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Bloomberg's Greenhouse Gas Emissions Estimates Model

A Summary of Challenges and Modeling Solutions

Bloomberg

Contents

Introduction

Governments, citizens and companies around the world are increasingly taking action to reduce greenhouse gas (GHG) emissions. For investors, monitoring the GHG emissions of their portfolio companies is becoming an important part of the investment process. However, the availability of reported GHG emissions data varies across countries and business sectors, and many companies do not report their emissions at all.

In order to bridge this gap, Bloomberg has created several models to estimate the GHG emissions of companies. These models differ in their complexity and also in their data requirements. The cornerstone of Bloomberg GHG estimates is a machine learning model that is able to produce estimated emissions for nearly 70,000 companies globally. However, this model has strict data requirements, so in order to expand coverage to non-listed issuers of fixed income instruments Bloomberg relies on an industry-implied model, which is based on industry intensity factors and can be applied to companies for which revenue and industry classification is known. Finally, a number of bottom-up, scope 3 models complete the offering by providing customized, sector-specific models that focus on key scope 3 components for each industry.

Bloomberg's GHG Models estimate direct (scope 1) and indirect (scope 2 and scope 3) emissions for companies with a sufficient amount of available data.

Scope 1 are GHG emissions directly related to a company's operating activities. Scope 2 are indirect GHG emissions resulting from purchased electricity, steam and heating/cooling. Scope 3 are other indirect GHG emissions not captured by scope 2 that occur in the value chain of the reporting company, including both upstream and downstream emissions. Bloomberg is able to provide GHG estimates for over 100,000 companies globally, compared with approximately 4,500 companies that self-reported their emissions in the Bloomberg ESG universe.

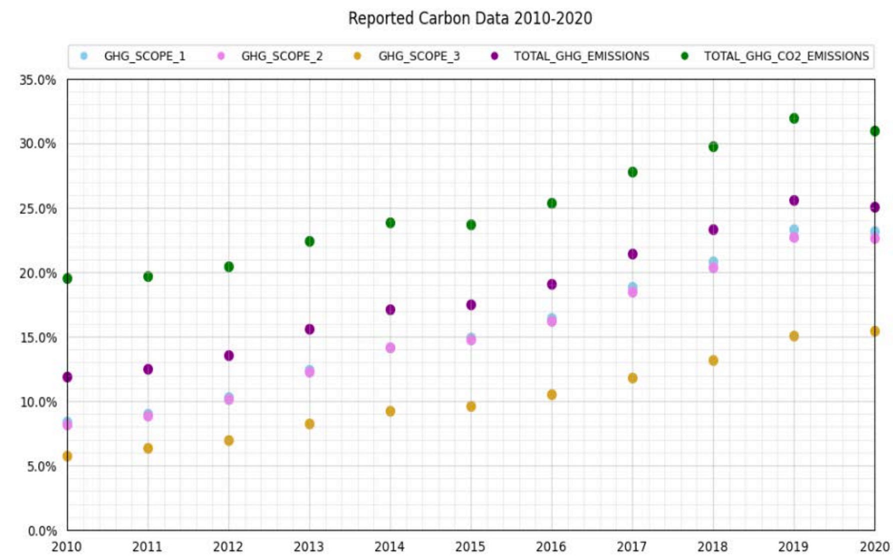

Figure 1. Percentage of companies reporting GHG emissions data in the Bloomberg ESG universe.

Coverage

The total number of companies covered since 2010 is over 130,000 companies globally; 51,000 of them are publicly traded companies and the remaining companies are private. The following tables show coverage broken down by index, region, country and type of company.

Scope 1 & 2 coverage per index

Index Name	Member companies with reported GHG data	Member companies with reported or estimated GHG data
MSCI World Index	72.39%	100%
MSCI ACWI Index	54.11%	98.83%
Bloomberg Emerging Markets Index	41.11%	99.72%
CSI 300 Index	23.67%	100%
Russell 3000 Index	33.15%	99.54%
STOXX Europe 600	81.83%	99.33%
Bloomberg Global Agg Corporate Index	58.70%	89.23%

Table 1. Scope 1 & 2 coverage per index

Scope 3 coverage per index

Index Name	Member companies with reported GHG data	Member companies with reported or estimated GHG data
MSCI World Index	68.57%	96.98%
MSCI ACWI Index	47.61%	90.96%
Bloomberg Emerging Markets Index	28.43%	87.93%
CSI 300 Index	6.0%	87.00%
Russell 3000 Index	13.60%	56.12%
STOXX Europe 600	78.67%	98.67%
Bloomberg Global Agg Corporate Index	51.58%	80.94%[1]

Table 2. Scope 3 coverage per index. [1](1) Percentage of corporate bonds covered in the index. Other asset classes not included in the count.

Coverage per region

Region	Number of companies covered
Americas	18,647
APAC	63,816
EMEA	47,537

Table 3. Coverage per region.

Coverage of top 4 countries

Country	Number of companies covered
India	32,021
China	11,492
United States	11,474
Italy	9,014

Table 4. Coverage per country.

Coverage per company type

Region	Number of companies covered
Private	79,683
Public	51,010

Table 5. Coverage per company type.

Model

How did we decide on the right model to estimate GHG emissions?

Estimating the carbon footprint of companies is a complex task in itself; additionally, the data required to perform the estimation is noisy and often missing for the companies that must be estimated. Linear models offer a high degree of explainability, but they struggle when the underlying data contains interdependent relationships, missing values and categorical information – precisely the issues faced when producing GHG estimates. More intricate machine learning models, such as regression trees, can naturally learn complex relationships in the data, handle missing values, process categorical data, and model the inherent noise of GHG emissions. Based on these considerations, we decided to use a machine learning model based on regression trees. A regression tree is a type of decision tree model that delivers a numerical value. Decision tree models are similar to flowcharts, so a regression tree is conceptually just a flowchart where the final outputs are all continuously varying numerical values, such as price, temperature, or in this case, GHG emissions.

What data goes into the model?

The quality of GHG emissions estimates greatly depends on the quality of the data being used to generate them, and this is where Bloomberg excels. The Bloomberg GHG model uses multiple datasets, such as company location; size; financial data; environmental, social and governance (ESG) data; the breakdown of revenue by industry sectors; and industry-specific company data. Examples of industry-specific data are the energy source (e.g., fossil fuel, solar, wind) used by utilities to produce electricity, or production data by cement, steel and oil & gas companies. In total, the model leverages over 800 individual features.

What does the model output?

The key output of the model is estimates for scope 1, 2 and 3 emissions. In addition, every estimate will have a unique distribution based on comparable companies, which allows users to select different percentiles in the distribution and use a more aggressive or conservative estimate than the one provided by the mean of the distribution.

Another element of the Bloomberg solution is the GHG Confidence Score, which is a measure of the depth and relevance of the data points available for the calculation of the GHG estimate for a particular company. The GHG Confidence Score is based on comparing the available data points for a given company and the most relevant data features for all companies in that same industry.

Finally, Bloomberg has created two sets of derived fields that complement the information provided by the estimate fields:

1. **Waterfall fields.** These fields are populated with reported GHG data, when available, and with estimated emissions for non-reporting companies.

2. **Intensity ratios.** These fields provide the amount of GHG emissions per unit of sales or enterprise value including cash (EVIC) to facilitate the comparison across companies.

How does the model come up with its estimates?

We train the model to learn the relationship between the data features of a company and the distribution of GHG emissions for companies with similar sets of features. The model training consists of applying a number of machine learning techniques, which are able to handle the complexity and challenges found in the data, to generate distributions. Finally, the model is able to apply these learned relationships to other companies.

Scope 3 Estimates

Estimating scope 3 emissions presents a bigger challenge than estimating scope 1 & 2 due to several reasons:

1. **Lack of reported scope 3 data.** Scope 3 is not as widely reported as scope 1 & 2 emissions.

2. **Inconsistency in the scope 3 time series.** Due to the complexity in measuring scope 3 emissions, many companies have updated their methodology over time, and this resulted in large jumps in the time series of reported data.

Because of those challenges, in addition to a general scope 3 model, Bloomberg has created industry-specific models to have the best possible scope 3 emissions estimates for sectors where those emissions are particularly relevant, like in the Oil & Gas sector, for example. The approach to create these models follows a similar pattern:

1. Perform in-depth sector research to determine what scope 3 components are relevant to each industry and the key drivers for the emissions across key scope 3 components.

2. Leverage company-reported data and generally accepted carbon emission factors to estimate emissions for those key components.

The following table shows the key scope 3 components being estimated for each sector.

Sector	Key Scope 3 Components	Key Drivers of Scope 3
Oil & Gas	1. Use of Sold Products	1. Sales / Production of oil & gas
Metals & Mining	1. Use of Sold Products 2. Processing of Sold Products	2. Sales / Production of coal, iron ore and other metals.
Airlines	1. Fuel & Energy-related Activities 2. Purchase of Goods & Services 3. Capital Goods	3. Country 4. Fuel used 5. Electricity used 6. Operating expenses 7. Capital expenses
Automobiles	1. Use of Sold Products 2. Purchase of Goods & Services	Sold vehicles (where possible, broken down per motorcycles, light trucks, light commercial and non-electric vs zero emissions)
Power Generation: Non-renewables	1. Fuel & Energy Activities 2. Use of Sold Products 3. Purchase of Goods & Services 4. Capital Goods	1. Country 2. Fuel used 3. Purchased electricity / Electricity used[1] 4. Gas sales 5. Capital expenses
Power Generation: Renewables	1. Fuel & Energy Activities2 2. Use of Sold Products 3. Capital Goods 4. Upstream Transport and Distribution	1. Country 2. Fuel used2 3. Gas sales2 4. Capital expenses 5. Operation expenses

Table 6. Scope 3 components being estimated for each sector.

[1] Applicable to power generation companies that purchase and resell electricity.
[2] Applicable to non-pure play renewable energy companies that generate electricity using non-renewable sources and/or act as distributors of natural gas.

An in-depth review of the industry-specific model for the Oil & Gas and Mining sectors can be found in the Appendix section.

Model distributions

Bloomberg's GHG emissions estimates model does not produce a single estimate but a full distribution of the estimated emissions. For each company and a given emissions metric, we provide the percentile values of its estimated emissions for percentiles between 1 and 99. We also provide the mean of the distribution.

As an example, let's take a look at what the 75th percentile of the estimate means:

The 75th percentile provides the level of GHG emissions that will be equal to or greater than the emissions of 75% of comparable companies within the same industry. Naturally, the greater the percentile, the more conservative the estimate will be, with the 99th percentile being the most conservative estimate in the distribution.

This is better than producing a single estimate for two reasons. First, this allows us to precisely quantify all of the uncertainty within a GHG emissions estimate. Intuitively, the more data that is available for a company and the more relevant that data is to emissions, the less uncertainty there should be about its estimated GHG emissions. In these cases, the distribution will be narrow, with values closely placed near the average. Companies with less data will display wider distributions with values further away from the average.

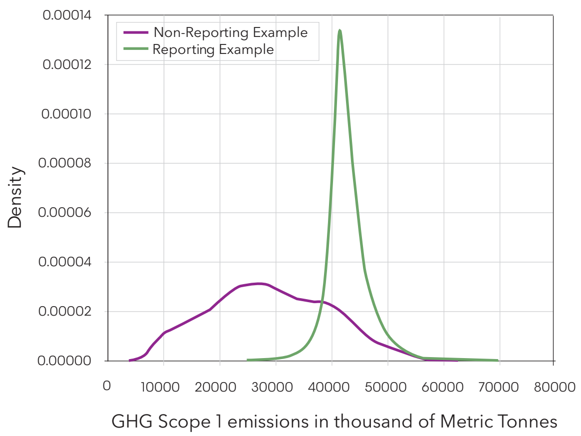

Figure 2. Examples of the scope 1 distributions for two companies. The green line shows a company with good data, low uncertainty and a high confidence score. The purple line shows a company with less data, high uncertainty and a low confidence score.

The second reason that a distributional estimate is more useful is that it allows users to adhere to the precautionary principle, as recommended by the European Union. This principle holds that when there is uncertainty in estimated emissions, it is more responsible to err on the side of protecting the planet and hence take an estimate at a high percentile. Using estimates at the 75th percentile when carbon footprinting, for example, will help incentivize companies to report their emissions.

In summary, the distributions empower users to be as cautious as they feel is appropriate. The larger the percentile used, the more conservative the estimate will be.

Scope 1 & 2 estimates across key percentiles for Spanish company Acciona SA.

Fiscal year 2021, all units in thousands of metric tonnes of CO2e.

Company Name	Acciona SA
GHG_SCOPE_1_ESTIMATE	12.742
GHG_SCOPE_1_ESTIMATE_25TH_PCTL	6.095
GHG_SCOPE_1_ESTIMATE_50TH_PCTL	9.8
GHG_SCOPE_1_ESTIMATE_75TH_PCTL	16.267
GHG_SCOPE_1_ESTIMATE_99TH_PCTL	46.83
GHG_SCOPE_2_ESTIMATE	120.844
GHG_SCOPE_2_ESTIMATE_25TH_PCTL	104.995
GHG_SCOPE_2_ESTIMATE_50TH_PCTL	121.542
GHG_SCOPE_2_ESTIMATE_75TH_PCTL	137.804
GHG_SCOPE_2_ESTIMATE_99TH_PCTL	277.282

Table 7. Scope 1 and 2 estimates across key percentiles for Spanish company Acciona SA.

Aren't companies that report GHG different from those that do not? Does this negatively affect the model?

This phenomenon is called distribution shift, and it is potentially a serious problem. One major source of distribution shift is the difference in the amount of data reported: companies that report GHG emissions also report many other related pieces of information, like energy consumption. To solve this problem, we train our model on data that is masked by applying the patterns of missing data from the companies that do not report their emissions to the ones that do.

For example, in the universe of carbon emissions-reporting companies, around 80% also report energy consumption, but in the universe of non-reporting companies only 5% do. This is a challenge that can introduce reporting bias. In order to prevent that issue, we create a "mask" that essentially blots out the energy consumption of reporting companies until that also falls to a 5% level and then train the model on that masked data. The result is that the model learns how to estimate the carbon emissions of companies that do not report much data.

Model Evaluation

How do we evaluate our model?

To evaluate our model, we use a technique called cross-validation.

CCross-validation is a technique in which we remove some of the reported data from the model training. Specifically, we split the reported data into 10 sections, use nine of them to train the model, and then evaluate the remaining section. We then repeat this procedure nine more times.

Cross-validation gives us estimates on data that was not used for model training. We then analyze the performance on those out-of-sample predictions over multiple subsets of the data (i.e., does the model perform consistently across different industries and for differently sized companies?) and compare that performance against other baseline methods.

We have collaborated with subject matter experts inside and outside Bloomberg to discuss the model and review the estimates it produces. At Bloomberg, we worked with BloombergNEF (BNEF) and Bloomberg Industries experts, as well as the ESG team at large. Outside Bloomberg, we consulted with Professor Andreas Hoepner, Ph.D., at University College Dublin, Ireland, who advised on the importance of incorporating precautionary principles in the use of GHG estimated data.

Comparison of accuracy against baseline methods

We have compared our model against two other methods:

- **Sector Intensity.** This widely used model consists of calculating a carbon intensity metric (e.g., Scope 1 Emissions divided by Sales) for reporting companies, aggregating the data on an industry level and then taking the mean or the median as the "industry intensity ratio." We can then estimate GHG emissions for non-reporting companies as long as we know the company's industry segment and its revenue.
- **Linear Model per Industry.** In this approach, we create a linear model per industry to estimate the GHG emissions of companies. In each linear model, we select features that are relevant to the carbon footprint of companies in that industry and try to find those that best explain the reported carbon emissions. Examples of relevant features are the industry classification, revenue, net fixed assets, energy consumption and number of employees. When the reported value of a feature is missing, it's replaced by the industry average.

The following charts and tables show how each of the two models above perform against the Bloomberg GHG emissions model. We break down the analysis into two separate groups.

1) **Firms with good disclosure.**
   Companies in this group disclose company financials, industry segmentation, and other relevant datasets that are related to their carbon footprint. This group primarily includes companies based in markets with good reporting standards and large international companies.

2) **Firms with average or poor disclosure.**
   These companies tend to omit some of the features available for companies in the first group. In general, they are smaller in size and often located in emerging markets or markets with weaker disclosure standards. Many private companies will be included in this group as well.

For firms with good disclosure, both the linear approach and Bloomberg's model outperform the sector intensity approach, which confirms that not all companies in the same sector have a similar carbon intensity profile and points out that using industry averages or medians is not a good approach to estimate the carbon footprint of these companies. The linear model performs well but below Bloomberg's model as indicated by both the R-squared (R^2) and the root-mean-square error (RMSE).

Both R^2 and RMSE provide a measure of how well the estimated GHG emissions match the actual GHG emissions reported by companies. In other words, they provide a measure of how well the model performs at predicting GHG emissions.

More specifically, R^2 shows how much of the reported carbon emissions can be explained by the model. Therefore, the larger the R^2, the better the model is at predicting the carbon emissions of companies. By contrast, the RMSE measures the difference between values predicted by a model and the values observed. In this case, the lower the RMSE, the better the model is at predicting carbon emissions.

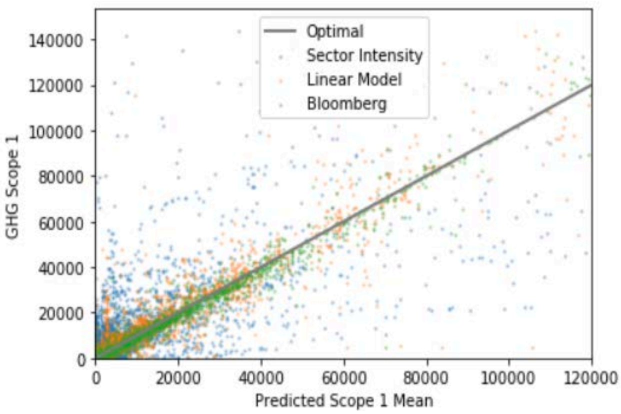

Figure 3. Scatter plot showing scope 1 predicted values versus observed values for companies with good data. Ideally, both values should be equal and all dots should be on the optimal line, but this is not always achievable due to missing features and noise in the data.

Model	R^2	RMSE
Sector Intensity	0.2997	7657.5
Linear Model	0.682	3464.8
Bloomberg GHG Model	0.8441	1703.9

Table 8. R^2 and RMSE for the sector intensity, linear model and the Bloomberg model for companies with good data. A large R^2 and a small RMSE indicates a strong model performance.

For firms with average or poor disclosure, Bloomberg's model continues to outperform both the linear model and the sector intensity approach. In this case, the linear model cannot handle the amount of missing data and performs very poorly. The sector intensity model is dependent on industry classification and revenue, so as long as that data is available its performance won't be affected.

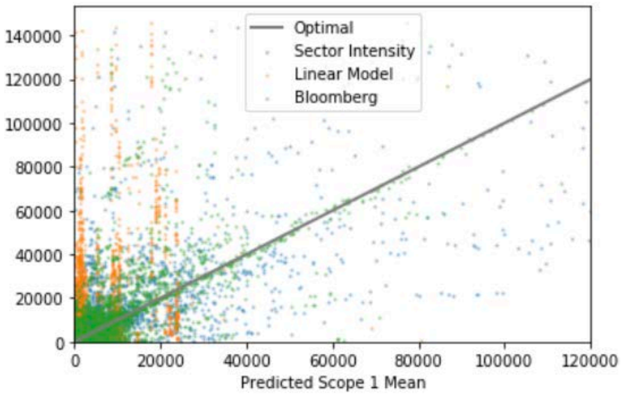

Figure 4. Scatter plot showing scope 1 predicted values versus observed values for companies with sub-optimal data. Ideally, both values should be equal and all dots should be on the optimal line, but this is not always achievable due to missing features and noisiness in the data.

Model	R^2	RMSE
Sector Intensity	0.3181	7474.2
Linear Model	0.110591	9690.5
Bloomberg GHG Model	0.4108	6453.8

Table 9. R^2 and RMSE for the sector intensity, linear model and the Bloomberg model for companies with sub-optimal data as seen in Figure 4. A large R^2 and a small RMSE indicates a strong model performance.

How do we know how well the model performs for companies that do not report?

In order to be able to fairly evaluate the models on non-reporting companies, we did a separate training pass in which we held out some companies with reported data from the training set, and also removed features from them that we would anticipate to be missing from non-reporting companies. This allowed us to get model predictions as close as possible to the situation of non-reporting companies, while still having reported values to compare against.

For example, say that we were to hold out Apple Inc., which does report its emissions. We would remove it from the training set entirely (so the model never sees it until evaluation time) and then mask out its data so that the remaining data is similar to what we would see for a non-reporting company. Then when we get the model's estimate of Apple's emissions using that masked data, we can actually compare to Apple's reported values.

Industry Implied Estimates

Bloomberg's GHG Emissions Model leverages a wide range of company data to estimate the carbon footprint of companies. However, the model requires that, at minimum, companies report their financial data, including a breakdown of their revenue per business segment. Due to that constraint, the carbon footprint of certain companies cannot be estimated using Bloomberg's GHG Model, and industry implied estimates are the solution to those carbon emission data gaps.

The industry implied model is based on the assumption that companies in the same industry will have comparable carbon intensity ratios. This hypothesis provides a framework to create estimates when company-specific characteristics are not available and more sophisticated modeling approaches are not viable. In the industry implied model, the only data requirements to generate an estimate are companies' revenue and industry classification. The industry sector is given by Bloomberg's Industry Classification System (BICS) level 4.

Coverage

The set of rules that determine what companies will receive an industry implied estimates are simple:

- Revenue and industry classification data are available for at least one of the last three fiscal years.
- The company is not classified as a financial company (for scope 3 estimates only).

In addition, similar to the approach taken in the GHG Emissions Model, we apply the parent company's estimates to subsidiaries that are issuers of equity or fixed income securities and fail to report revenue and industry classification data.

Methodology

The calculation of the industry implied estimates performs the following steps:

- Calculate the carbon emission intensity for all reporting companies in each industry. Carbon intensity is defined as scope 1, 2 or 3 individually, divided by the company revenue.
- The assigned industry sector defaults to BICS level 4 or a level higher in the classifications hierarchy, when a company belongs to a sector with less than 5 reporting companies.
- Calculate the median carbon intensity for each industry and fiscal year, denoted as the industry carbon intensity. Median is the value lying at the midpoint of a set of observed values, such that there is an equal probability of falling above or below it.
- Calculate the industry implied estimate per company and per fiscal year as the result of multiplying the company revenue by the industry carbon intensity.

Waterfall Fields

Bloomberg provides separate fields for carbon reported data and estimates. In the case of estimates, there are two sets of fields, one set to carry Bloomberg's GHG model estimates and another set to deliver industry implied estimates.

Waterfall fields provide a single answer to understand a company's emissions by consolidating the different available emissions data into a single field that will give priority to reported data first and, if not available, to Bloomberg's proprietary GHG model and as a last option, to an industry implied model.

There are individual waterfall fields for scope 1, 2 and 3 and then another two for the combination of scope 1 & 2 and scope 1, 2 & 3, respectively. Each waterfall field is also divided into sales or the enterprise value including cash (EVIC) to create carbon intensity ratios.

Two sets of fields, the "Data Type" and "PCAF Data Quality Score" fields, provide color into the type of carbon data, i.e., reported or estimated, delivered by each key waterfall field (scope 1, scope 2 and scope 3 waterfall).

Data type fields

The "data type" fields specify the source of the GHG emissions data that populates their respective waterfall field. As an example, the field GHG_SCOPE_1_EMISSIONS_DATA_TYPE is associated with the GHG_SCOPE_1_ESTIMATE_WATERFALL field. There are three possible returns for each data type field:

- **Reported** – the company has reported GHG emissions
- **Smart Estimate** – GHG emissions is estimated using Bloomberg's GHG Emissions Estimates model
- **Industry Implied** – GHG emissions is estimated using an industry GHG intensity model

PCAF Data Quality Scores

The Partnership for Carbon Accounting Financials (PCAF) is an industry-led partnership that was launched to harmonize GHG accounting methods and enable financial institutions to consistently measure and disclose the GHG emissions financed by their loans and investments.

PCAF has developed the Global GHG Accounting and Reporting Standard for the Financial Industry (the Standard). This Standard has been reviewed by the GHG Protocol and conforms with the requirements set forth in the Corporate Value Chain (Scope 3) Accounting and Reporting Standard for category 15 investment activities.

The Standard also provides guidance on data quality scoring per asset class, facilitating data transparency and encouraging improvements to data quality in the medium and long term. The data quality score table for listed equity and corporate bonds includes five possible scores with score 1 being the highest data quality for GHG emissions and score 5 representing the lowest data quality. As an example, score 1 is obtained when verified company reported emissions are available.

Bloomberg has created fields that return the data quality score for the waterfall field of each scope, company and fiscal year, as defined by PCAF. More information available on the PCAF website:

https://carbonaccountingfinancials.com/files/downloads/PCAF-Global-GHG-Standard.pdf

Additional Reading
Want to learn more about Bloomberg's model?

Read the extended white paper, "***Distributional Greenhouse Gas Emissions Estimates***." In addition to the information in this report, that white paper includes additional data and exhaustive information on our research approach.

If you have any questions or would like to speak to a representative, please email eprise@bloomberg.net.

Appendix.

Scope 3 Model for the Oil & Gas and Mining Sector

The scope 3 model for Oil & Gas and Mining companies combines a bottom-up model with a top-down machine learning model.

The bottom-up model uses companies' sales and production numbers on oil, gas, natural gas liquids, coal, iron ore, and more, alongside carbon emission factors, i.e., the amount of CO2 equivalent emitted per unit of product. It then calculates the indirect emissions produced when using or processing those products. The top-down machine learning model sits on top of the bottom-up model and estimates carbon emissions by learning the relationship between calculated scope 3 emissions, revenue per industry and other key factors.

Using sales and production metrics works well because the most significant contribution to scope 3 emissions for these sectors comes from the downstream processing and use of their products. Other scope 3 components contribute in a much lesser way to the overall scope 3 footprint of firms in the Oil & Gas and Mining sectors.

In a more detailed description of the process, we first reviewed reported scope 3 data by companies in the Oil & Gas and Metals & Mining sectors and included the last three fiscal years' worth of data across 44 reporting companies. The outcome showed a clear pattern for a set of sub-sectors within the two large groups, where companies reported most of their scope 3 emissions within two downstream components: "Use of Sold Products" and "Processing of Sold Products." On average, those two components together represented around 90 percent of the total scope 3 across reporting companies in those sectors.

Specifically, that was the case with the following sub-sectors as per the Bloomberg Industry Classification System (BICS) Level 4:

Specifically, that was the case with the following sub-sectors as per the Bloomberg Industry Classification System (BICS) Level 4:

- Exploration & Productionn
- Refining & Marketing
- Integrated Oils
- Iron
- Base Metals
- Coal Mining

As a second step, we set out to find a way to estimate those two components by using other company-reported data. Fortunately, both scope 3 components, "Use of Sold Products" and "Processing of Sold Products," are related to the amount of product sold by companies, and Bloomberg captures the amount of sold products for the Oil & Gas and Metals & Mining industries, so where available we would use that information to estimate the components. Bloomberg captures the amount of sold products for the oil & gas and metals & mining industries, so where available, we would use that information to estimate the components.

When the amount of sold product was not available, we used production data as a proxy. There is a high correlation between the amount of physical sales and production data; even though those two metrics don't necessarily match on any specific year, over long periods it's fair to assume that the amount of sold product will be similar to the amount of product extracted/mined.

Following this, we had to convert the amount of sold product into GHG emissions, noted as tCO_2e (tonnes of CO_2 equivalent). In order to do this, we use the conversion factors available in the tables published by the UK Government with "Greenhouse gas reporting: conversion factors 2022." (https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2022)

Thanks to these tables we can translate the amount of sold product data into units of CO_2e emissions.

In the last step, we combine revenue and industry segmentation data as key inputs to estimate scope 3, alongside training data from the companies for which we have calculated Scope 3 emissions using the bottom-up model described above. This allows us to produce estimates for companies that do not report the amount of product being sold or produced in each period.

Other sub-sectors within Oil & Gas and Metals & Mining do not behave in the same way as the sectors listed above and Use of Sold Products and Processing of Sold Products are not key drivers of scope 3 emissions. Those are Midstream - Oil & Gas, Oilfield Services & Equipment, Drilling & Drilling Support, Mining Services, and Precious Metals. Scope 3 for those companies was estimated using a similar model to the one explained for scope 1 & 2 emissions.


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