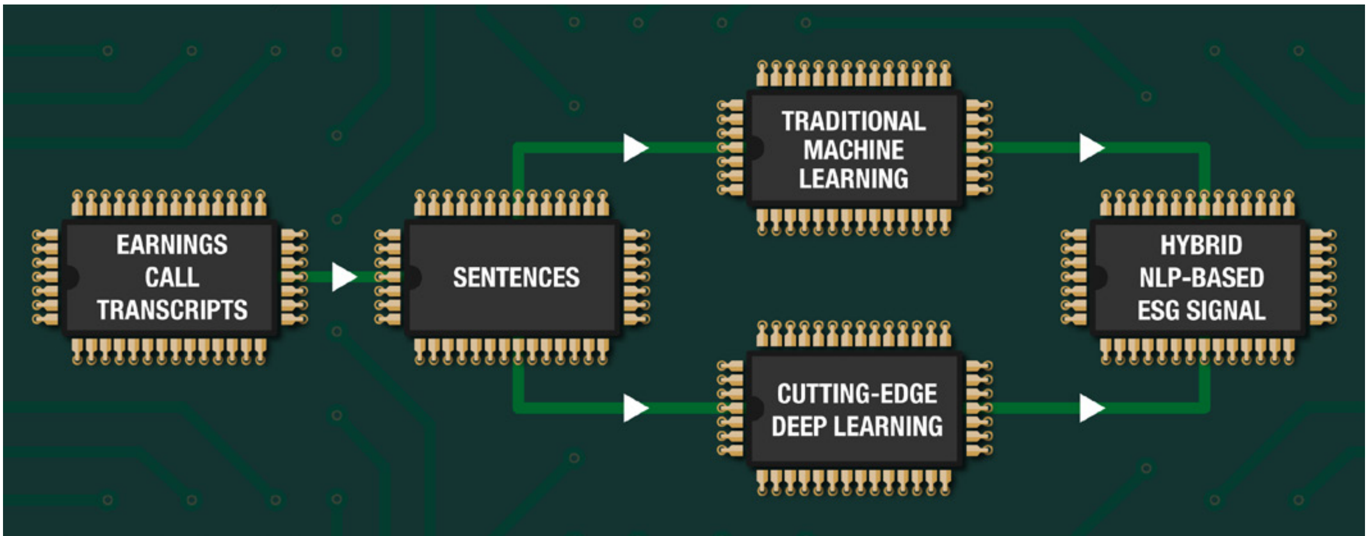
A UNIQUE HYBRID NLP APPROACH TO STOCK SELECTION

The example sentences shown above give a general sense of how we use NLP to analyze earnings calls and indicate how company ESG features under the SASB framework can influence financial performance. Next, we'll explain how we rank stocks according to this metric.

The essential task of the algorithm is to determine whether sentences match an SASB ESG category and then classify matches as positive or negative instances. This does not, however, necessarily guarantee the best performance for stock selection.

We take advantage of the distinctiveness of two NLP approaches to create a hybrid stock selection signal that blends traditional machine learning and cutting-edge deep learning techniques. The highly simplified flow chart in Fig. 7 gives an overview of the approach. We run two separate NLP analyses on earnings call transcripts, one using traditional machine learning and one using deep learning techniques, to generate two ESG scores for a given company. The two separate ESG scores are then combined to form a hybrid ESG score for that company.

The hybrid ESG score is used to rank stocks and build the portfolios represented in Figs. 1 - 4.



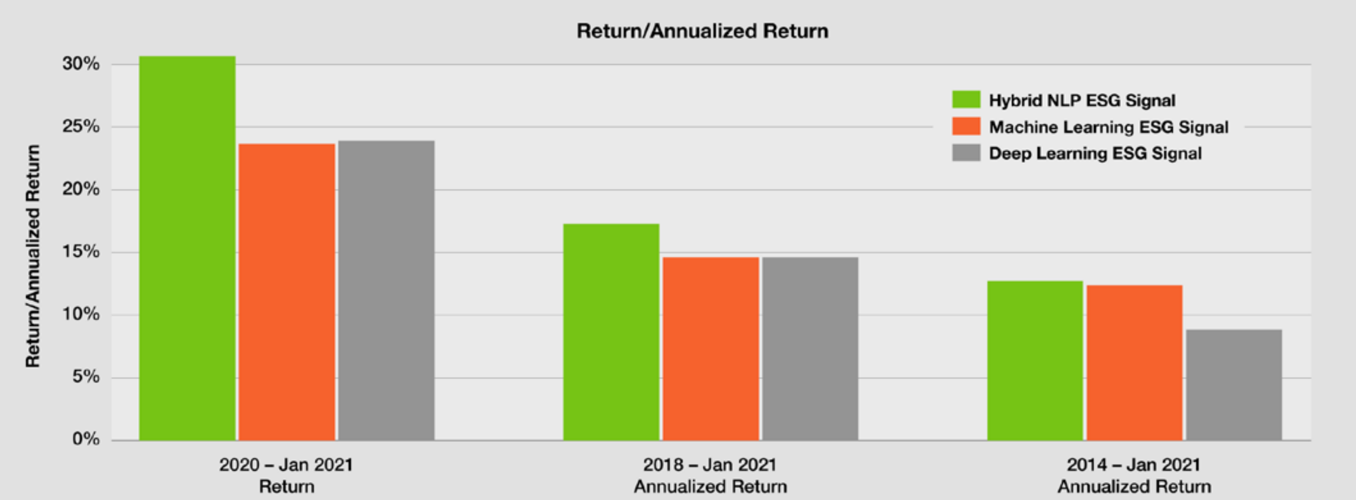
Note: Shows the flow diagram for the NLP algorithm.
Source: Nomura.

Fig. 7: NLP Workflow

Figs. 8 and 9 shows the advantage of a hybrid NLP approach, both for portfolio performance and for portfolio ESG quality.

The long-short 5% portfolio returns depicted in the table in Fig. 3 are represented by the green bars in Fig. 8. We call this the hybrid ESG signal return, since the signal is generated by a hybrid of a traditional machine learning approach and a deep learning approach. The orange and gray bars in Fig. 8 depict the returns produced by stock selections guided by ESG signals of the two approaches separately. The hybrid approach produces portfolios that yield superior returns compared to that produced by either of the two approaches separately.

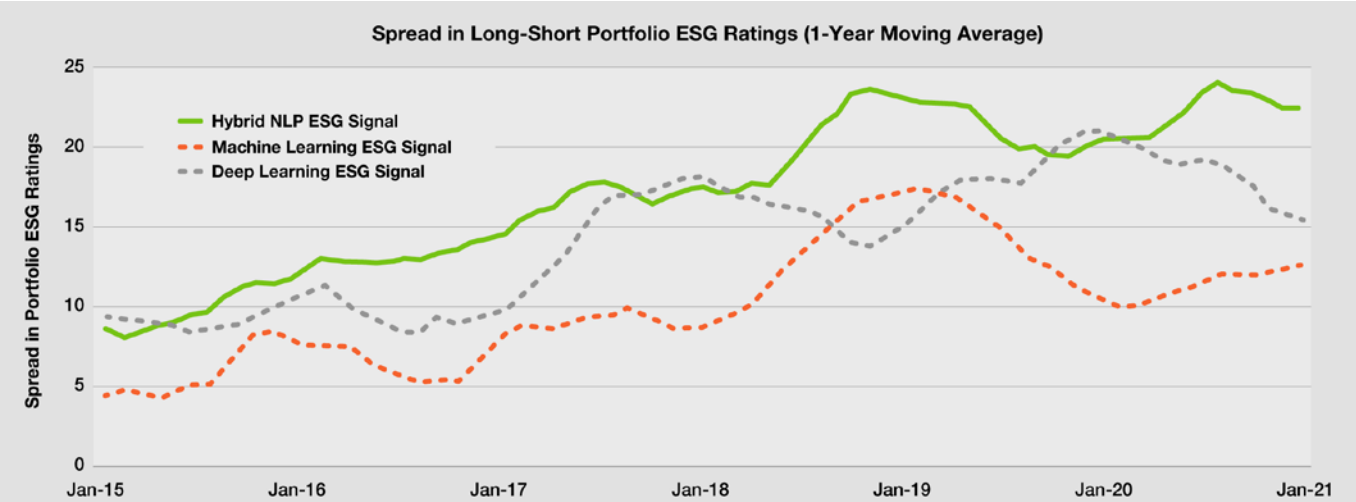
Fig. 9 shows the corresponding spread in ESG ratings between the equal-weighted long and short NLP ESG portfolios that generate the returns shown in Fig. 8. The green line in Fig. 9 shows the ESG rating spread for the hybrid approach, which is simply the difference of the red and blue lines shown in Fig. 4. Since deep learning tends to provide better matching of sentences to the most appropriate ESG category, the long-short portfolio based on a deep learning ESG signal (gray line in Fig. 9) tends to provide a larger ESG rating spread than the portfolio based on traditional machine learning (orange line in Fig. 9). The hybrid ESG signal (green line in Fig. 9) achieves greater ESG ratings spread than does either signal independently. Recall that our approach to measuring ESG ratings uses the consensus ESG score, which does not include our NLP ESG ratings.



Note: Shows return/annualized return of the equal-weighted long-short 5% NLP ESG portfolios. NLP ESG signals are generated from earnings call transcripts through traditional machine learning, deep learning, and a hybrid approach. Universe is the Russell 1000. Long and short portfolios are rebalanced monthly. Period is from January 2014 through January 2021.

Source: Compustat, Factset, Russell, Nomura.

Fig. 8: Hybrid Approach vs. Machine Learning vs. Deep Learning Learning



Note: Shows the (1-year moving average) spread in portfolio ESG ratings of the equal-weighted long and short 5% portfolios based on NLP ESG signals. NLP ESG signals are generated from earnings call transcripts through traditional machine learning, deep learning, and a hybrid approach. Portfolio ESG ratings are calculated using consensus ESG scores from OWL Analytics. Universe is the Russell 1000. Long and short portfolios are rebalanced monthly. Period is from January 2014 through January 2021.

Source: Compustat, Factset, Russell, OWL Analytics, Nomura.

Fig. 9: Portfolio ESG Rating Spread: Hybrid Apporach vs. Maching Learning vs. Deep Learning

CONCLUSION

We describe our use of Natural Language Processing (NLP), applied within the framework of the Sustainability Accounting Standards Board (SASB) ESG categories, to analyze the transcripts of companies' earnings calls. Our goal with the approach described above, is to extract more information from earnings calls than their explicit content reveals. In particular, we seek to uncover signals of company's ESG quality and ESG impact on current and future financial performance. The SASB framework is well suited to this NLP task, since it establishes ESG categories that correspond both to financial materiality and to sustainability materiality of companies.

There is considerable disagreement among analysts concerning whether good company ESG quality leads to good stock performance. Our unique NLP approach achieves exceptional stock selection performance for good ESG quality. Portfolios constructed based on our NLP ESG ranking of stocks show both superior performance (Figs. 1 & 3) and better ESG quality as measured by consensus ESG ratings (Figs. 2 & 4). Good ESG quality can indeed produce good investment returns.

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