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Artificial intelligence for sustainable finance: why it may help

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Amundi ASSET MANAGEMENT

Contents

Authors

Marie BRIÈRE
Head of Investor Intelligence and Academic Partnerships, Amundi Institute

Matthieu KEIP,
Head of Innovation, Amundi Technology

Tegwen Le BERTHE,
Head of ESG Methods & Solutions

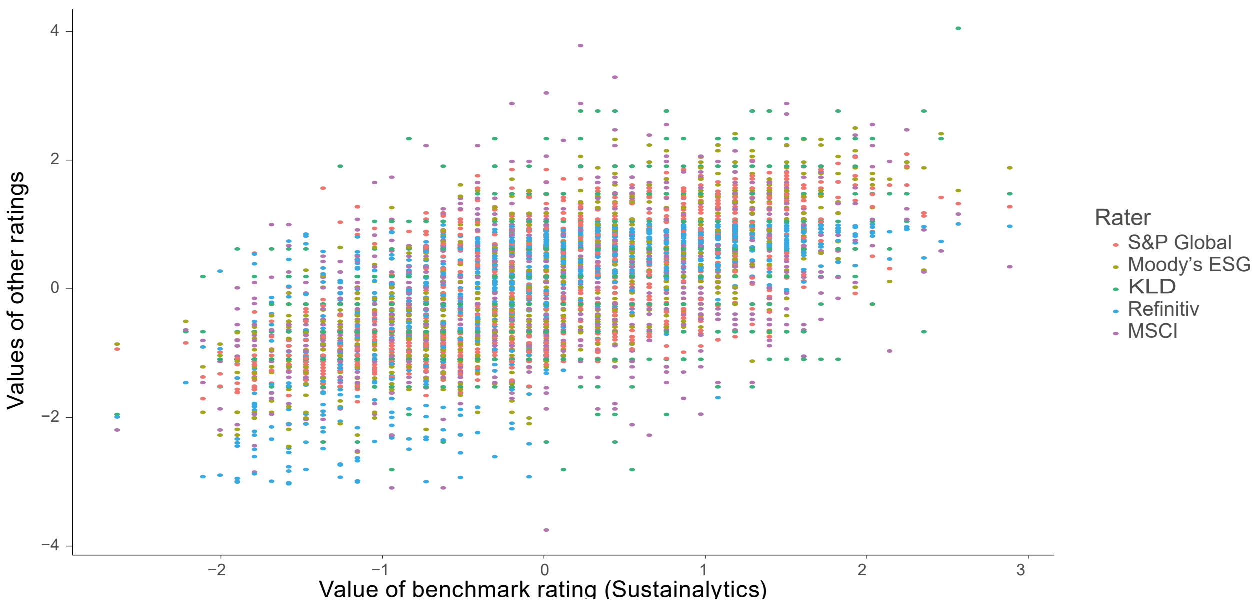
Artificial intelligence for sustainable finance: why it may help

Developments in Artificial Intelligence (AI) and machine learning have led to the creation of a new type of ESG data that do not necessarily rely on information provided by companies. This paper reviews the use of AI in the ESG field: textual analysis to measure firms' ESG incidents or verify the credibility of companies' concrete commitments, satellite and sensor data to analyse companies' environmental impact or estimate physical risk exposures, machine learning to fill missing corporate data (GHG emissions etc.). We also discuss potential challenges, in terms of transparency, manipulation risks and costs associated with these new data and tools.

I. Challenges with traditional extra-financial data

Data provided by extra-financial rating agencies are essential but raise a number of questions about their use. Based on company reporting, supplemented by human analysis, there is a certain degree of **subjectivity in the choices made by each rating agency** on the relevant ESG criteria and their weightings. The different methodological choices made by the various agencies cause these ratings to be **loosely correlated** with one other[1]. In addition, ratings are reviewed infrequently, sometimes with different timings depending on the company, and ratings tend to be revised in the direction of a stronger correlation with financial performance (Berg *et al.*, 2020). Finally, the differences in the imputation methods used by ESG analysts to deal with missing data can cause large 'discrepancies' among the providers, which are using different gap filling approaches. Interestingly, the discrepancies among ESG data providers are not only large, but actually **increase with the quantity of publicly available information.** Companies that provide greater ESG disclosure tend to have more variations in their ESG ratings (Christensen *et al.*, 2019).

Figure 1: ESG rating disagreement



This graph illustrates the ESG rating divergence. The horizontal axis indicates the value of the Sustainalytics rating as a benchmark for each firm (n= 924). Rating values by the other five raters are plotted on the vertical axis in different colors. For each rater, the distribution of values has been normalized to zero mean and unit variance.

Source: Berg Koelbel and Rigobon (2022)

[1] *Between 38% and 71% depending on the ratings (see for example Berg Koelbel and Rigobon (2022) for an analysis of six different rating providers; or Billio et al. (2021) for a comparison of 9 providers).*

II. How can AI help? The rise in alternative data sets

In recent years, developments in AI and machine learning have led to the creation of a new type of ESG data providers that analyse and collect (or "scrape") large amounts of unstructured data from different internet sources, using AI and without necessarily relying on information provided by companies.

Textual analysis to measure firms' ESG incidents

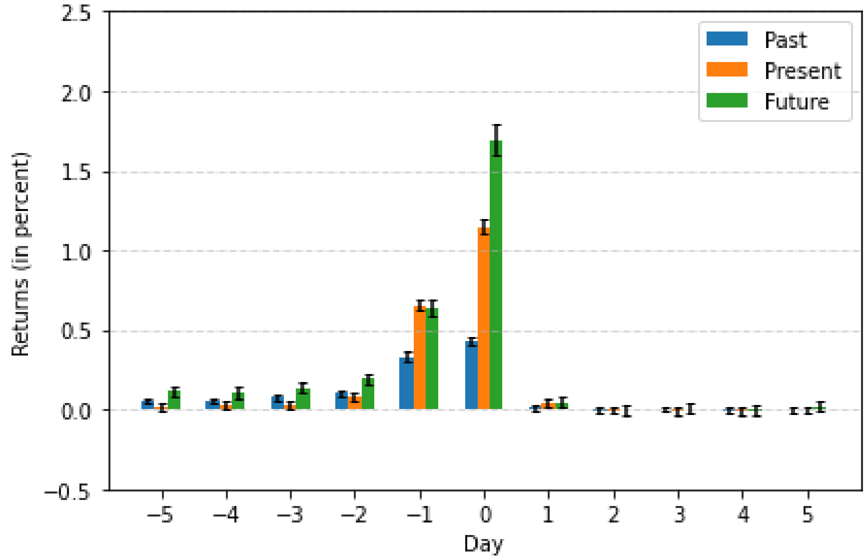
Textual analysis tools (e.g., Natural Language Processing (NLP) and knowledge graphs) help **identify controversies and important ESG news.** A large number of textual analysis software has been developed over the last decade, including Reprisk, Truvalue Labs, and others. They make it possible to finely measure controversies involving companies on various subjects such as environmental policies, working conditions, child labour, corruption, etc. Compared with traditional ratings, they have the advantage of **more frequent revisions, incorporating real-time company information.** For example, Reprisk analyses more than 80,000 media, stakeholders, and third-party sources daily, including online media, NGOs, government bodies, regulatory texts, social media, blogs, etc. and detects incidents that occur in companies' ESG policies, through screening methods using machine learning combined with human analysis. This information has a high informational content. For example, in a recent research work (Bonelli, Brière and Derrien, 2022), we evaluated how **employees react to controversies involving their employer when they decide to invest in their companies' shares.** We identified that employees are very sensitive to news concerning their company's social policy, they react particularly to news on working conditions.

Amundi partnered with Causality Link and Toulouse School of Economics to study the informational content of financial and ESG news about firms on a large scale. The Causality Link Artificial Intelligence system collects and analyses textual data from different sources, including news stories, call transcripts, broker research, etc. Some 50,000 texts per day are analysed, enabling us to build an aggregate news signal that captures not only the positive or negative tone of news but also how popular such news is in the market on a given day. The texts pass through the filter of a proprietary algorithm, which transforms them into structured data. Given a news statement about a particular firm, the AI platform of Causality Link is able to identify the firm's name, its Key Performance Indicator (KPI), the direction of change in this KPI and the tense of the statement.

In our study (Brière, Huynh, Laudy and Pouget, 2022), we investigated how and when new fundamental information is incorporated into prices. We explored the possible heterogeneity of price reactions across various firms and types of news: financial versus ESG news, tense of news (past, present, future), horizon of the news (short versus long), and the firm's size. In practice, we used this information to test what information made the stock market react, the speed of the market's reaction to news, and the construction of portfolios betting on these reactions. Our analysis highlights the **strong informational content of the news understood by the software.** Not only do the markets react strongly to the news identified on the day of the announcement, but we were able to show that they react **more strongly to information concerning the future of the company than to information relating to its past achievements.**

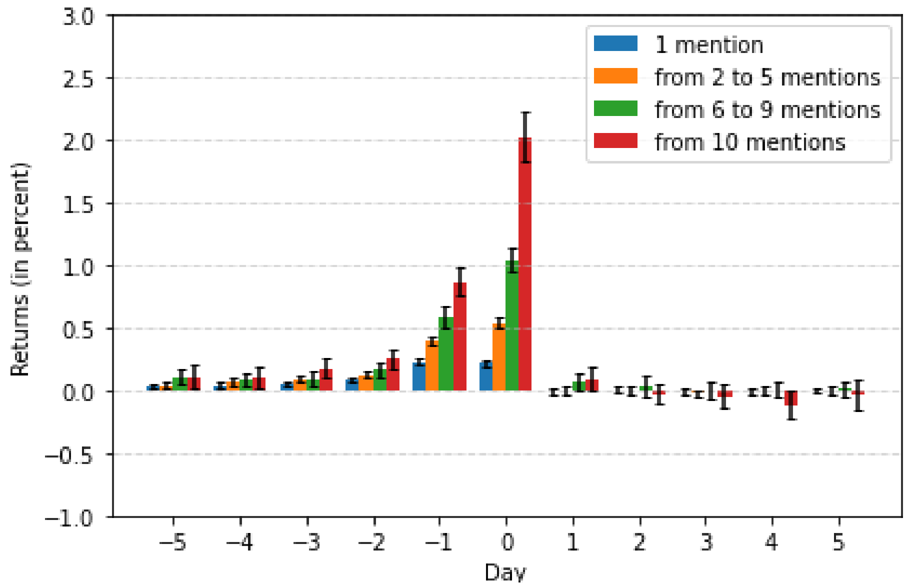
Figure 2: Stock market reaction to news

2a: News about the past, the present and the future



The bar charts present the average returns of the Long - Short strategy for the period [-5, +5] days around the portfolio construction days, on the sub-samples based on different news tenses. The error bars are the 95% confidence interval.

2b: High, medium and low coverage news



The bar charts present the average returns of the Long - Short strategy (for stocks in Russell 1000 index) for the period [-5, +5] days around the portfolio construction days, on the sub-samples concerning news coverage. The error bars are the 95% confidence interval.

Source: Brière, Huynh, Laudy and Pouget (2022)

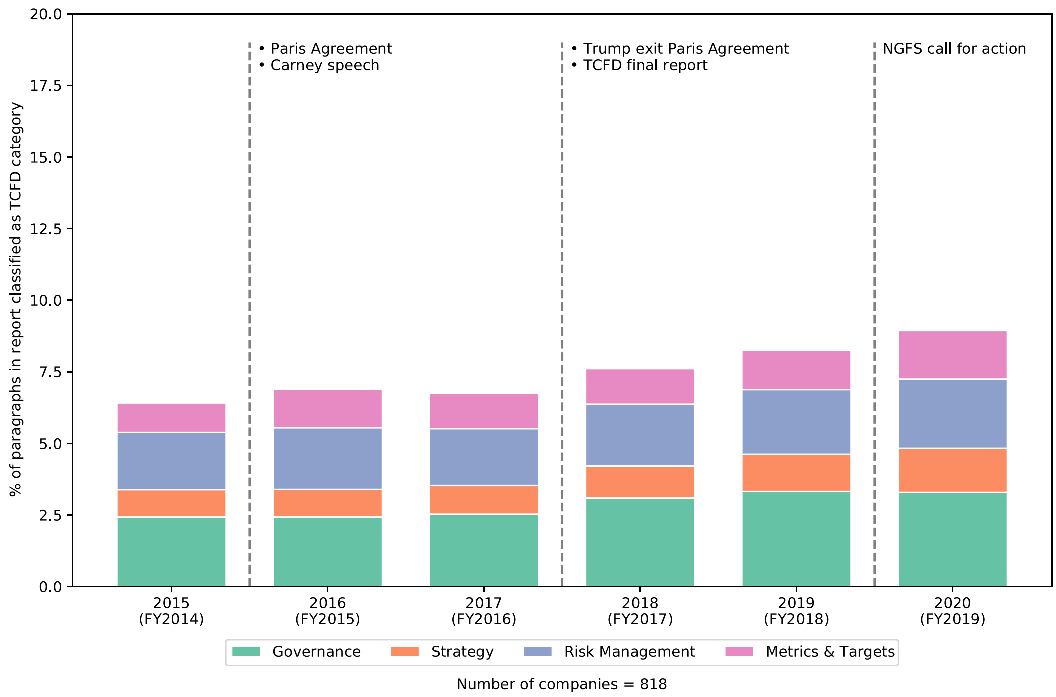
NLP techniques are also a powerful tool to **identify "market narratives"** (economic reasoning, geopolitical risks, environmental and social risks, etc.) as expressed by prints and broadcast media, etc. Blanqué *et al.* (2022) analysed the informational content of the Global Database of Events, Language and Tone (GDELT) to build time series that represent how some "market narratives" appear to the market. They show that this information has forecasting power on the US equity market.

Textual analysis to measure/verify the credibility of companies' concrete commitments

Researchers and organizations have recently started to use AI to assess company disclosures. The Task Force on Climate Related Financial Disclosures (TCFD) has conducted an "AI review," using a supervised learning approach to identify compliance with the TCFD Recommended Disclosures (TCFD, 2019). Kolbel et al. (2020) analyse climate risks disclosure in 10-K reports using BERT, an advanced language understanding algorithm, and identified an increase in transition risks disclosure that outpaced those of physical risks. Friederich et al. (2021) use machine learning to **automatically identify disclosures of five different types of climate-related risks in companies' annual reports** for more than 300 European firms. They find that risk disclosure is increasing and confirm that disclosure is expanding faster in transition risks than in physical risks. There are marked differences across industries and countries. Regulatory environments potentially have an important role to play in increasing disclosure. Sautner et al. (2020) use a machine learning keyword discovery algorithm to identify climate change exposures related to opportunity, physical, and regulatory shocks in corporate earnings' conference calls. They find that their measures can predict important real outcomes related to the net-zero transition: job creation in disruptive green technologies and green patenting. They contain information that is priced in options and equity markets.

Bingler, Kraus, Leippold and Webersinke (2022) introduce ClimateBERT[2], a context-based algorithm to identify climate-related financial information from the reports (annual reports, stand-alone sustainability-, climate-, or TCFD reports, firms' webpage) of 800 TCFD-supporting companies. They assess whether climate disclosures improved after supporting the TCFD and analyse the development of TCFD disclosures in different sectors and countries. Their results show that **firms tend to cherry-pick disclosures on those TCFD categories containing the least materially relevant information,** supporting the idea that TCFD disclosure is currently "cheap talk". Disclosures on strategy, and metrics and targets, are particularly poor for all sectors besides energy and utilities. They observe a slight increase in the information disclosed as required by TCFD categories since 2017.

Figure 3: Corporate climate risk disclosure of TCFD supporting companies, by TCFD categories



The bar charts present the percentage of paragrahs in report classified as TCFD category per year for the years 2015 to 2020. The sample comprises 818 international funds supporting TCFD reporting initiative.

Source: Bingler, Kraus, Leippold and Webersinke (2022)

[2] *ClimateBERT is based on the BERT model, a deep neural network currently seen as the state-of-the-art method for many tasks in natural language processing (NLP).*

Satellite and sensor data to analyse companies' environmental impact or estimate physical risk exposures

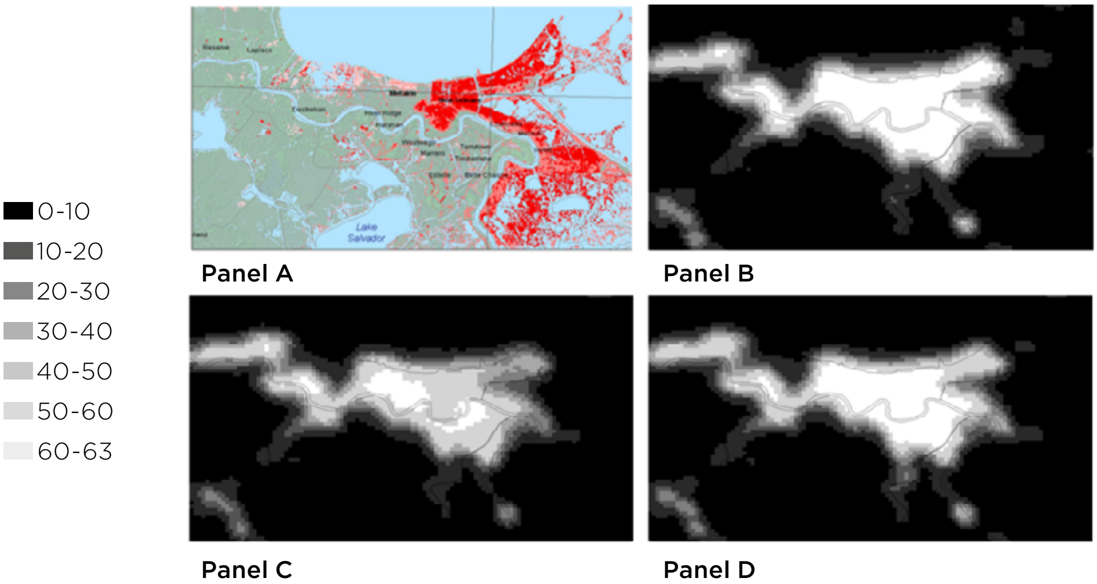
Satellite data and ground sensors are another source of alternative data making it possible to collect essential information that can be used to **verify the carbon emissions of companies or to analyse the impact of their activity on ecosystems:** air pollution, groundwater quality, waste production, deforestation, etc. Recent years have seen a remarkable increase in the temporal, spatial, and spectral information available from satellites (Burke et al., 2021). These data, which would be difficult to collect by other means, offer a wide geographical coverage and **high resolution and do not bear the risk of data manipulation.** These alternative sources of data can also be used to measure certain physical risks, such as floods, hurricanes, or monitor biodiversity evolution. Finally, they can be a key ingredient of climate stress tests models (Strzepek et al., 2021; Bressan et al., 2022).

For example, Bellon (2020) constructed a measure of "gas flaring" (burning of natural gas associated with oil extraction) using satellite data from the NASA IR public files. He identifies the practice of flaring based on the fact that it emits a temperature between 1600º C and 2000º C, not to be mistaken with forest fires, which generally reach about 800º C. He measures how much firms engage in "flaring", which involves burning the gas contained in oil wells to save the fixed cost of connecting the well to a pipeline or to treat the gas, and whether private equity ownership of the firms has any impact on the flaring practice.

Ground-based air pollution monitoring stations are not widespread in developing countries, and they are potentially subject to government manipulation. Jayachandran (2009) measures the air pollution caused by forest fires in Indonesia. Streets et al. (2013) review studies of satellite data applied to emission estimations and find that geostationary satellite imagery provides accurate air pollution estimation for various types of polluants. Satellite imagery such as Medium-Spectral Resolution Imaging Spectrometer (MERIS) can also allow real-time water quality supervision, for example for transboundary rivers, that would otherwise require efficient cross-border cooperation and transparency (Elias et al. 2014; Mohamed, 2015). Satellite data has also largely be used to monitor deforestation (see for example Tucker and Townshend, 2000; Grainger and Kim, 2020) or reforestation programs (Li et al., 2022).

Kocornik-Mina *et al.* (2020) analyse the **impact of floods,** which are among the costliest natural disasters, having killed more than 500,000 people and displaced over 650 million people over the past 30 years. Their paper analyses the effect of large-scale floods. They conduct their analysis using spatially detailed inundation maps and night lights data spanning the globe's urban areas, which they use to measure local economic activity, the damage sustained by such activity, and how it recovers from floods. New technologies, such as satellite-based remote sensing, but also cameras, acoustic recording devices and environmental DNAs can also allow to monitor biodiversity evolution (Stephenson, 2020).

Figure 4: Inundation and light intensity maps for Hurricane Katrina, New Orleans



Panel A shows a detail from one of the inundation maps associated with Hurricane Katrina, concentrated on the area around the city of New Orleans. Red and pink areas were inundated during the flooding. Panels B, C and D show the average annual light intensity in 2004, 2005, 2006 respectively, for the city of New Orleans. There is a notable dimming of lights city-wide in 2005, in particular in the eastern parts of the city, worst affected by the flood. In Panel D a recovery of light intensity is apparent.

Source: Kocornik-Mina, McDermott, Michaels and Rauch (2020)

Finally, **social indicators can also be derived from satellite imagery.** Engstrom *et al.* (2017) use a large number of features (such as the number and density of buildings, prevalence of shadows, number of cars, density and length of roads, type of agriculture, roof material, etc.) extracted from high spatial resolution satellite imagery to estimate poverty and economic well-being in Sri Lanka. They show that these features have great explanatory power on poverty headcount rates and average log consumption.

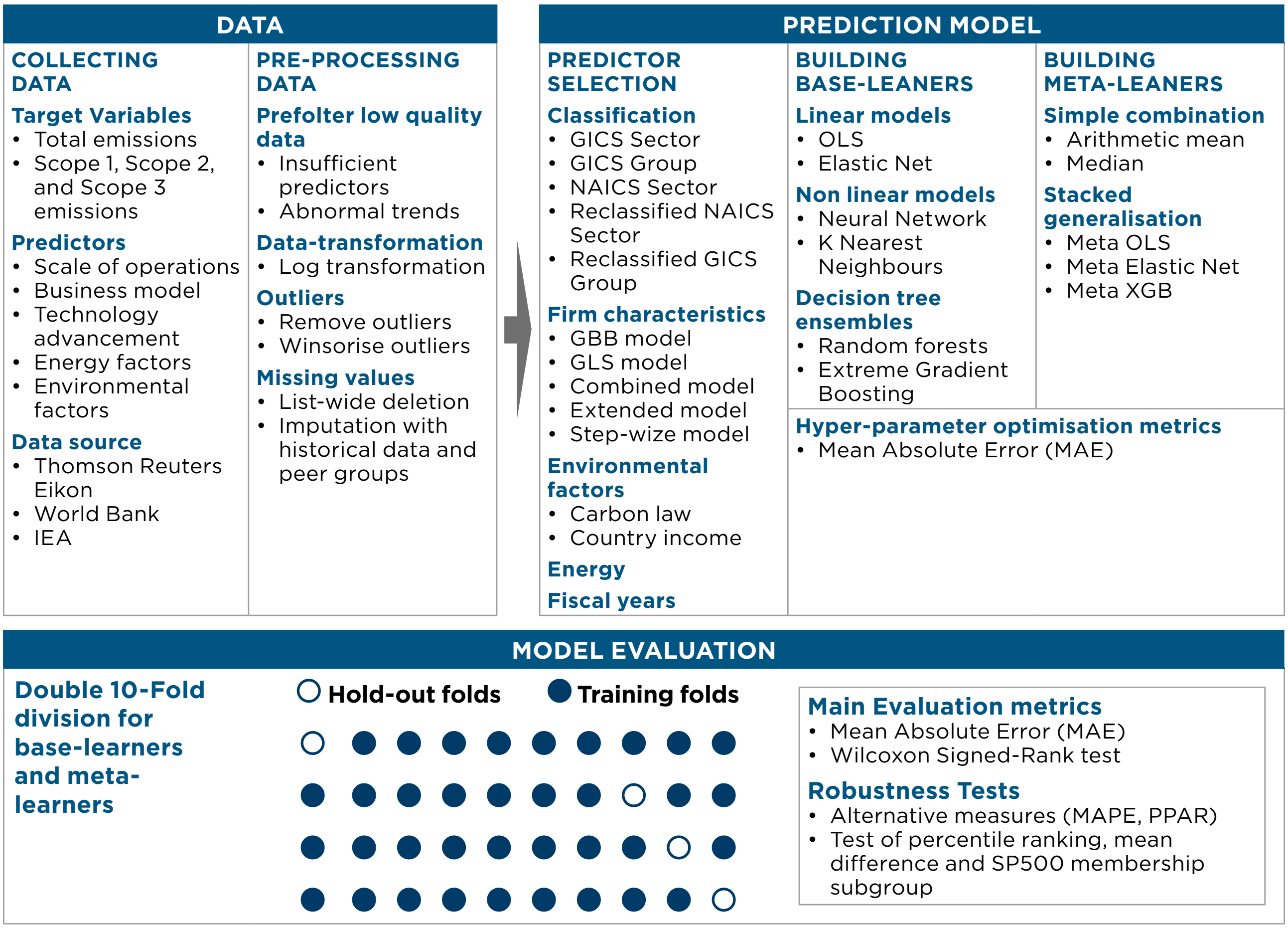
Machine learning to fill missing corporate data (GHG emissions etc.)

Large companies now report their GHG emissions based on the GHG Protocol of the World Business Council for Sustainable Development (WBCSD). According to this Protocol, reporting on Scopes 1 and 2 is mandatory, while reporting on Scope 3 (indirect emissions that occur in the company's value chain) is optional. But in some sectors, Scope 3 is often the largest component of companies' total GHG emissions.

Estimating total GHG emissions requires to link, for each company, each stage of its industrial processes with their carbon emissions. However, the information required to quantify companies' use of those processes, or their intensity in the overall annual production chain, is rarely publicly available. This makes it difficult to apply such models for calculating company emissions at a global level. Specialised data vendors (for example, MSCI ESG CarbonMetrics, Refinitiv ESG Carbon Data, S&P Global Trucost etc.) rely on simple models to predict the likely GHG emissions of some of the companies that do not currently report, based on sector level extrapolations (sometimes based on regression models based on the company's size, number of employees, income generated, etc.).

Nguyen, Diaz-Rainez and Kuruppuarachchi (2021) proposed the use of **statistical learning techniques to develop models for predicting corporate GHG emissions** based on publicly available data. The machine learning approach relies on an optimal set of predictors combining different base-learners (OLS, ridge, LASSO, elastic net, multilayer perceptron neural net, K-nearest neighbours, random forest, extreme gradient boosting). Their approach generates more accurate predictions than previous models, even in out-of-sample situations. Heurtebize *et al.* (2022) and Reinders and (2022) also propose a model based on statistical learning techniques to predict unreported corporate greenhouse gas emissions.

Figure 5: Modelling strategy to forecast carbon emissions with Machine Learning methods



This figure illustrates the modelling framework that is used to train and evaluate the proposed machine learning approach. Block: Data shows the sample selection and data pre-processing process. Block: Prediction Model implements (1) Predictor Selection, where the optimal set of predictors from the listed alternative choices is selected based on OLS regression. (2): Build Base-Learners, where three groups of base-learners are tested, namely linear models, non-linear models, and decision ensembles, and (3) Building Meta-Learners, where predictions are combined using a simple combination or stacked generalization. Finally, block: Model Evaluation: describes the model evaluation with mean absolute error and a set of robustness tests via double-K fold validation.

Source: Nguyen, Diaz-Rainez and Kuruppuarachchi (2021)

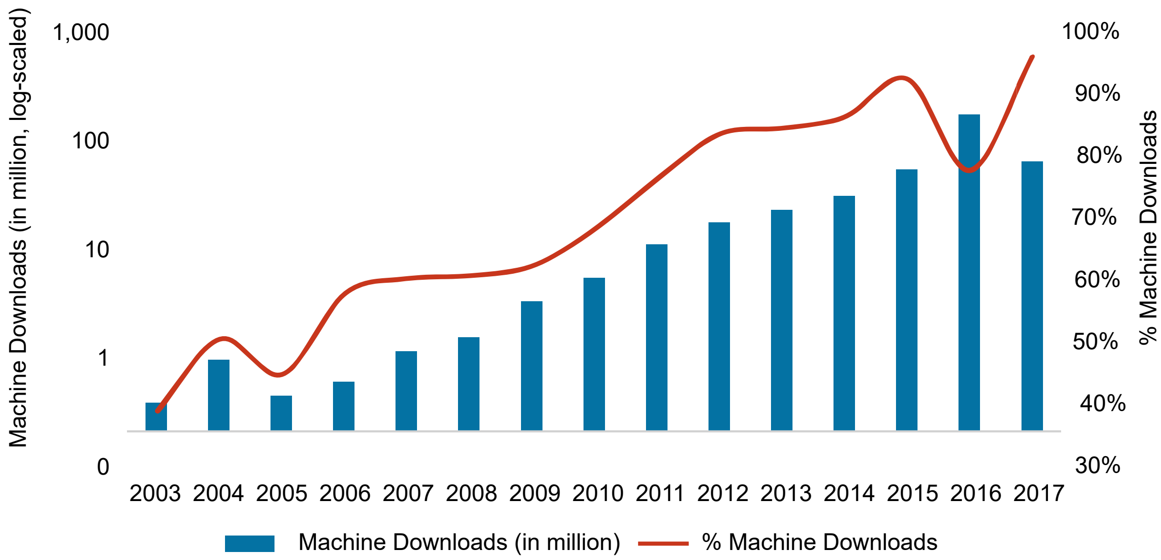
III. Discussion and challenges

AI provides interesting avenues to fill ESG data. However, there are a number of challenges. **AI methods can be a black box, subject to the same types of revisions in the methodologies as in traditional ESG ratings.** For example, NLP techniques relying on an ontology can be incomplete and revised ex-post. Hughes *et al.* (2021) show that the criteria used by Truvalue Labs to assess ESG risks of companies tend to largely overweight certain key issues (the ones that generate the more ESG controversies), defined at the company level[3] and which can fluctuate over time, while for traditional rating providers, the weightings tend to be more stable and evenly distributed. These alternative ratings based on NLP signals **become more of a public "sentiment" indicator**. This also means that they are also **more prone to manipulation**. This is particularly true when the primary source of data comes from blogs or social media.

Corporate disclosure can also be subject to manipulation. Cao *et al.* (2020) show that firms' communication has been reshaped by machine and AI readership. Managers are now avoiding words perceived as negative by computational algorithms, exhibiting speech emotion favoured by machine learning software.

[3] *In the case of Microsoft for example, Data Security dominates the weighting at 56%.*

Figure 6: Trends in Machine Download



This graph plots (1) the annual number of machine downloads of corporate filing (blue bars left axis) and annual percentage of machine downloads over total downloads (red line right axis) across all 10-K and 10-Q filings from 2003 to 2016. Machine downloads are defined as downloads from an IP address downloading more than 50 unique firms' filings daily. This serves as an upper bound as well as a proxy for the presence of "machine readers."

Source: Cao, Wei, Yang and Zhang (2020)

Another issue is that alternative datasets do not necessarily offer a wide coverage, due to lack of historical data, missing news sources, etc., which might lead to **biases and representativity issues.** In the end, the same issue of low correlation between rating providers might also apply when considering alternative ESG datasets. Hain et al. (2022) compare six physical risk scores from different providers and find a substantial divergence between these scores, even among those based on similar methodologies. In particular, they identify a low correlation between physical risk metrics derived from model-based approaches (Trucost, Carbon4 and Southpole) and language-based approaches (Truvalue Labs, academic scores). Curmally *et al.* (2021) document a positive (albeit small) correlation between sentiment derived from NLP analysis on incidents and traditional ESG scores. Satellite remote sensing in insolation is no panacea. Access to relevant **field-based information is key for satellite imagery to be properly calibrated, analysed and validated.** This need for close collaboration between modellers and remote sensing experts to derive meaningful information can represent a serious challenge (Pettorelli et al. 2014).

Financial institutions aiming to integrate these new metrics into their analysis should be aware that the choice of one measure over another has a large impact on the outcome. In the end, a comprehensive process should avoid placing too much confidence in a single measure, and strive to integrate the uncertainties around the measures being used. Once used on a large scale in a given institution by fund managers, analysts or even clients, the scope, use and limits of these alternative ESG measures should also be properly explained (Nassr, 2021; OECD, 2021). Finally, one should not neglect the costs of maintaining alternative datasets: not only acquiring the data, but also storing, checking, and integrating these large datasets might necessitate a dedicated team and can be very costly (Denev, 2020).

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Chairman, Amundi Institute

Monica DEFEND
Head of Amundi Institute

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