Tracking Companies' Real Time Sustainability Trends: Cognitive Computing’s Identification of Short-Term Materiality Indicators

[working title]

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(comments appreciated)

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Abstract:

The article argues that what as known as big data analytics using cognitive computing can be applied to sustainability (environmental, social and corporate governance) analysis. This can supplement what is now almost entirely done by human analysis, but this new technology is scalable and can create multiple real time data points (trends). Proprietary sustainability data analytics has been developed by a technology start up, TruValue Labs, Inc. Using early data for a six month period, we have found statistically significant short term volatility variations correlated against what is called (and defined as) compounded TruValue (cTV), a sustainability indicator. This has been especially true in the E and S, and to a lesser degree, G areas. We argue that such short-term movement, previously undetected, and therefore not measured, has potential materiality (hence value) implications. The article sets the stage for these conclusions with a review of sustainability ratings and measurement systems currently in use, a brief review of cognitive computing, a discussion of materiality and sustainability as well as how TruValue data is generated.

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I. Introduction

The last decade witnessed a growth in firms and analysts reporting and measuring corporations’ sustainability performance in a variety of ways. From large (e.g. MSCI, Bloomberg, Thompson-Reuters, GRI) to smaller (e.g. Sustainalytics, Vigeo, Climate Disclosure Standard Board) sustainability reporting and measurement has responded to perceived needs of investors, consumers and other stakeholders for ESG (environmental, social and governance)/sustainability indicators. In 2014 the European Union adopted a form on mandatory reporting of ESG data, beginning in 2017 for the largest firms. Potentially similar developments in the U.S. are taking place, most notably in the work of the Sustainability Accounting Standards Board (SASB).6 The consulting firm KPMG in a recent report characterizes the sustainability challenge this way: “The bold, the visionary and the innovative recognize that what is good for people and the planet will also be good for the long term bottom line and shareholder value. Competitive advantage can be carved out of emerging risk.”7 Emerging risk (and opportunity), until incorporated into share price, is by definition not-yet-financial, although it is or may be material.

In a similar vein in early 2015 Morgan-Stanley argued for the integration of traditional financial information with ESG data in order to “…better understanding the environmental, social and governance (ESG) risks and opportunities that a company faces, investors can improve their investment processes and decisions.” The report suggests that ESG contains huge amounts and too often-overlooked information that is or may be material to investment valuations.8

Evaluating what heretofore was called ‘intangible’ risk and opportunity factors in the sustainability arena has fostered the significant growth from the investment side of sustainable investment products and services. This has been response to the ongoing and significant demand by both individual and institutions for sustainable investment products. As the website “SustainAbility” writes:

“There are a dizzying number and variety of external ratings, rankings, indices and awards that seek to measure corporate sustainability performance. Stakeholders of all kinds – investors, consumers, employees, etc. – are increasingly relying on these ratings to help inform their decisions (to invest, purchase, work, etc.). Companies also rely on such ratings to gauge and validate their own sustainability efforts, with some even linking management performance evaluation and compensation to external ratings. These ratings, therefore, must be robust, accurate and credible.”9

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The website might also have added ‘tracking changes in real time’ to ‘robust, accurate and credible’. The reason it did not is that until recently, no rating or ranking firm has tracked sustainability/ESG data in real time using big data analytics, widely used in other arenas. This article presents both the theory behind big data sustainability analytics, as well as analysis of early data from one firm which has developed and uses this technology.\(^{10}\)

How do we make sense of this array of ESG/sustainability raters, rankers and index creators? What almost all have in common is that they rely on human analysts to follow individual companies’ performance along a series of overlapping but oftentimes very dissimilar standards, weighting systems and measurements. Additionally, they also suffer similarly long time frames in issuing reports, sometimes quarterly, typically annually, and sometimes as long as 18-month cycles. Augmenting these are updates and alerts in near real-time when perceived material changes occur. An exclusive reliance on human analysts makes scaling difficult and expensive, while still failing to provide enough data points for even basic analytics.

The use of ESG analysis from current ESG providers necessitates receiving opinions on infrequent data once it has been processed, rather than placing real-time data directly in the hands of investment decision makers. This has always been a limitation of current ESG research providers, as it requires a de facto acceptance of a given provider’s point of view on ESG.

Along with the growth of the rating and ranking industry a number of national and global initiatives attempt to provide what might be called overlays or standardized reporting, such as SASB, the GRI and IIRC.\(^{11}\) As of this writing, these standard-setting initiatives also share an implicit or explicit reliance on human analysts, a costly and inherently non-real time undertaking.

This article presents an alternative model of what we call sustainability trend analysis (STA), based on existing technologies of big data analytics, natural language processing (computer linguistics), machine learning and artificial intelligence — together known as cognitive computing. These technologies, when well trained and applied to the sustainability arena, can provide real time trend analytics along a number of ESG dimensions without human analysts. Like other technological developments, it is a scalable and disruptive technology, which brings the ability to observe, measure, analyze and compare real time trends, something not possible using human analysts — as the yearly or quarterly data points are too far apart and infrequent to provide meaningful and actionable results. With the advent of real

\(^{10}\) TruValue Labs, San Francisco, California. The authors are all affiliated with the firm.

\(^{11}\) The GRI database, for example, had in 2014 5980 organizations that produced sustainability reports. (The Integrated Reporting Movement, Robert G. Eccles, Michael P. Krzus and Sydney Ribot, Workiva Press: 2014), chapter 2, np.) (GRI is Global Reporting Initiative; IIRC is International Integrated Reporting Council.)
time trend data, a host of new avenues for evaluating corporate value creation (and risk mitigation) are possible. Similarly on the investment side: real time ESG/STA enables what is often called ‘extra financial value indicators’ to be taken into account.\(^\text{12}\) We argue that adoption of such technologies is a game changer: it can bring better analysis of firms’ risk/opportunity profiles, return on capital, and on growth prospects, as such data is usable in real time.

Eccles et al conclude in their study on global integrated reporting developments with a call for using IT (big data, analytics, cloud computing and social media) in the sustainability space,. They write that, “...IT [can] dramatically improve the process and quality of integrated reporting to the benefit of both the company and its audience, it can improve both parties’ integrated thinking.”\(^\text{13}\)

Cognitive technologies can take information (necessary but not sufficient for any market to approach efficiency) and transform it into knowledge (which makes information useful and actionable). Thus, real time tracking is the only way to build and develop trend analytics. As pointed out by Clark, Feiner and Viehs, ESG practices result in better operational performance, sustainability practices results in lower capital costs, and that stock price is positively correlated with sustainability practices.\(^\text{14}\)

The ability to identify trends in real time makes for a more efficient market than is currently possible. Eccles et al sketch four types of big data analytics: descriptive, diagnostic, predictive and prescriptive.\(^\text{15}\) Currently non-big data work uses human labor-intensive work to cover descriptive tasks, while consultants do diagnostics and an element of prescriptive. All of the work cannot take advantage of real time data, meaning over time there is not the ability to have even descriptive trends revealed as there are too few data points, which are as well too far apart to be useful. Using cognitive computing prediction is something that becomes feasible. Additionally, access to real-time data should enable faster access to event risk developments.

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\(^\text{12}\) What is ‘extra financial’ at one time period may well become ‘financial’ in the next, as the valuation of corporate governance indicates. In the early 1990’s ‘the market’ did not perceive governance is material, yet by the turn of the century it was being valued as material and therefore financial. Indeed, the larger issue is how the market values intangibles, which some have estimated currently to account for up to 80% of value of many if not most large firms.

\(^\text{13}\) Robert G. Eccles, Michael P. Krzus and Syndey Bibot, *The Integrated Reporting Movement* (Workiva on-line, 2014., np. chapter 9). They add, “...paper based reports [which include pdf files] have severe inherent limitations [while] corporate reporting websites of the largest 500 companies in the world today only scratch the surface when it comes to using currently available IT. “


\(^\text{15}\) Eccles et al 2014, chapter 9, np.
Below we first present a brief description of what cognitive computing technologies are and how they may be used in the sustainability space. We then present initial data and methods from one firm (TruValue Labs, with which the authors are affiliated) focused on the movement of six sustainability indicators. We argue this data suggests that materiality may be identified not only in the long term (as most ESG/sustainability analysts argue) but most importantly in the short term. We conclude with a look at some possible future potentials of using the new data made accessible with the new technologies.

**II. The current state of ESG raters, rankers and index creators**

Currently the vast majority if not all of ESG rating and ranking organizations (as well as ESG index creators) rely on traditional means of gathering information. (We use ESG as synonymous with sustainability and responsible investment.) While there is variation all rely on analysts who in turn use various forms of manual data collection and analysis. This includes automated single and combined key word searches using web based and other sources of information. Some analysts additionally make use of automated sentiment analysis typically searching for one type of content using a binary yes/no (0/1) metric. Additionally, analysts’ ratings and rankings reflect the considered views of a few individuals and are usually limited in scope. If making use of key word sentiment analysis (which most ESG data generators do not) a computer program typically scans blogs, tweets and various forms of commentary, reporting results in a strictly binary manner.

Both traditional and sentiment enhanced ESG rankings, ratings and index creation are necessarily retrospective. They do not have built in feedback loops. They are not designed to be, nor cannot be, predictive or prescriptive in spite of the fact that many suggest their ratings are forward looking. Such suggestions rely solely on analysts’ best estimates of what is likely to happen, rather than being supported by data analytics’ probabilistic predictive powers. Scaling up is extremely expensive (due to the costs of hiring analysts, as well as not having adequate tools or time to utilize and manage massive data sources with, in many cases, each analyst covering hundreds of companies). Therefore, traditional ESG raters and rankers do not update frequently, typically issuing reports or updates once a quarter, occasionally monthly, often only annually and in some cases longer. While some organizations issue alerts based on important developments, these occur irregularly even among

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16 This is similar in usage by, for example, BlackRock (http://www.blackrock.com/corporate/en-us/about-us/responsible-investment); Context reporting (http://www.contextreporting.com/top-global-1000-companies/methodology); the Carbon Disclosure Project (https://www.cdp.net/Documents/Guidance/2014/CDP-2014-Climate-Change-Scoring-Methodology.pdf)

17 Sentiment analysis has a high error rate, as it cannot contextualize its key word combinations. See, for example, http://data-informed.com/enterprise-looking-to-integrate-social-media-analytics-into-business-decisions/. Using natural language processing (NLP) with machine learning (ML) leads to far higher levels of accuracy.
the largest organizations. Further, these alerts almost exclusively focus on negative or risk-focused information, thereby missing positive sustainability actions by firms.

While these limitations are inherent to the methods used, this is not merely or even mostly a methodological issue. Rather it is an inherent restriction which limits content, access and timeliness and therefore the usefulness of information.

This situation need not exist as there are new emerging and developing technologies which are able to improve on the quality, quantity and timeliness of ESG data. These technologies (cognitive computing) are primarily three:

1- the ability to automatically data-mine all web based material.

2- the use of natural language processing (NLP, also called computational linguistics) to summarize, analyze, interpret and in an advanced form answer queries (e.g. how does company x compare to company y on carbon emissions, water use efficiency or supply chain conditions and supply chain management?)

3- the use machine learning (ML) analytics (a form of artificial intelligence) to continuously enhance functions 1 and 2.

Combined these three open the possibility of not only making so-called ‘intangibles’ (read: ESG data) ‘tangible’ (read: gauging their materiality), but doing so on a broader and deeper basis than what currently exists (and implicitly more accurately as well), and to do so in real or near real time.¹⁸

Access to real time sustainability information enables both investors and corporates to respond to the growing demand for sustainable processes, products and investment vehicles. On the investment side, portfolio managers and analysts can stay on top of current information more easily, and can track, quantify, and report on larger and larger amounts of information. Investment product creators can assemble investment indexes, ETFs and other vehicles with greater accuracy and can take account of real time changes in those products’ and offerings’ compositions and weightings. Long-term investors can both track portfolio sustainability movements, but also scan the investment horizon for future sustainable investment prospects. Corporate governance monitors can similarly follow real time events more easily, including both ongoing engagements and potential future engagement

¹⁸ As of this writing the authors are aware only of two early stage companies in the ESG space making use of these or some of these technologies. One is KPX Global (http://www.kpxglobal.com) and the other is TruValue Labs (www.tru360.com and www.truvalue.me). Additionally, the authors are aware of Climate Disclosure (http://climatedisclosure.org ) which uses key word searches on U.S. SEC 10-K, 20 and 40-F filings, with the intent of expanding into NLP in the future.
prospects. On the corporate side, individual firms can track both their own sustainability profiles and reputations, and those of their competitors, both within sectors and across sectors.

The following section presents a brief overview of the technologies which makes these developments possible.

III. Natural Language Processing and Machine Learning: cognitive computing in the sustainability space

Natural language processing (NLP) is a field of computer science concerned with deriving meaning out of human input. NLP analyzes what are called unstructured texts that are read by a computer at extremely rapid speeds and become structured data outputs. These data outputs can be used to form humanly readable sentences from large amounts of text and data. NLP can be used for content summarization, allowing humans to understand the meaning of long form content by summarizing it and still maintaining the key aspects of the original meaning. Additional uses are topic segmentation and recognition, where an algorithm parses and segments a chunk of text into segments and associates topics and meaning to those segments. NLP can be used for relationship extraction, using algorithms to identify entities and relationship amongst entities within a chunk of text. Lastly, after the meaning of the text has been understood, sentiment analysis needs to be run. This is used to determine polarity about a specific object or subject within a body of text.

Most modern NLP sentiment techniques use stochastic, probabilistic and other statistical methods to derive actual meaning from text. In order to train the algorithm to discern the correct meaning it needs to be fed with corpus of words or sentences with the correct values that it learns.

Machine learning (ML) is the ability of the computer to learn from data and its own processing of new data based on what it has learned from past processing. This learning can happen in multiple ways, supervised or unsupervised. ML does not follow explicit programmed instructions. An example of supervised learning is the classification of content by a human to aid the learning process. In unsupervised learning the computer will use large amounts of input to start creating clusters.

IV. Cognitive Computing and ESG Materiality

The potential of the new technologies in the sustainability arena is its application to focusing in on emerging trends and events which are or may be material to investors. As noted above this is the focus of the Morgan Stanley report as well as SASB, among others.
This formulation of materiality is closely related to Keynes' view of equity markets as similar to the 1920’s British version of newspapers’ beauty contest. What matters is not what an individual holds as beautiful (who is most ‘beautiful’) but rather what the crowd of beauty voters thinks. If each individual in the investor crowd plays a game of attempting to guess or ‘know’ what all others think, the process is entirely refractive. While there is certainly more to market movement (e.g. fundamental factors, momentum factors) there can be little doubt that the investor beauty contest plays a critical role in multiple dimensions and multiple iterations. It is a classic iterative game. One of those dimensions, most important for our purposes, is materiality. But from our vantage it is the trend that counts, whatever the trends merits post hoc. This is not to deny the importance of expertise and ‘true’ knowledge, but rather to point to the importance of social subjectivity as a defining element in materiality. In this regard it is performative, that is, has the ability, based on the production of symbols, to create (or have significant input into creating) a reality. Investment analysts have made use of NLP and other data analytics to gauge market sentiment in real time. But to date few have made use of these techniques in the sustainability/ESG space.

For the purposes of this paper we adopt a definition of materiality that was initially developed by Lydenberg, Rogers and Wood, and elaborated by SASB. As the more developed SASB version suggests in its ‘materiality map’ (developed to parallel to the SEC's view of materiality) the focus is on the ‘reasonable investor’ (as defined in a number of U.S. Supreme Court decisions). What defines what is ‘material’ to the reasonable investor? The reasonable investor is a moving target. To cite only one example, in the early days of corporate governance activism (1990’s in the U.S.) the G in ESG had little salience for the then ‘reasonable’ investor, yet by the turn of the century after the scandals of Enron, WorldCom and the like governance

19 http://www.economicsnetwork.ac.uk/sites/default/files/Ashley/6%20References%20for%20KP C.pdf
20 Keynes wrote: "We have reached the third degree where we devote our intelligences to anticipating what the average opinion expects the average opinion to be. And there are some, I believe, who practice the fourth, fifth and higher degrees.” (Keynes, chapter 12, General Theory of Employment Interest and Money, 1936). 

22 “From Transparency to Performance”, Initiative for Responsible Investment, Harvard University, no date.
23 Hawley is on the Board of Advisors of SASB.
24 Lydenberg et al write: "Our working definition of materiality is a modified version of the materiality test developed by AccountAbility and advocated by the Global Reporting Initiative. Our major substantive revision to the AccountAbility definition of materiality was to increase the emphasis on positive material opportunities for sustainability innovation (in business models or offerings) that might bring competitive advantage.” (Harvard, p. 20, no date)
was well on its way to becoming a ‘material’ issue. For example, measures of governance were incorporated in Moody’s and Standard and Poor’s bond ratings. Why? Because the ‘reasonable investor’ thought it was a component that need be included in firm valuations, present and future. The parameters of reason had changed. Similar developments have in the last fifteen years have taken place with various components of E and S. SASB captures this trend in its materiality process called ‘forward looking adjustments’, focusing on ‘emerging interest’ in elements of sustainability concepts among, for example, management or mismanagement which creates (or mitigates) negative externalities or fosters positive ones. It also tracks views among stakeholders.

In short, our view of materiality is what is accepted among a critical mass of ‘reasonable investors’, which in turn is closely linked to broad (or specific) social, political, economic and other trends in society as a whole, e.g. climate change and supply chain management. SASB (unlike some other raters and rankers), formulates KPI’s (key performance indicators), which attempt to track materiality ‘that matters’ or that is emerging as directly relevant to specific industrial sectors.25

But how would a traditional analyst use SASB’s KPI’s and overlays? Such an analyst would be forced to use a rather simple, incomplete and labor-intensive work process. For example, the SASB ’map’ ‘...relies heavily on investor interest...’ which then is analyzed using quantitative and qualitative processes by a research team. In a similar fashion using SASB’s ‘evidence of interest’ would be done using key words for each sustainability issue “...in order to arrive at a profile of the intensity with which issues arise in each industry.” Sensitivity analysis measures intensity, which is quite different from as it is able to ‘understand’ in a human manner the text at hand. Accessing typical sources would rely on search of sources such as :10-k’s, legal news, CSR reports, shareholder resolutions, media reports and innovation journals. These are critically important sources but barely begin to tap what is available and useful, notably missing are social media sources of all (and rapidly growing) sorts as well as much other web-based data, both qualitative and quantitative.26 The idea is not that more data is necessarily better, but that ‘big data’ (in depth and scope) analytics can yield both new and (perhaps) different insights, and can do so in real or near real time. Indeed, these types of sources parsed using key work searches could much more efficiently be parsed and analyzed using NLP.
For the purposes of this paper we have used SASB only as a representative example of how various raters and rankers tend to operate. Each uses its own categories and weighting systems, but to our knowledge none have as yet made full or even partial use of NLP and machine learning.

We suggest there are large opportunity costs in tapping only a small slice of data currently available and digestible. This data can be mined and automatically analyzed by what we are calling the new technology. Trends, so important to the moving target of materiality, are not likely to be picked up, or only picked up only after they are well formed. Much more is both possible and more importantly, useful.27

V. The current state of ESG Reporting

Figure 3 pictorially suggests current stages of ESG/sustainability data analysis. To our knowledge the current and most advanced state of sustainability raters and rankers stops at the first two methods: sentiment analysis (as in the SASB example above) and report creation based on it and the labor-intensive research of reading through a host of source material. The first two methods are in widespread use, relying on manual analyst labor. Cognitive computing has the ability and future promise of moving beyond the first two stages. TruValue Labs is (and possibly other software innovators are) developing algorithms that can analyze data automatically gathered and generate real-time ratings, rankings and trends.

27 Other financial sectors are beginning to use the new technology. For example, seekingalpha.com (08/21/14) points out that “.a performance-tracking dashboard includes tabs for creating/previewing ads, tracking ad impressions/reach, and monitoring user engagement. Facebook has been taking a go-it-slow approach to monetizing Instagram’s 200M+ users, even as many top brands gain huge followings on the photo/video-sharing platform. Similar technology can be used to mine ESG related information.
The following section presents early stage sustainability data produced by TruValue Labs’ NLP and ML processes.

**VI. Initial TruValue (TV) Data Analysis**

In this section we present results focusing on volatility analysis of real time sustainability data generated by the first six months of TruValue’s NLP and ML technology operations (July 19 2014-January 21 2015). We then analyze what we call the trends and swings based on the volatility analysis.

TruValues’ InsightEngine™ parses thousands of content pieces daily automatically from a growing set of web and electronic sources available on the Internet... Most of that material is not germane to sustainability and is discarded. The remainder is sorted into six meta-categories: leadership/governance, workplace stability.\(^{28}\) The data are of two types: static and dynamic. Static data is

\(^{28}\) These are defined as follows:
released by its source at a particular set period, e.g. annually, quarterly. Dynamic data occurs at any moment; it is real time (e.g. press release, news story, regulatory filing such as an 8-k).

**Volatility**

This paper analyzes volatility within the six meta categories. We define volatility as a measure of the dispersion of time series values over a particular interval. We analyze volatility for two reasons. The first is the widely held idea that changes in the E,S and G categories are slow and long term. We have found this not to be the case. Secondly, volatility, where it is statistically significant, can provide real-time indicators of investment risk and/or opportunity for portfolio construction and monitoring, as well as impact corporate reputation. To our knowledge, no such analysis has been previously undertaken, as this level of granular ESG data has simply not been available. Relating volatility to a new metric we will define below, we find that for two of the meta categories (environment and social) there is statistical significance at lower than a 5% alpha level (0.02 and 0.01). In the meta category of leadership and governance, there is an important but not statistically significant result of 0.08.

These findings are at first glance seem counter-intuitive. We find strong correlation between Compounded TruValue and Coefficient of Variability Volatility for the E and S (and to a lesser degree G) categories. We examine possible elements of

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**Leadership/governance:** relation with stockowners and stakeholders, integrity, strategy/vision and implementation, interaction with regulators, pending governmental actions, major lawsuit potential liabilities, executive compensation, supply chain monitoring (also in workplace as appropriate), political lobbying and contributions.

**Product integrity and innovation:** services and products that are cutting edge, revolutionary, competitive; high safety and high quality; delight consumers; state-of-the-art minimal negative environmental impact; respect for privacy and data protection.

**Environment:** using clean state-of-the-art technology; sustainable (including through full life cycle of product); accounting for negative externalities (e.g. on water, fuel consumption, biodiversity, clean up costs).

**Workplace:** properly motivate, compensate and respect employees; enhance diversity; focus on safety and health of employees; employee engagement; training and education opportunities; adequate benefits and retirement systems; monitoring supply chain for basic rights (e.g. health/safety, child and forced labor).

**Social impact:** attempts to benefit society; treat stakeholders fairly and ethically along with, stockowners, suppliers, vendors, contract workers; good community relations and, where relevant, meaningful philanthropy; customer satisfaction.

**Economic sustainability:** strong business/financial model and outlook; loyal customer base; positive return to shareowners (not necessarily short term); long-term focus.
causation behind this correlation in the conclusion, but a fuller, definitive examination awaits additional study focusing on event analysis among other approaches.

It has been the general view among both academics and practitioners that ESG is materially important in the long(er) term. Examining ESG materiality has been therefore widely viewed as part of fiduciary duty of, for example, pension fund trustees as part of their due diligence. The same has been true for long-term investors of all types when considering returns that fully account for externalities, which often take years if not decades to manifest as value destroyers. A finding that E and S (and perhaps G) have short-term significant volatility means that they may well be material in the short as well as the long term. As such, debating time horizons in terms of years and decades may be beside the point if E and S (and to a lesser degree, G) factors have value impact in the short term. By definition if this is the case, they will also have impact over longer time frames. We consider these findings to be a major contribution to both discussions of fiduciary duty, as well as to portfolio construction, monitoring and valuation. Additionally it is of use in monitoring corporate governance monitoring and engagement activities, and for monitoring corporate reputation.

Our analysis proceeds as follows. From TV’s database of the S&P 500, we determined we had robust data across all six meta categories for 58 companies.

We developed a metric called Compounded TruValue (CTV) over the approximate six-month period during which the data was generated. We compute CTV as a time series by applying a compounding rate in the compounding expression \( P(\text{new}) = P(\text{old}) \times (1 + q \times r)^{(Dt)} \), where \( Dt \) is the number of time ticks between events, and \( r \) is the compounding rate per time tick. The prevailing compounding rate \( r \) is based on a maximum metric goal \( M \), and in our case we set that if a company sustains a TruValue rating of 100 for an entire year, then it is rewarded with a 2x multiple at the end of the year. Anything below that diminishes the return rate by a factor \( q \), and it is diminished negatively if the rating falls below a neutral value \( N \), which is 50 in our case. For our particular time tick, we currently use minutes (but could use nanoseconds), so our parameters are set thusly:

- \( \text{maxReturnRatioPerYear} = 2 \)
- \( \text{returnIntervalInMinutes} = 365 \times 24 \times 60 \)
- \( r = \text{Math.Pow(maxReturnRatioPerYear, (1 / returnIntervalInMinutes))) - 1} \)
- \( M = \text{maxValue} = 100 \)
- \( N = \text{neutralYvalue} = 50 \)
- \( q = (TV(\text{new}) - N)/(M - N) \)

\( TV(\text{new}) \) is the latest TruValue rating that triggered the scoring event. The very last value in the series spread over a particular interval, such as the six months here in our sample set, is the Compounded TruValue for that interval that can then be compared with that of other companies. To the layperson, this is analogous to
compounding bank interest.

A distribution of these final, interval-completing, compounded TruValues, aggregated across our six meta categories is depicted in Graph 1. The percentages along the x-axis represent the percentage increase in CTV.

In order to present the median and the spread of the final compounded TruValues (CTV), graph 1 is presented where x-axis represents the percent increase in CTV and y-axis represents percentage of sample companies that show lower than a particular percent increase in CTV that is left hand side of median, or higher than a particular percent increase in CTV that is right hand side of median. Please note that the graph shows relatively narrower spread because aggregate measures tend to cancel out noise at the individual category level.

We were struck by the fact that three of the meta categories (environment, social and leadership/governance) all have more dispersed distribution (the first two are statistically significant, the latter one nevertheless important) than product integrity, economic stability and workplace. Our hypothesis (which awaits further investigation in a future study) is that product integrity and economic stability tend to receive (on a firm level) far more positive than negative news, leading to a rightward shift of the six aggregated categories (graph 1, below). We ran statistical tests for all six categories, but only report here on the two for which we found statistical significance, as described above. In short, the aggregate band (graph 1) is tighter than the E, S and leadership/governance bands, due to the tighter bands in the economic sustainability, product integrity and workplace categories. ²⁹

²⁹ We believe this is, as stated, an artifact of news feed inputs and generally reflects that ‘good news’ tends to impact firms more and more intensely in product and economic stability areas. Why workplace also fits this pattern is not clear will be investigated in a future study.
Graph 1

Compounded TruValue: Aggregate (representative S&P 500 companies)

Graph 2 displays the distribution of CTV in the environmental meta category.

Compounded TruValue: Environment (representative S&P 500 companies)
Graph 3 displays a distribution of CTV for the social meta category.

In addition to computing CTV for the aggregated six meta categories and each meta category separately, we also calculated the coefficient of variation (CV) over the real-time series of core ratings as a measure of their volatility. The coefficient of variation was selected as a primary measure of volatility because unlike standard deviation it is calculated by dividing standard deviation of TV index by the average of TV index over a time period, and it is a relative measure. For example, CV of 0 means no variation relative to the mean and 1 means standard deviation is equal to the mean.

The findings are displayed graphically for each meta category below, along with the correlation, R squared and p values.
Graph 4

Compounded TruValue vs. Coefficient of Variation Volatility: Economic (representative S&P 500 companies) [correlation = -0.16566, RSQ = 0.02744, p-value = 0.22240]
Compounded TruValue vs. Coefficient of Variation Volatility: Leadership (representative S&P 500 companies) [correlation = -0.23411, RSQ = 0.05481, p-value = 0.08245]
Graph 6

Compounded TruValue vs. Coefficient of Variation Volatility: Product (representative S&P 500 companies) [correlation = 0.01258, RSQ = 0.00016, p-value = 0.92665]
Graph 7

Compounded TruValue vs. Coefficient of Variation Volatility: Environment (representative S&P 500 companies) [correlation = -0.30823, RSQ = 0.09501, p-value = 0.02083]
Graph 8

**Compounded TruValue vs. Coefficient of Variation Volatility: Workplace**

(representative S&P 500 companies)

[correlation = -0.14426, RSQ = 0.02081, p-value = 0.28880]
To sum up, we can observe that, for the samples and intervals we studied, it is statistically significant that, for social, environment (and somewhat less for leadership/governance) meta categories, as TV volatility decreases, compound TV increases, while for the others, there is not a significant relationship. What is likely happening with these meta categories that show a reasonable relationship (social, environment, and to a lesser degree, leadership/governance) is that across those companies, when there was volatility, it consistently eroded the higher ratings.

30 It is worthwhile to note that the more volatile the time series, the less it contributes to the ongoing accumulation because volatility usually involves both upward and downward movements.
more than it did for the other categories. In other words, the more a signal bounces around, the less it will sustain a value, thus compounding less.

Finding that there is a significant correlation for E and S (and a lesser degree, G) between Compounded TruValue and Coefficient of Variation, we further investigate the sources of variation: variation due to trend and variation due to magnitude (swing).

**Trends and swings**

Please note that volatility is caused by trend or magnitude of swings in TV index. We define the Trend as the percentage change (either upward or downward) of CTV over the timing horizon, in our case, six months. The "Swing" metric is based on curve arc length. The longer the arc length of a curve over common time duration, the more it must oscillate or swing through that duration. Our metric here is calculated by first taking the Pythagorean incremental arc segment lengths between data points and summing them across the entire range. The baseline arc length of a straight line through the duration is then subtracted. (As our data is on a per-minute basis, we scale it into a daily basis to keep the numbers less fractional.)

Increasing TV index trend is due to both more positive news than negative news while decreasing TV index trend is contributed by more negative news than positive news. Another important source of volatility is the swing in the TV index, which is caused by the magnitude or significance of news. This means a company may show a high volatility due to a few significant news inputs without showing strong trend over time or vice versa.

Distributions of Swing metrics for our sample set of companies are shown in Charts 10 through 12 for our two categories of Environment and Social, along with the overall aggregate. [In cases where the distributions appear asymmetrical, with truncations on the left, the swing value was zero for the points not appearing – thus not displayable on the logarithmic scale.]
Graph 10

Swing: Environment (representative S&P 500 companies)

Swing over the 6-Month Period 19-Jul-2014 through 21-Jan-2015
Swing: Social (representative S&P 500 companies)

Swing over the 6-Month Period 19-Jul-2014 through 21-Jan-2015
Graph 12

Swing: Aggregate (representative S&P 500 companies)

Swing over the 6-Month Period 19-Jul-2014 through 21-Jan-2015
Note that the correlation coefficients between E, S, G and CTV are all negative. This implies, as we have previously mentioned that higher variability is associated with lower CTV. One possible reason for this result may be that negative information on ESG tends to have stronger impact on CTV than positive information. A potentially related conjecture is that negative information is more newsworthy, hence making a greater impact than positive information. Although providing clear explanation on potential causes on why E, S, & (and to a less extent G) show significant negative correlation with the CTV is beyond the scope of this study, it is our intention in the future to provide a more definitive explanation based on more detailed study of individual firms.

As stated earlier, a major focus of this paper is to understand the relevance of real time movement of sustainability information of firms. In particular, in order to understand the relationship between the variability of CTV and the CTV itself, we have selected coefficient of variation (CV) as a relative measure of variability. Analogous to sum of squares due to regression (SSR) and sum of squares due to error (SSE) in regression setting, our variability measure CV can be further decomposed into trend and swing components. Since both CVs of E and S turned out to be statistically significantly correlated with CTV, we present the following two by two tables with trend and swing for E and S separately.

Our motivation in creating the two-by-two table is to illustrate sample firms that belong to each of the four quadrants, which will guide us to develop testable hypothesis regarding firm or perhaps industry specific causes for a particular type of interaction between swing and trend in our future study. For example, it will be interesting to know which companies belong to upper left hand quadrant, which is reserved for firms with either increasing or decreasing CTV value with significant short term swings, i.e., firms accumulating significant amount of positive or negative points in spite of the presence of both positive and negative news.

Table 1 presents the four possible types of interaction between swings and trend.

<table>
<thead>
<tr>
<th>High Swings</th>
<th>Strong Trend</th>
<th>Weak Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>highly volatile</td>
<td>moderately volatile</td>
</tr>
<tr>
<td>Low</td>
<td>moderately volatile</td>
<td>not volatile</td>
</tr>
</tbody>
</table>

In tables 2 and 3 (environmental and social respectively) are eight examples of firms from our data universe that are the strongest examples of each quadrant.
### Environmental

<table>
<thead>
<tr>
<th></th>
<th>Strong Trend</th>
<th>Weak Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Swing</td>
<td>Salesforce.com</td>
<td>Lorillard</td>
</tr>
<tr>
<td>Low Swing</td>
<td>Wells Fargo</td>
<td>Chevron</td>
</tr>
</tbody>
</table>

### Social

<table>
<thead>
<tr>
<th></th>
<th>Strong Trend</th>
<th>Weak Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Swing</td>
<td>Adobe Systems</td>
<td>UPS</td>
</tr>
<tr>
<td>Low Swing</td>
<td>Raytheon</td>
<td>Chevron</td>
</tr>
</tbody>
</table>

[Note about Trend figures below, for the purposes of the charts that follow, it is the quantity defined above expressed relative to that of the benchmark compounding for the aggregated portfolio group. The relative differences between the companies are thus similarly discernable.]
Graph 13, Environment: high swing, strong trend

Salesforce.com: Environment TruValue
[Trend = 0.42143, Swing = 819.399, Volatility = 0.15512]
Wells Fargo: Environment TruValue
[Trend = 0.61111, Swing = 0.000, Volatility = 0.00000]
Graph 15, Environment: high swing, weak trend

Lorillard: Environment TruValue
[Trend = -0.02833, Swing = 555.370, Volatility = 1.07211]
Graph 16, Environment: low swing, weak trend

Chevron: Environment TruValue
[Trend = -0.01139, Swing = 12.307, Volatility = 0.17529]
Adobe Systems: Social TruValue
[Trend = 0.39210, Swing = 143.360, Volatility = 0.04583]

Graph 17, Social: high swing, strong trend
Graph 18, Social: low swing, strong trend

Raytheon: Social TruValue
[Trend = 0.51067, Swing = 9.461, Volatility = 0.02951]
Graph 18, Social: high swing, weak trend

United Parcel Service: Social TruValue
[Trend = -0.08423, Swing = 336.530, Volatility = 0.56454]
Graph 19, Social: low swing, weak trend

Chevron: Social TruValue
[Trend = 0.03897, Swing = 11.080, Volatility = 0.04336]
VI. Conclusion and Future Analysis

We have presented an overview of what the authors see as the potentials for cognitive computing in the ESG arena using NLP and machine learning. These technologies can draw on and analyze real-time developments that were previously a limiting factor in ESG analysis. Together they produce not merely ‘data’ but data analytics. Our analysis based on initial data generated by TruValue Labs suggests that there are statistically significant short-term volatility variations correlated against compounded TV, strongly in the E and S meta categories, and somewhat less so in the leadership/G meta category. Our trend and swing analysis for eight firms as examples suggest that such short-term volatility is more than correlational, but a more complete analysis needs to examine the specific drivers of causation; analysis such as event studies. Yet even without definitive causative analysis our finding indicate that the widely held idea that ES (and G) change is long term is not correct. Thus, the potential materiality of E and S (and G) is indicated in these findings. Such analysis needs to be extended and deepened once more data is available.