Sustainable Investment – Exploring the Linkage Between Alpha, ESG, and SDG's[1]

SSRN Working Paper

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August 2020

Abstract

Environmental, Social and Governance (ESG) investing has been one of the most important topics in asset management this past decade. Yet, for all the attention, only a fraction of asset managers truly consider ESG issues when making investment decisions. This is partly due to the perceived conflict of ESG investing with an asset manager's fiduciary duty and partly due to low-quality ESG data despite the near ubiquity of sustainability reports. We analyze the relationship between alpha generation and ESG metrics, and measure the impact companies have on the U.N.'s Sustainable Development Goals (SDG´s). First, we construct a sector-neutral portfolio using MSCI ESG momentum scores from 2013 to 2018, and determine that it is feasible to generate positive alpha vis a vis the MSCI US index. Second, we utilize structured and unstructured data to determine a company's net influence on the SDGs, what we call its SDG 'footprint.' We show that an ESG momentum portfolio both outperforms the MSCI US index and has a relatively better SDG footprint than that of the index. Third, we establish a positive contemporaneous connection between the portfolio's ESG ratings momentum and its SDG footprint. Thus, a positive linkage exists between ESG, alpha, and the SDG's.

Keywords: ESG, SDG, asset management, alpha, fiduciary duty, risk factors.

[1] We thank the Office of Investment Management at the United Nations Joint Staff Pension Fund for initiating the original idea of this research and their work on testing the alpha assumption of the active ESG momentum portfolio. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the United Nations.

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I. Introduction

In 2005, the late Kofi Annan, the United Nations Secretary-General launched the Principles for Responsible Investment (PRI) supported by "leading institutions from 16 countries, representing more than $2 trillion in assets owned." The PRI provide a framework for institutional investors to take environmental, social and governance (ESG) issues into their investment decisions. The fundamental underpinning of the PRI was to encourage investing for long-term sustainable development rather than short-term gains (United Nations, 2006).

Two years later the tenets of the PRI and the need for taking a long-term view on sustainability took on a greater meaning and sense of urgency with the release of the United Nations Intergovernmental Panel for Climate Change. This report linked human action to global warming and laid bare the need to address sustainability in a more systematic manner (United Nations, 2007). Responding to this report many national pension funds managing intergenerational assets and already keenly focused on driving long-term performance were interested in finding an investment instrument which could support climate change. This pursuit of an investment instrument led a group of Swedish pension funds to approach the World Bank Treasury and together they co-created the World Bank's first green bond "demonstrating the potential for investors to support climate solutions through safe investments without giving up financial returns" (World Bank, 2018).

At the same time the advent of the Great Financial Crisis (GFC) brought to life the need for a greater emphasis on governance and protecting an entity's reputation, arguably one of its most valuable intangible assets. Poor governance was shown to have had direct, and significant negative financial consequences for companies and their investors such as was seen with Lehman Brothers that suffered the largest bankruptcy in history (Antoncic, 2018).

In other words, so-called "nonfinancial" risks, become financial risks. (Antoncic, 2019a). This is more true today than ever before with intangible assets at $21 trillion, the majority of which are unreported on balance sheets due to accounting standards, representing 84% of the S&P 500 market value, up from just 17 percent four-and-a-half decades ago (Visual Capitalist, 2020).

This new focus on nonfinancial risks entailed a significant "shift from short-termism to focusing on the long-term sustainability of companies" and on the needs of all stakeholders. In other words, companies have to uphold their "contract with society in order to maintain their license to do business" (Antoncic, 2020).

Yet, while "more than 2,300 organizations, representing more than $86 trillion in assets, have become signatories to the PRI," (Antoncic, 2019a) double of what it was just four years ago and up from just $20 trillion a decade ago, only a fraction of asset managers are truly 'walking the talk.' In its 2019 Responsible Investing Survey of nearly 800 participants from around the world, RBC Global Asset Management found that while many asset managers and asset owners are signatories, when asked "to what extent are ESG principles used as part of your investment approach and decision making," 30 percent responded "not at all," 46 percent responded "somewhat" and only 24 percent responded "significantly" (RBC Global Assets, 2019). In fact, the results of this survey are consistent with other research which "conclude(s) that only select funds improve ESG while many others use the PRI status to attract capital without notable changes to ESG." An important implication is a "need for a systematic way to measure and assess how asset managers execute ESG" (Kim and Yoon, 2020).

So why is this? Part of the answer can be found in the belief by some institutional asset owners and managers that ESG issues, also known as nonfinancial risks and opportunities, are in conflict with their fiduciary duties to act in the best interest of their beneficiaries. In fact, the recent Department of Labor (DOL) proposal to limit the ability of asset managers of Employee Retirement Income Security Act of 1974 (ERISA) accounts to take ESG risk factors into consideration promulgates this view of a conflict. The new proposal codifies the DOL's position that "private employer-sponsored retirement plans are not vehicles for furthering social goals or policy objectives that are not in the financial interest of the plan. Rather, ERISA plans should be managed with unwavering focus on a single, very important social goal: providing for the retirement security of American workers." (Department of Labor, 2020)

Part of the answer can also be found in the lack of high-quality ESG data. In fact, 63% of hedge funds polled by KPMG responded to a recent survey that ESG investing is "hampered by the lack of robust reliable data." (KPMG, 2020). Moreover, there is a lack of generally accepted agreed-upon standards and reporting requirements. While corporations now largely self-report some ESG data, "the

practice has been widely criticized for lacking the rigor of traditional financial reporting" which results in significant 'green-washing' and data biases. Moreover, ESG metrics are updated infrequently, typically on an annual basis. Thus, investors "may be fundamentally constrained by a lack of high-quality, firm-level ESG data, to serve as key inputs in assessing, managing, and monitoring the ESG risks and opportunities that a company faces" (Antoncic, 2019b).

Due to the lack of agreed ESG standards, major discrepancies exist across vendors who rate, rank and provide company ESG scores. This has led to significant noise and a lack of useful ESG data for investment purposes. This is not surprising since ESG ratings can only be as good as the underlying data and the methodologies used to impute missing data. Comparing a company's ratings from the different raters and rankers shows that not only is there a low correlation of a company's ESG rating and ranking across the data providers, (Antoncic, 2020) but at least one study showed, all else equal, there is a significant amount of variability in a company's rating depending on the methodology a rater or ranker uses (Kotsantonis and Serafeim, 2019).

In this paper we propose a new alternative to investing through a sustainability lens based on the intersection of Artificial Intelligence and the United Nations Sustainable Development Goals (United Nations (2020) which can help overcome existing shortcomings of measuring the sustainability footprint of companies. Moreover, the use of large-scale unstructured data can provide more comprehensive and timely insights.

The U.N. Sustainable Development Goals (SDGs) are a much broader set of sustainability issues than traditional ESG issues and focus on "good health and well-being, the elimination of poverty, zero hunger, quality education, clean water and sanitation, reduced inequity," as well as the environment and other issues encapsulated in ESGs. Most importantly, the SDGs call for "leaving no one behind." The SDGs have more factors and address the full spectrum of *global macro systemic issues* that matter to all stakeholders, all businesses and all countries. The SDGs "are a universal call to action" established in 2015 by 193 countries "to end poverty, protect the planet and ensure that all people enjoy peace and prosperity by the year 2030." (United Nations (2020).

COVID-19, its rapid spread and the insidious toll it is taking on humans as well as on the global economy is a perfect example of why the SDGs are more important now

than ever. For example, SDG 6 Clean Water and Sanitation[1] addresses the simplest and "most effective measure one can take to protect against the virus which is out of reach for 40 percent of the global population, or 3 billion people, who do not have a handwashing facility with water and soap at home." (UNICEF, 2019) As of the time of this writing, this virus has hit just about every corner of the world. Estimates from the International Monetary Fund (IMF) show "the cumulative loss to global GDP over 2020 and 2021 from the pandemic crisis could be around $9 trillion," slightly greater than a 10 percent loss of the global GDP of $86.6 trillion in 2019 (Gopinath, 2020).

Big Data developed through cutting-edge statistical models, provides the solution for ESG/SDG reporting, scores, rankings, ratings and benchmarking. Big Data enhances reported data with 'alternative data' using artificial intelligence algorithms (AI), including natural language processing (NLP) and machine learning (ML) to cull through tens of thousands of data and reports in dozens of languages providing ESG and SDG information for thousands of firms. "Big Data makes information available on a daily basis for investors, governments and all stakeholders – not just annually when a firm reports unaudited nonfinancial data." Through these advanced statistical techniques, data are made available which one would not get from using only unaudited, self-reported annual firm reports (Antoncic, 2020).

In this article, we explore the possibility of creating an active portfolio that achieves the goals associated with ESG investing but still generates alpha, consistent with fiduciary duties. In addition, we measure the SDG impact of the resulting active portfolio relative to the benchmark. Specifically, we consider the US MSCI Index as the benchmark to beat. Among the roughly 600 stocks in the index, we create an active portfolio of about 50 stocks using the MSCI ESG ratings which show positive ESG momentum, to measure ESG performance and track its performance relative to the index. We find that the portfolio significantly outperforms the index when relative momentum is used and this outperformance persists when controlling for the Fama French three- (Fama and French, 1993) or Fama and French five-factor models (Fama and French, 2014). We then rely on data from Global AI Corp. to measure the SDG impact of the active portfolio relative to the benchmark. Global AI Corp. uses state-of-the-art Big Data techniques to examine a comprehensive set of unstructured data, including news articles, self-reported company data, blogs, NGO reports and social media and then

[1]SDG 6 has six targets to ensure availability and sustainable management of water and sanitation for all.

creates daily SDG scores at the company level. The scores are available at the individual SDG level, (i.e., company scores are available for each of the 17 SDGs as well as an overall SDG rating), and can be interpreted as z-scores reflecting sentiment regarding a particular SDG in recent information releases involving the company. Overall, the ESG portfolio shows better sustainability footprint than the benchmark, which persists for at least a year.

The remainder of the paper is organized as follows. Section II describes the ESG data, the methodology to create an active portfolio, and contains detailed portfolio results. Section III describes the SDG scores in some detail, and characterizes the SDG footprint of the selected portfolio. Section IV concludes.

II. ESG Investing and Asset Returns

In this section, we describe the ESG data, the active portfolio construction, and its performance.

ESG Database

MSCI ESG ratings are widely used by the investment community as a proxy for ESG performance.[2] The MSCI coverage universe is based on major MSCI indices (such as the MSCI World Index), which include the world's largest and most liquid stocks. For a detailed description of the MSCI's methodology, see MSCI (2019) and Serafeim (2020); we provide a short summary here.

MSCI attempts to quantify the risk and opportunity exposure of each company on 37 so-called "Key Issues." These issues are divided into three pillars (environmental, social and governance) which correspond to one of ten macro themes identified by MSCI as a concern to investors, inter alia; climate change, pollution and waste, product liability, social opportunities, and corporate governance. For issues focusing on a firm's risk exposure, both the firm's exposure and risk management are taken into account. Specifically, a company is not penalized for minimal risk management strategies on a low exposure risk issue, however, must have strong risk management practices in place for large exposure issues. For issues quantifying opportunity, such

[2] Alternative ratings are available, see Walter (2019) for a survey, and a discussion of some conceptual and practical issues plaguing such ratings. Berg, Koelbel and Rigobon (2019) quantitatively studies the differences across ratings from different rating agencies.

as opportunities in renewable energy, 'risk exposure' indicates the relevance of this opportunity to a given company given its location and business focus, whereas 'risk management' means the capacity of the firm to seize the opportunity. The MSCI ESG scores use company-specific operations data from annual reports and financial and regulatory filings, coupled with information from a variety of other sources, including news media, and trade and academic journals. They also use relevant macro-level data associated with a key issue and related to a company's geography of operations and business segments. In addition, MSCI directly communicates with companies to verify the accuracy of company data for all MSCI ESG research reports.

MSCI aggregates the key issue data to an overall score where each key issue is weighted according to its assessed materiality in each industry. Given that ESG issues tend to vary systematically across industries, MSCI calculates an industry-adjusted score so that the actual ratings are industry specific and comparisons across industries are not meaningful.

ESG Investing

Incorporating ESG into the investment process is not without challenges. If firms with high ESG scores manage to lower their cost of capital by their ESG actions and/or increase their future cash flows by avoiding certain risks, all else equal, firms with good ESG performance would be valued more highly than similar firms with less exemplary ESG performance.[3] If a lower cost of capital is the source of the valuation premium, it should be associated with lower returns going forward. Clearly, this might clash with the fiduciary duty of some institutional investors.

Several research papers written by MSCI show evidence that MSCI ESG rating changes ("ESG momentum") may be a useful financial indicator (Giese et al., 2019; Giese and Nagi, 2018). Companies with higher ESG ratings, on average, experienced fewer stock-specific risks and smaller drawdowns, suggesting ESG represents a "risk-mitigation premium." In this article, we focus on the return implications of investing in ESG momentum, which may not entail paying valuation premiums. ESG performance measurement is complex and uncertain, and in a world where capital may move slowly to eliminate mispricing (Duffie, 2010), active portfolios that incorporate ESG

[3] Recent research from AMUNDI, a large French asset management company (Bennani, Le Guenedal, Lepetit, Ly, Mortier, Roncalli, Sekine, 2019) suggests that ESG could become a risk factor itself, if most investors use ESG scores in their decision to over- or under- weight a company's stock in their portfolio.

momentum may succeed in creating alpha while satisfying the goals of ESG investing. One caveat applies to all current research regarding ESG investing: the available sample periods are relatively short (our data go back to 2013), and ESG ratings have a much shorter history than traditional factors, rendering the statistical confidence regarding statements about ESG factors and investing rather limited. Moreover, as discussed above, the ESG data are far from perfect.

ESG Momentum Portfolio Construction Process

To test the potential alpha due to the change in a US stock's ESG score, we construct two sector neutral portfolios – one on the basis of the relative percentage change in the industry-adjusted ESG score, and the other on the basis of the absolute change in industry-adjusted ESG scores. Using the 11 GICS (Global Industry Classification Standard) sectors stocks in each sector are ranked, at the end of each year, based on their absolute and relative ESG momentum. The 10% highest ranking stocks in each of the 11 GICS sectors based on their absolute and relative ESG momentum are then selected for inclusion in the portfolios. These stocks are held for a full year, after which the portfolios are rebalanced. The stocks within each industry, and the industry -portfolios themselves are market value-weighted. Appendix A describes the portfolio construction in more detail. [4]

The portfolios performance over the past 6 years is then analyzed against its relevant benchmark, using the MSCI US index. We chose the MSCI US index as a benchmark since it is more comprehensive than the S&P 500 Index, featuring close to 640 constituent stocks, and it provides the universe for our active stock selection.

Portfolio Results & Alpha Analysis

[4] In this paper we use the United Nations joint Staff Pension Fund portfolio, which excludes the tobacco and weapons industries. The controversy around ESG investing raising the question of the "costs to being good" arises not only because of the poor quality of the data but also due to the fact that ESG funds frequently exclude companies based on various criteria, which can create conflicts with fiduciary duty. SDG investing does not seek to exclude any company but instead measures their impact to society across a variety of angles. This means that while the ESG approach reduces investment flows to sectors, an AI-driven SDG approach can be used as an objective investment tool for the assessment of non-financial risks and can help identify positive and negative spillover effects that go far beyond the narrow ESG lens. The fact that SSDGs are applicable to investments at the corporate, infrastructure, and sovereign levels, makes it a powerful alternative to traditional ESG investing.

Our analysis tracks both the daily and monthly returns of the active ESG portfolio and the MSCI US index for the selected sample January 2013 - December 2018. Figure 1 plots the cumulative return performance over the sample period, showing the relative ESG momentum portfolio having the best performance followed by the absolute ESG momentum portfolio, and the benchmark index performing worst. For the purposes of this analysis, the most important test is whether the portfolio provides alpha with respect to the relevant benchmark. Table 1 (Panel A) reports the constructed portfolio alphas and the betas with respect to the index return (Market Model). The portfolio alphas are also shown relative to the Fama-French three- and five-factor models. In addition, we report the factor exposures to verify whether the ESG portfolios show particular tilts relative to existing factors. The Fama-French (1993) three-factor model adds two portfolios to the market model: the Small Minus Big (SMB) portfolio, representing the return difference between an index of small versus an index of large capitalization firms, and the High Minus Low (HML) portfolio, representing the difference between returns on portfolios of value and growth firms. The relatively new five-factor model (Fama and French, 2015) complements the three-factor model with the Conservative Minus Aggressive (CMA) and Robust Minus Weak (RMW) spread portfolios. CMA represents the return difference of a portfolio investing in firms with conservative investment strategies minus a portfolio investing in firms with aggressive investment strategies. RMW represents returns on firms with robust operating profitability minus returns on firms with weak operating profitability.

The beta with respect to the index is 0.96; not surprisingly, close to 1. Importantly, the relative momentum portfolio generates an alpha of 0.47 basis points (or 5.64% per year), with a standard error of less than 15 basis points. The alpha is thus highly statistically significant. Relative to the Fama-French three-factor model, the ESG portfolio still generates an alpha of 0.47% per month, and the alpha remains statistically significant. Adding two additional factors does not change this conclusion.

The SMB and HML loadings are not statistically significantly different from zero, suggesting the ESG portfolio has neither a value nor a size bias. In the five-factor model, the CMA exposure is borderline statistically significant and negative. The negative CMA exposure suggests the ESG portfolio includes firms with aggressive investment strategies, which is typically associated with low future returns.

While the alphas for the relative momentum portfolio are significantly different from zero, the alphas for the absolute ESG momentum portfolios, reported in Panel B of Table 1, are positive but no longer statistically significant. The factor exposures of the

absolute ESG momentum portfolio are very similar to those of the relative ESG momentum portfolio.

Table 1. Alphas Relative to the Market Model and Fama-French Factors

Panel A: Relative Returns

		Market Model	Fama-French 3 Factor Model	Fama-French 5 Factor Model
Alpha	*Estimate*	0.004735	0.004677	0.004686
	(Standard Error)	(0.001432)	(0.001462)	(0.001432)
Market	*Estimate*	0.959445	0.962752	0.950190
	(Standard Error)	(0.045051)	(0.047258)	(0.046476)
SMB	*Estimate*		-0.017547	-0.056601
	(Standard Error)		(0.057987)	(0.064175)
HML	*Estimate*		-0.006275	0.098387
	(Standard Error)		(0.061313)	(0.079406)
RMW	*Estimate*			-0.108616
	(Standard Error)			(0.104741)
CMA	*Estimate*			-0.230713
	(Standard Error)			(0.124946)

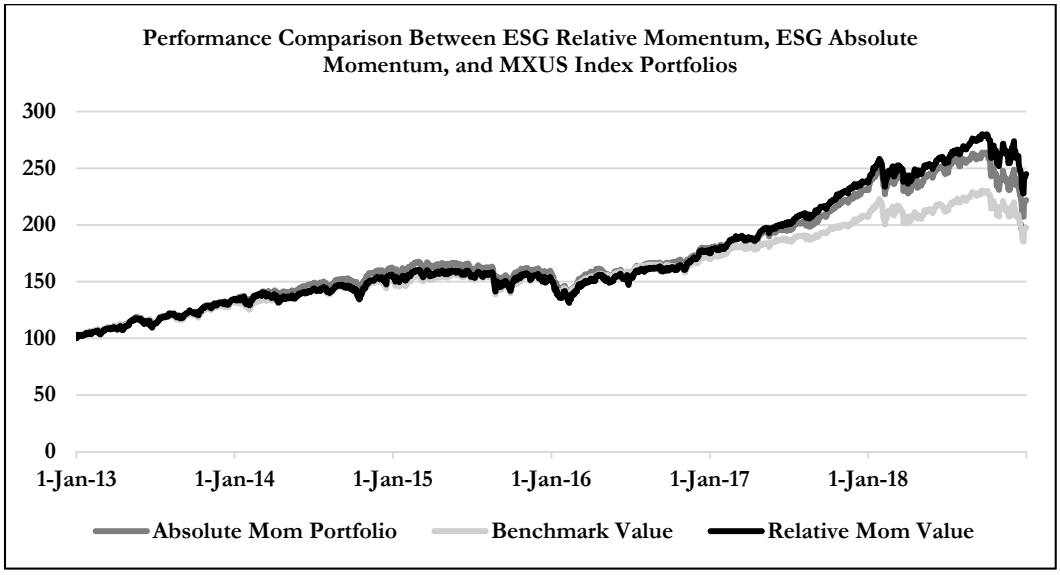
Panel B: Absolute Returns

		Market Model	Fama-French 3 Factor Model	Fama-French 5 Factor Model
Alpha	*Estimate*	0.002313	0.002171	0.002051
	(Standard Error)	(0.001382)	(0.001404)	(0.001387)
Market	*Estimate*	0.978585	0.987856	0.977050
	(Standard Error)	(0.043481)	(0.045390)	(0.044996)
SMB	*Estimate*		-0.047132	-0.049242
	(Standard Error)		(0.055694)	(0.062132)

HML	*Estimate (Standard Error)*		-0.004952 (0.058889)	0.098565 (0.076878)
RMW	*Estimate (Standard Error)*			0.019261 (0.101406)
CMA	*Estimate (Standard Error)*			-0.247199 (0.120968)

Note: The analysis uses monthly returns. Standard errors are reported in parentheses. The market model uses the MSCI index as the benchmark.

Figure 1. Cumulative Return Performance



One possible explanation for this result is that the relative measure has more chance of selecting firms that have low absolute ESG scores, i.e., firms that may be less likely to be on investors' radar screens as potential ESG target firms. However, it also raises the possibility that the selected firms may not rank very high on ESG performance in an absolute sense. Indirect evidence addressing this issue is presented in the next section.

III. Measuring the SDG Footprint of an Investment Portfolio

In this article, we broaden the dialogue of sustainable investing beyond just ESGs to measuring the societal impact of a portfolio on the UN Sustainable Development Goals (SDGs). From a societal perspective, building a framework which measures the net SDG contribution of entities can potentially incentivize public corporations and investors to mobilize capital towards achieving the SDGs which will make our world a safer, more prosperous and equitable place.

The SDGs are a much broader measure of sustainability risks and opportunities than the ESGs. The SDGs have more factors and address the full spectrum of *global macro systemic* issues that matter to all stakeholders, all businesses and all countries.

A company's SDG 'footprint,' which one can think of as its 'reputational footprint' - its either positive or negative net effect on externalities - reveals hidden risks that can impact its long-term performance and global perception across the world. This creates incentives for corporations to quantify and increase their net SDG contributions and SDG score in order to become more attractive to investors controlling trillions in assets under management and concerned with sustainable investments. It can also provide increased transparency for investor engagement strategies.

Leveraging their role as allocators, asset owners can ensure more long-term centric practices among corporations through the lens of an SDG investment strategy and thus support the goals of all facets of sustainable growth, not just those embedded in ESGs and ultimately contribute to long-term economic growth and development.

Measuring the SDG Footprint of Companies

While corporations now largely self-report some sustainability data, due to the lack of standards and metrics, significant 'green-washing' and self-reporting data biases, ESG scores contain a significant amount of noise and thus are of limited use for investment purposes. In fact, typically, companies carry out voluntary reporting on their sustainability performance in order to assure their shareholders and investors of their compliance to regulations (Braam and Peeters, 2017). However, as more companies are wary of the adverse impact of negative sustainability performance on investor decisions, they may fail to disclose negative information (Reimsbach and Hahn, 2013).

A useful complement to the reported sustainability data, is Big Data leveraging Artificial Intelligence technologies to extract, process, and analyze large-scale structured and unstructured data on ESG and SDG-related factors, which can then enable the integration of these sustainability factors into the decision-making of global investors.

Big Data enhances reported data with "alternative data" using Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) to cull through tens of thousands of news items, social media, and reports in dozens of languages, providing up-to-date information beyond what is in unaudited annual firm reports or firms' marketing efforts. Moreover, Big Data can make this information available daily for investors, governments, and all stakeholders – not just annually when a firm generates an unaudited sustainability report. Thus, a Big Data approach significantly reduces self-reporting bias and 'greenwashing' and can show which firms are effectively having a positive or a negative SDG footprint.

There are scenarios in which the technology can go wrong or provide imperfect information; relying on publicly available information such as newspaper articles, may lead to false or biased scores, for example. Other issues include fake news, articles that commemorate negative events from the past, major discrepancies between reported and third-party data, etc. For these reasons, it is necessary to perform extensive manual verification of data to evaluate if the analysis corresponds to reality and implement preventive measures. Extreme scores should be further examined using the underlying data sources.

In this paper, we use Global AI Corp.'s (GAI) specific SDG scores. The company extracts, filters, and cleans massive amounts of structured and unstructured data, including self-reported company data, news articles, blogs, NGO reports, social media, etc. to provide "raw," short-term and long-term scores. The full data set covers information across 60 languages from more than 100 countries. Specialized algorithms map the raw data to specific companies and associated entities, such as subsidiaries and companies in the supply chain, using different combinations of company names, abbreviations, tickers, and ISINs. Proprietary technology then ranks and filters content by relevance using domain-specific taxonomies based on the SDGs.

The algorithms analyze the filtered content at a daily level: recording the number of relevant news items, providing a sentiment score per news item, and tracking volume

and dispersion of sentiment across news items. This information is aggregated into daily, company-specific "raw" scores, which represent aggregate sentiment of the SDG data. GAI then aggregates data from 7 days of information, using statistics on the precision of the scores and the volume of the news sources, accommodating sparsity in the data while weighting recent information more heavily. For each company scores are available for all 17 SDGs, and the system also provides an overall company score measuring the overall SDG footprint of a company. The scores can be interpreted roughly as "z-scores," varying mostly between -1 and +1, and having a standard deviation of roughly 1. While we use the short-term scores in our current analysis, longer-term scores are also available.

The higher the score, the more positive the news is in relationship to each SDG, and vice versa. For example, for SDG 13 (climate action), a company would get a more negative score after a chemical spill that pollutes the ecosystem than a company that increases its carbon emissions by 5%. The combination of positive and negative SDG scores can be used to better assess non-financial risks and calculate a 'net' SDG footprint that measures the effect of positive and negative externalities at both long- and short-term frequencies.

SDG Footprint of the ESG momentum Portfolio

We use GAI's data across the MSCI US index universe over the Jan-2015-Dec. 2019 period to measure the SDG footprint of the active portfolio relative to the benchmark. For this purpose, we apply the portfolio and benchmark weights to the SDG scores, averaged for each year.

Our analysis addresses two different questions. Firstly, we verify whether ESG momentum relative to the benchmark coincides with positive SDG footprint in the year the ESG momentum was detected for the active portfolio constituents. In other words, we test whether an ESG momentum strategy selects firms with an SDG footprint that is better than that of the benchmark. Secondly, we investigate the SDG footprint of the selected companies in the investment year (the year after ESG momentum was observed). This exercise measures whether firms with ESG momentum continue to relatively improve their SDG footprint in the year after their ESG scores increased and whether ESG momentum is associated with a persistent (relative) positive SDG footprint. Neither question needs to necessarily receive a positive answer. Because the SDG scores are relatively fast moving, it is conceivable that they pick up certain ESG issues even before the MSCI ESG rating change occurs. Unless companies continue to

generate (relatively) positive SDG contributions for a few years, it may not show up in our measurement.

Figure 2: SDG Footprints of Momentum Portfolio

Contemporaneous Raw SDG Scores

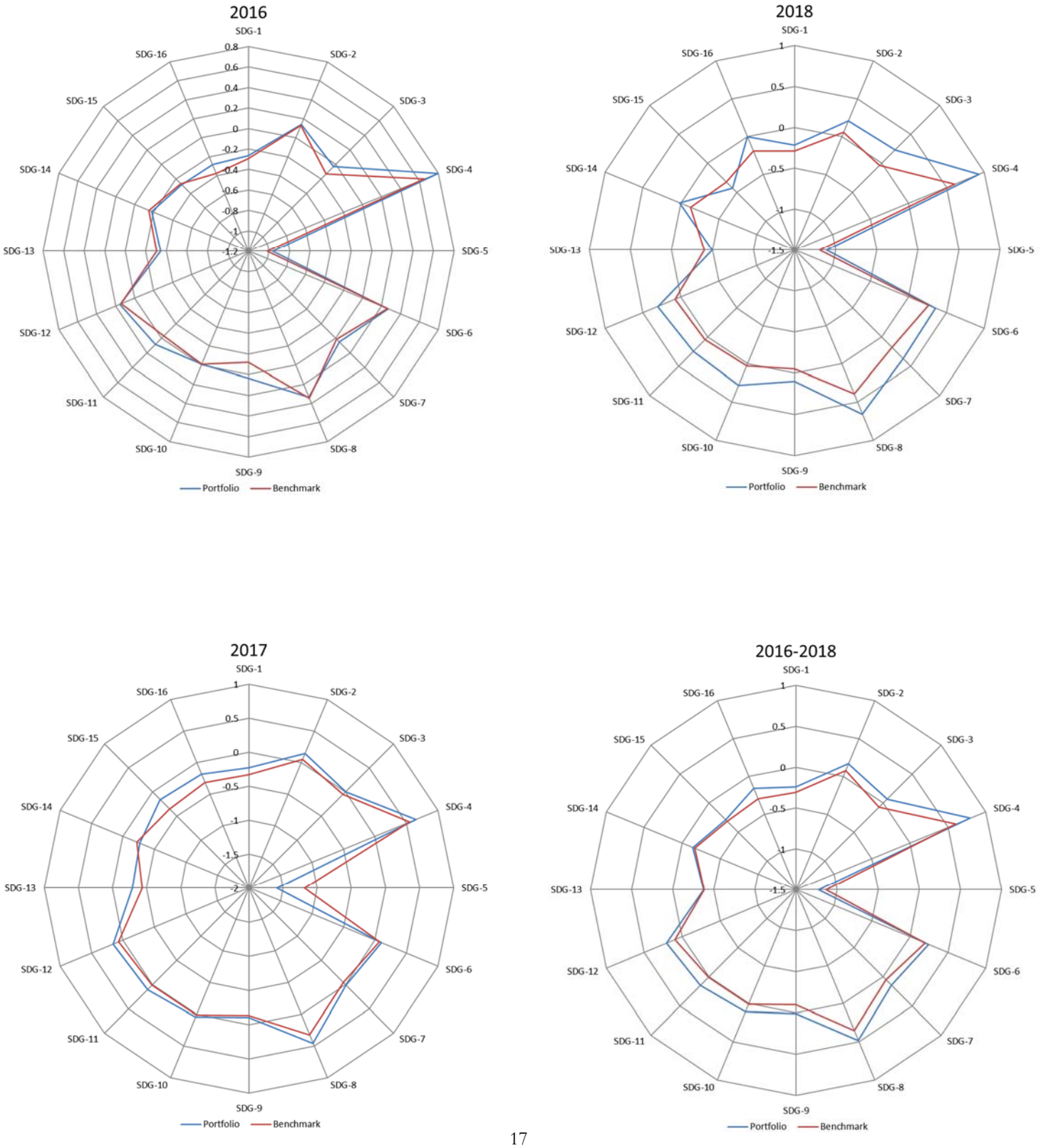
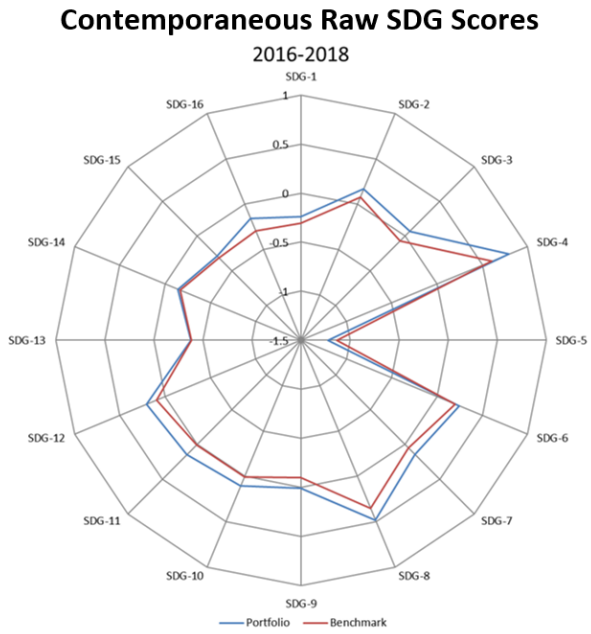


Figure 2 shows "contemporaneous" sentiment scores of SDG content for the portfolio and the benchmark. The years indicated are the investment years, while as indicated above the scores are contemporaneous with the time ESG momentum was measured and which was one year before the investment year recorded. The so-called polar plots arrange the scores for the first 16 of 17 SDGs, around a circle. Appendix C contains a list of the 17 SDGs, taken from "United Nations Sustainable Development Goals" (UN, 2020). Each SDG is on a radius from the center, with the center representing a negative score of between -2.0 or -1.5 depending on the year analyzed. Moving away from the center outward represents an improvement in SDG scores. Thus, for example in 2017, one can see in the polar plot SDG scores range from a low of -2.0 to a high of 1.0. The portfolio's scores are in blue, the benchmark portfolio scores are in red. Thus, if the portfolio has better SDG footprint than the benchmark, the red lines should be inside the blue lines. Note that in any particular year, this is true for the majority of SDGs. For SDGs 1 through 4, 7, 11, 12 and 16 this is true for all three years. The first four SDGs, represent "End poverty in all its forms everywhere" (Goal 1), "End hunger, achieve food security and improved nutrition and promote sustainable agriculture" (Goal 2), "Ensure healthy lives and promote well-being for all at all ages" (Goal 3), and "Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all" (Goal 4). Goal 7 is to "Ensure access to affordable, reliable, sustainable and modern energy for all;" Goal 11 is to "Make cities and human settlements inclusive, safe, resilient and sustainable;" and Goal 12 to "Ensure sustainable consumption and production patterns." Finally, Goal 16 aims to "Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels." The portfolio does not do as well on environmental issues, with its footprint with regard to Goal 13 "Take urgent action to combat climate change and its impacts," Goal 14 "Conserve and sustainably use the oceans, seas and marine resources for sustainable development" and Goal 15 "Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss" only being better than the benchmark in one of the three years.

The last plot in Figure 2 averages the scores over the three years. Averaged over all three years, the SDG footprint of the portfolio is better than the footprint of the benchmark for all SDGs except for Gender Equality, SDG 5. The differences are relatively small, however, and most of the scores (14 out of 17) are negative. This is not

surprising as companies on average have not yet fully internalized SDG goals with many companies still on their journey of understanding the role of the private sector in delivering on the SDGs by 2030.

Figure 3:



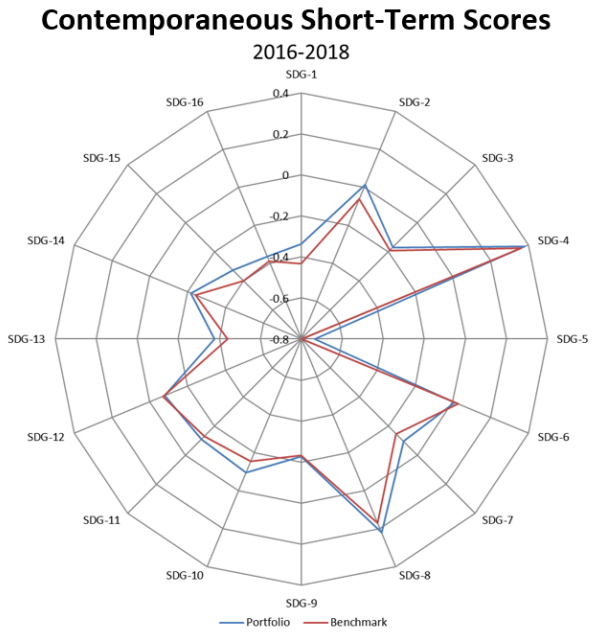
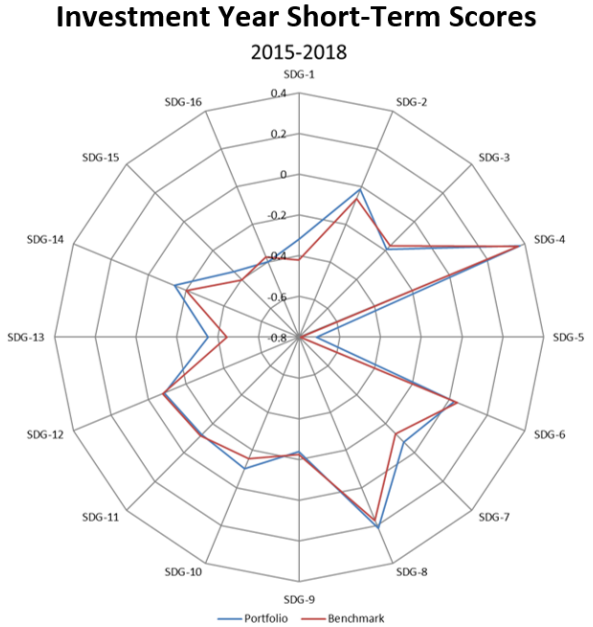


Figure 4:



In Figure 3, we juxtapose the 2016-2018 scores using "raw" SDG scores from Figure 1 with the same results for GAI's actual 7-day scores. These scores use the last 7 days of SDG information, using a weighting scheme to weight the most recent data with older information downweighed, and adjust the sentiment of the daily information source for accuracy. The results are largely the same with some small differences, e.g. the portfolio performs slightly better on Gender Equality (SDG 5), but worse on Clean Water and Sanitation (SDG 6), and Responsible Consumption and Production (SDG 12), relative to the benchmark.

In Figure 4, we focus on the persistence of the outperformance of the portfolio in terms of SDG footprint, by looking at the SDG footprint of the portfolio relative to the benchmark in the investment year. We show the same summary graphs over all years for the raw scores and the 7-day scores. Because we focus on the SDG scores during the investment year, we can add 2015 to the computations. The SDG footprint of the portfolio is again better than that of the benchmark, but the differences are often small. An exception for the raw scores is SDG 15, an environmental goal regarding life on land, where the benchmark performs better. For the 7-day scores, there are 6 SDGs (3, 6, 9, 11, 12 and 16) for which the benchmark has slightly better scores than the portfolio, suggesting the better SDG footprint may not always do better over a period of several years.

Statistical Significance

The polar plots show that the SDG footprint of the ESG portfolio is better both in the year ESG momentum was observed ("contemporaneous") and the subsequent investment year. We now verify whether the differences were statistically significant. The lack of observations prompts us to increase statistical power by comparing SDG footprints on a monthly basis. For the contemporaneous comparison we have 3 years of data, or 36 monthly observations; for the investment year we have 4 years, or 48 monthly observations. A simple t-test is performed to address whether the average difference between the monthly SDG footprint of the portfolio and the benchmark is statistically significantly different from zero. These observations may be serially correlated which we control for by using 6 Newey-West (1987) lags in the creation of our standard errors.

Table 2 reports the results, both for the raw scores and the short-term SDG scores. As observed from the polar plots, all differences are positive, indicating that the SDG footprint of the portfolio is better than that of the benchmark. Moreover, these

differences are larger in the year ESG momentum was established relative to the investment year, which is consistent with the idea that relatively greater SDG footprint persists, but the differences may not be permanent. Finally, the differences are not statistically significant for the 7-day scores, but they are statistically significant for the raw scores in both reported cases. The statistical significance is highest for the contemporaneous case, with a t-statistic of 3.38.

Table 2:

		Raw Scores	**Short-Term Scores**
Contemporaneous	*Coefficient*	0.1411	0.0438
	(Standard Error)	(0.0417)	(0.0408)
Investment Year	*Coefficient*	0.1138	0.0295
	(Standard Error)	(0.0593)	(0.0480)

IV. Conclusion

Assessing company performance regarding ESG issues and SDG fitness profile is challenging for the investors, academia, and NGOs. Because companies with good ESG performance may enjoy a valuation premium, ESG investing has been thought to create a potential conflict for asset owners who have a fiduciary duty not to sacrifice long-term return opportunities. In this paper we dispel that view. Ours is the first paper to investigate the SDG footprint of an active portfolio using algorithms and alternative data. We show it is feasible for an asset owner to both uphold his/her fiduciary duty and have a positive impact on achieving the SDGs.

We explore the possibility of creating an active ESG portfolio to consistently generate alpha, considering the MSCI US Index as the benchmark to beat. Our research shows that the active ESG portfolio significantly outperforms the index when relative momentum is used, and this outperformance persists when controlling for the Fama-French three- and five-factor models. In the next step, we verify the ESG portfolio's congruence with the SDGs, utilizing SDG scores from Global AI Corp. relative to the benchmark. These daily SDG scores at the company level reflect a comprehensive set of unstructured data, including news articles, self-reported company data, blogs, NGO reports, and social media regarding SDG-related issues. The scores can be interpreted

as z-scores reflecting sentiment, or SDG fitness, regarding an SDG in recent information releases involving the company. We find that the active ESG portfolio shows a higher SDG footprint than the benchmark over the full period, but this is not true for every SDG and every sub-period. This paper underpins that the positive linkage between ESG, alpha, and SDG footprint is fully consistent with asset owners' fiduciary duty. There is no trade-off between financial returns vs. positive societal footprint. Our research shows that these elements reinforce each other.

Big Data can help investors and policy experts make smart, globally relevant decisions helping investors better understand the underlying risks in corporate behavior, and ultimately, make more sustainable investment decisions. By measuring SDG indicators, Big Data can help attract investment flows to where they are needed in order to align financing with National Development Plans providing countries with the necessary information needed to deliver on the SDG goals. Quantifying the SDG indicators potentially improves policy-making via data-driven analyses of SDG trade-offs, inter-linkages, scenario analysis and systemic risks and can show which firms and countries are delivering on the SDGs and where capital needs to be redeployed for long-term sustainable economic growth and development. In future work, we will also verify the relationship between financial returns and SDG footprint directly, rather than through the narrower ESG lens.

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Appendix A – Portfolio Construction

1. Universe: Determining the customized benchmark

   a. MXUS Index members stocks list for each Dec 31st of 2012, 2013, 2014, 2015, 2016, and 2017.

   b. Remove the stocks that either did not have MSCI industry adjusted ESG scores or were no longer listed or were acquired since then.

   c. Remove the stocks belonging to the tobacco and weapons industries.

2. Security Selection from the customized benchmark: Determining portfolio stocks for each year

   a. Determine the number of stocks to be used in the investment strategy portfolio as 1/10th of the number of stocks in each sector in the customized benchmark on a particular rebalancing date. For e.g., If IT sector had 62 stocks in the customized benchmark on a particular rebalancing date, it would have 6 stocks in the strategy portfolio.

   b. Relative Momentum: Calculate the ESG 1 year Momentum for each stock in the customized benchmark. Formula used: ESG_MOM_1Y = ESG_Score(t)/ ESG_Score(t-1) – 1 {Here ESG_Score is the MSCI published Industry Adjusted ESG Score}

   c. Absolute Momentum: using the following formula: ESG_MOM_1Y = ESG_Score (t) - ESG_Score (t-1)

   d. Remove the stocks that had infinite calculated 1 year ESG Momentum as such companies had only recently started disclosing their ESG metrics and this infinite momentum was not an accurate representation of improvement in their ESG practices.

   e. Within each sector group, rank the stocks in the descending order of their ESG Momentum values.

   f. For each sector, select the highest ranked stocks (number of stocks to be selected is determined using Step 2.a.). E.g.: 9 stocks selected in Information Technology sector on 31 Dec 17 will have the highest 1 yr ESG momentum in the IT sector on that particular day.

g. Same logic would be applied to all the other sectors to select the top ranked stocks. Finally, we end with the total number of stocks for a particular year. For E.g. 46 stocks selected on Dec 31, 2012 will be held in the portfolio till Dec 30, 2013.

3. Portfolio Allocation: Determining Stocks weights- The stock weights are determined such that the final portfolio stays sector-neutral with respect to the custom benchmark at the different rebalancing dates. This step is implemented through the following steps:

   a. Calculate the sector weights % (Si) for all 11 sectors in the customized benchmark for each of the 6 rebalancing dates (i.e. 31 Dec of each year from 2012 to 2017).

   b. Determine the market cap value (Ms) of each stock on the corresponding rebalancing date when the stock was selected.

   c. Calculate the total market cap (MT) of the selected stocks for each year as the sum of market cap values of all stocks selected in that year.

   d. Calculate the sector weight value (Sa) to be allocated to each sector each year as

      $Sa = Si * (MT)$

   e. Calculate the annual sector weight value (Sv) of selected stocks by summing up the market cap values of all stocks in each sector each year.

   f. Calculate the stocks' final value weight (Sf) to be allocated each year as –

      $(Sf) = ((Ms) / (Sv)) * (Sa)$

   g. Determine the stocks' final % portfolio weight (Ws) as –

      $(Ws) = (Sf) / (MT)$

4. Portfolio Rebalancing:

   a. The selected stocks will remain in the portfolio for 1 yr until the next rebalancing date (i.e. 31 Dec of next year).

Appendix B – Natural Language Processing (NLP) Background

Artificial Intelligence is a computer science field that aims to understand intelligent entities and enable machines to perform human tasks (Russell and Norvig, 1995). Natural Language Processing ('NLP') is a sub-field of artificial intelligence ('AI'), which seeks to program computers to process, understand and analyze large amounts of human (or 'natural') language . NLP technologies perform several tasks like machine translation, speech recognition, sentiment analysis, question answering, automatic summarization, chatbots, market intelligence and text classification. On the 1980s, NLP systems were primarily based on complex sets of hand-written rules, and statistical algorithms started to replace the hand-written rules and gain ubiquity only in the late 1980s. In 2020, State-of-the Art NLP is extensively using supervised and self-supervised deep learning.

NLP models can be used to assess information on how companies have a positive/negative impact regarding the United Nations SDGs or ESG. One approach is to combine a domain expert's knowledge pool with a set of text paragraphs generated from a list of keywords and then build a training set which can be used by a supervised machine learning algorithm to score paragraphs of corporate documents; another approach consists of using statistical features of the text and a third one is to used deep learning self-supervised models.

The integration of natural language processing NLP outputs into an SDG framework can help cover a broader universe of companies in a time-effective manner. In addition to SDG scores, other uses include sentiment analysis, topic classification, summarization, controversies as well as insight discovery.

In terms of implementation we can define 3 major steps in an NLP pipeline:

1. Data Preparation:
    a. Tokenization: the process of converting a text (a list of strings) into tokens.
    b. Text preprocessing that includes noise removal, lexicon normalization and objective standardization.
2. Text to features includes syntactical parsing, entity parsing, statistical features and word embedding.

3. Lastly, the testing and refinement step includes the designing, the calibrating and the refining of a model that is the engine which helps users to extract useful information from a content set or perform an automated task.

There are two main approaches to modeling NLP tasks: traditional - rule and machine learning based models and deep learning models.

1. Traditional - Rule and machine learning based models

Traditional Natural Language Processing is based on a pipeline where words in the text are annotated with various linguistic properties and relations. Each step adds properties or relations of increasing refinement. Typical processing steps include part-of-speech tagging, syntactic parsing, and named entity recognition. The result is a fine-grained account of the structural properties of the text and its component words.

Traditional sentiment models try to measure sentiment in a text by counting positive and negative words. What if we had a long list of all the positive and negative words that could appear in our documents? We could then simply get a computer to count these words and compute an aggregate score: That is, we simply subtract the number of negative words from the number of positive words, and normalize this score by the total number of words in a document.

In fact, this is exactly the approach taken by one of the first highly influential academic papers in the fields of text analysis in finance. In 2007, Professor Paul Tetlock (Tetlock, 2007) showed that counting negative words in a particular column of the Wall Street Journal had predictive power over the future price moves of the Dow Jones Industrial Average Index and the daily volume traded on the New York Stock Exchange.
Some of the examples used in the literature use a bag-of-words approach where the sentiment word lists are from the Loughran and McDonald financial dictionary (2009). Machine learning approaches involve using tf–idf or TFIDF and then a supervised learning algorithm, like support vector machines (Cortes and Vapnik, 1995). TFIDF, short for term frequency–inverse document frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus (Rajaraman and Ullman, 2011).

2. Deep Learning Based models

In the deep learning approach, first, word embedding is performed. In word embedding words or phrases from the vocabulary are mapped to vectors of real numbers, thus involving a mathematical embedding from a space with many dimensions per word to

a continuous vector space with a much lower dimension. The most popular libraries are Word2Vec (Mikolov et al., 2013) andGLoVE (Pennington et al., 2014), which can be applied for word embedding analysis and other applications. The function Word2Vec is able to translate a large input of text into a vector space with a few hundred dimensions. A deep neural network architecture will then use these word embeddings to perform tasks like translation or sentiment analytics once trained. These deep neural networks typically use convolutional neural networks, recurrent neural networks or long short term memory networks and lately transformers (Vaswani et al., 2017).

In 2018, NLP witnessed a substantial leap in performance regarding various natural language understanding tasks with unsupervised pre-trained language models like ELMo and BERT.

The state-of-the-art NLP deep learning model is the Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2018) and the transformer architecture, which enables parallel inputs. BERT shattered previous NLP records on multiple datasets including Stanford Question Answering Dataset (SQuAD). SQuAD is a reading comprehension question and answer of 100,000 questions from Wikipedia articles. The answer to each question is a free form text from the corresponding reading passage.

More recent models like GPT-2 (Radford et al., 2018), XLNet (Yang et al., 2019), and Compressive Transformer (Rae et al., 2019), have shown impressive results in a variety of tasks, and more advanced methodologies are being developed as we speak.

The General Language Understanding Evaluation (GLUE) (Wang et al, 2018) benchmark is a collection of resources for training, evaluating, and analyzing natural language understanding systems. In the leaderboard of this benchmark, all top models are deep learning models. In a variety of contexts, deep learning methods beat traditional machine learning methods with improvements of 5-10% in general topic classification accuracy and sentiment. In September 2020 different enhanced versions of BERT are on the top of the GLUE leaderboard.

To summarize NLP methods can effectively be used in the SDG and ESG modeling and measurement for investing purposes in areas like in sentiment analysis, topic classification, summarization, controversies as well as insight discovery. SDG and ESG experts can combine their domain expertise and enhance their results by using these models.

Appendix C: List of SDGs

For ease of reference, we copy the UN's list of SDG's here (see "Sustainable Development Goals," available at https://www.un.org/sustainabledevelopment/sustainable-development-goals/)

- Goal 1. End poverty in all its forms everywhere
- Goal 2. End hunger, achieve food security and improved nutrition and promote sustainable agriculture
- Goal 3. Ensure healthy lives and promote well-being for all at all ages
- Goal 4. Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all
- Goal 5. Achieve gender equality and empower all women and girls
- Goal 6. Ensure availability and sustainable management of water and sanitation for all
- Goal 7. Ensure access to affordable, reliable, sustainable and modern energy for all
- Goal 8. Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all
- Goal 9. Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation
- Goal 10. Reduce inequality within and among countries
- Goal 11. Make cities and human settlements inclusive, safe, resilient and sustainable
- Goal 12. Ensure sustainable consumption and production patterns
- Goal 13. Take urgent action to combat climate change and its impacts
- Goal 14. Conserve and sustainably use the oceans, seas and marine resources for sustainable development

- Goal 15. Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss
- Goal 16. Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels
- Goal 17. Strengthen the means of implementation and revitalize the global partnership for sustainable development