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Assessments of the environmental performance of global companies need to account for company size

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While the awareness of the corporate world toward sustainability is growing, how to assess corporate environmental performance objectively and efficiently remains an open question. Here we estimate the relationship between company size and four environmental indicators to understand the environmental performance of nearly 6500 companies, building on the concept of allometric scaling and using Thomson Reuters EIKON data for the year 2018. We highlight that carbon dioxide emissions, energy use, water and waste production scale with the size according to a power law. This can be used as a benchmark to assess unambiguously a company's environmental performance. We find that the adopted Environmental, Social & Governance rating is uncorrelated with the environmental performance. Our results suggest that a fair and effective environmental policy should consider the nature of the scaling relationship. Scaling laws suggest the existence of a nexus between an underlying network and corporate metabolism, whose understanding would help in discerning the determinants of environmental impacts.

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In 2018, less than seven thousand of the largest international corporations, accounting for 50% of World Gross Domestic Product (GDP) and employing 123 million people, released more than 14 billion tonnes of carbon dioxide equivalent (CO_2e), i.e., 30% of global emissions. The average carbon intensity per worker is 117 tonnes CO_2e, three times higher than the most densely populated mega-cities[1]. Environmental, Social & Governance (ESG) practices and policies are meant to address emission reduction targets. However, many voices, corporate and non-corporate, are being raised over the issue of the lack of a transparent and unbiased *benchmark* to assess the environmental performance of companies[2,3]. We propose here a benchmarking approach based on scaling analysis of corporate metabolism and self-reporting (EIKON database[4]). This approach could represent a solution to gauge how a company performs compared to the sector to which it belongs and its size, according to the most suitable metrics (revenue, employees or capitalization).

Ahead of the United Nations Climate Action Summit of 2019, a coalition of almost 90 major global corporations committed to bring their emissions to zero before 2050[5]. This is the last step in a process of progressive engagement by the corporate world into a decades-long path toward sustainability. It began in the aftermath of the Rio Earth Summit of 1992[6] and the foundation of the World Business Council for Sustainable Development[7]. This commitment has become more stringent since it was joined by the sphere of finance, in a parallel quest for sustainability which began essentially 20 years ago with the Equator Principles and culminated in 2019 with the Principles for Responsible Banking[8]. All these initiatives have been so far voluntary in nature and have led to very different ESG practices and approaches, with different results and degrees of alignment with the proclaimed environmental goals[9,10] or emission targets[11].

The global corporations met the commitment for greater (biosphere) stewardship with a growing and vocal call from science and other societal actors[12]. This willingness to engage, however, come with some major challenges, the most cogent of which, is that of *assessing the real impact* of corporate activity, both in terms of emissions and other environmental pressure[13]. Global value chains make this task even more difficult[14,15]. The problem of establishing a harmonized analytical framework and unbiased metrics is long-standing[16,17]. The issue of how to *benchmark* corporate emissions and environmental impact, once the conundrum of scholars and the concern of policymakers and environmentalists, is now haunting financial investors[18,19].

Typically, existing ESG ratings have a lack of scientific basis and cross-country and cross-sector comparability[20]. Despite few attempts, and at least until the zero-emission target is achieved, the question of how to gauge objectively the emissions of a corporation remains challenging[21,22]. Currently, there are no general, universally accepted criteria upon which the environmental impact of companies is measured[23–25]. Moreover, the measurement methods that do exist are typically prone to subjectivity as they are based on self-reporting[26]. Several attempts have been made to standardize sustainability reporting, such as the Global Reporting Initiative (GRI) Sustainability Standards[27]and the United Nations Principles for Responsible Investments[28]. See the supplementary material (SM1) for a brief overview of these approaches, their advantages and limitations,[25,29,30] and the methodologies used to quantify them[26,31]. Parallel to the problem of assessing environmental performance, the scientific and corporate communities are engaged in finding Science-Based Target (SBT) methodologies for setting emission in line with climate targets, identified by the Paris agreements. Among them are those considering sector-specific emission reduction pathways, such as the Sectoral Decarbonization Approach, accounting for the constraints peculiar to every sector/industry in determining such paths[32]. A paper by Bjorn et al.[33] offers an overview and assessment of six of SBT methods, some of which, like the Context-Based Carbon Metric, include also size as a factor. Although these approaches simplistically assume linearity between size and impact, they are often too complex to be independently implemented and interpreted by practitioners or they set zero-targets (or the more ambiguous net-zero, based upon improbable carbon offset practices) that are perceived as going too far or too difficult to be achieved in the medium term[34]. A more practical though solid (science-based) approach should enable operators, businessmen and stakeholders to independently assess the environmental impact of their economic activity *hic et nunc*, with respect to the (scale of) size and sector of operation.

Building on the concept of scaling, describing a functional relationship between two variables over a significant interval, we propose here a method to unambiguously assess the environmental performance of a global corporation with only two variables: size, such as revenue or a number of employees, and an impact variable, such as emissions or waste. Scaling laws relating body size to shape, anatomy or physiology have a long history in science, dating back to Galileo[35]. According to the metabolic theory of ecology, a universal exponent of 3/4 bounds the energy consumption (basal metabolism) of species to their body mass[36]. The existence of an underlying (transport) network, such as the vascular system, has been proposed as an explanation for this universal scaling[37,38]. More recently scaling law has been successfully applied to social organizations, such as cities and companies, to explain the relationship between size and activity or metabolism[39,40], finding that some features, differently from ecological scaling, show an unbounded (superlinear) growth with size, meaning that some metabolic activities grow faster than the growth rate of the size[41]. Based on this tradition we aim at interpreting sector-specific corporate metabolism as a criteria to assess their environmental performance unambiguously.

Results

The four Environmental Impact indicators selected from the EIKON database ([4]) to assess corporate metabolism are––CO_2 emissions, energy use, water withdrawal and waste. For every dependent variable, i.e., the environmental indicator, a linear regression model was fitted using company's characteristics, i.e. assets, employees, market capitalisation and total revenue, as independent variables. In its linear form, the constants β (slope) and η (intercept) in the scaling equations can be assessed by performing linear regression analysis for the 10 main sectors and 133 industries (see Methods). The definition of industries and sectors follows Thomson Reuters Business Classification (TRBC), developed by the Reuters Group. (Since 2020 it has been rebranded to The Refinitiv Business Classification keeping the same acronym, TRBC, but owned and operated by Refinitiv). Consumer cyclicals are a category of stocks that rely heavily on the business cycle and economic conditions. Industries are: Basic Materials, Consumer Cyclicals and non-cyclicals, Energy, Finance, Healthcare, Telecom, Tech and Utilities. Consumer cyclicals include industries such as automotive, housing, entertainment, and retail)[42]. β and η are specific for every sector or industry and determine unambiguously the environmental impact of a company according to the benchmark. 15% of global emissions come from corporations above the benchmark, signaling a potential for reduction. If more and more companies perform better or as good as the benchmark, the benchmark would shift downward, enhancing the environmental standard, until limiting environmental and technical constraints are reached.

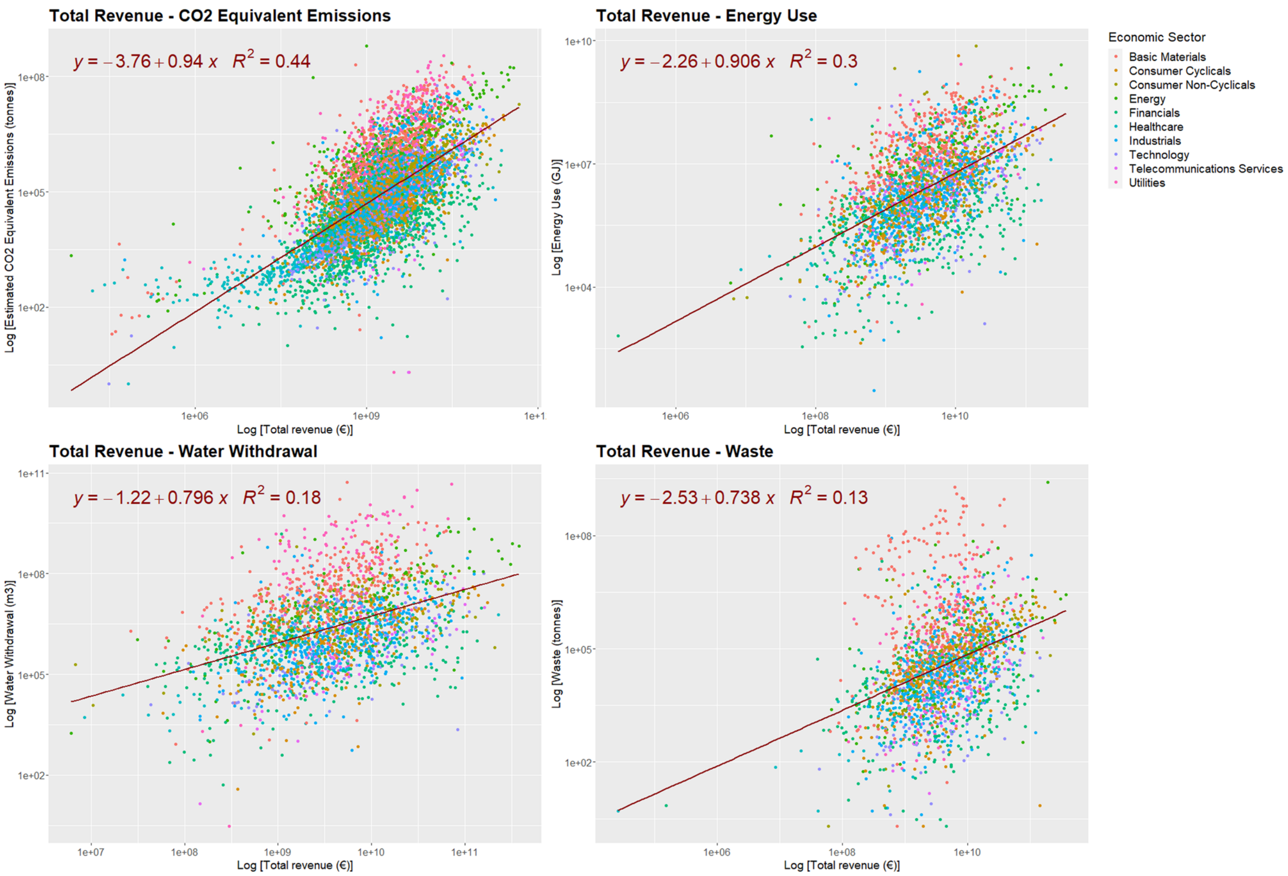

Fig. 1 Log-log scale plot of total revenue vs. impact indicators. The four quadrants show the scaling laws of emissions, energy, water withdrawal and waste production; different colours indicate different economic sectors. Red line = linear regression line, with the regression model statistics reported on top (including the R^2-value).

Emissions. When plotted on a log-log scale, total revenue and estimated CO_2 equivalent emissions for all the companies show a linear relationship (Fig. 1), first quadrant) with R^2-value of 0.45, despite the diversity in companies, industries and economic sectors. In the plot several clouds of sectors can be observed and by dis-aggregating the data the fitting improves: at the sector level of aggregation the fitting shows a mean R^2 of 0.58; the best fitting is obtained at industry level (see supplementary material, SM2). The three most emitting economic sectors were found to be utilities, basic materials and energy. Companies from these sectors were found to often be above the regression line (i.e. benchmark). In contrast, companies of sectors with lower emission intensities lie often below the benchmark. Examples of such sectors are healthcare and finance. The slope of the regression equation shows a sublinear relationship, with β=0.94. Sublinearity suggests that as companies grow, they become more efficient in terms of emissions per € revenue (or other size unit). Most of industries show sublinearity, with few exceptions, like Airlines, Marine Freight, Power Equipment, Commodity Chemicals and Rubbers (see SM2 for a the full list). With respect to the estimated emissions, total revenue, number of employees and total assets seems to be good predictors. Of these size indicators, the total revenue has proved to have the highest correlation and best fit. In most industries, 119 out of 123 showed to have a statistically significant relationship with emissions at the 5% level and 107 industries at the 0.1% level. From the size indicators, market capitalisation was most frequently the worst predictor. Slightly more than half of the industries showed a significant relationship at 0.1% level. Additionally, market capitalisation also showed the lowest correlation and R^2-values (see Table 1).

Energy use. Reported information about the energy use of companies is not as widely available as the estimated CO_2 equivalent emissions. Therefore, only 2416 companies were included in the sample for analysing the scaling of energy use. There is only a marginal difference in β, namely 0.91 for energy use compared to 0.94 for the emissions (Fig. 1). Splitting the sample into industries again proved to give a better fit as the R^2 increased for every size variable (Table 2). On average, revenue had the highest adjusted $R^2 = 0.47$ closely followed by assets with an adjusted R^2 of 0.46. Moreover, employees also showed a good average adjusted $R^2 = 0.42$. The adjusted R^2-values of energy use are lower than for the emissions, implying that the CO_2 equivalent emission data fit the regression models better than the energy use data. In contrast to the exponents of the emissions, most of the industries scale superlinearly with revenue, as can be seen in Fig. 1. More precisely, 43 of the 91 industries scale superlinearly, meaning that the relative increase in energy consumption is higher than the relative increase in size (i.e. per revenue or employee).

Water withdrawal. From the results of the analysis for water withdrawal, it can be concluded that the relationship is weaker, although in most cases still statistically significant for employees, assets and revenue (Table 3). However, in almost half of the industries, market capitalisation did not show a significant relationship. When looking at the water withdrawal data for the whole sample, it was found that it best fitted to the revenue. Yet, the data was best fitted to employees when dividing the sample into sectors. Thus, at a lowest level of aggregation, employees

Table 1 CO_2 equivalents emission vs. company size.

Sector	*n*	Employees			Market Capitalisation			Assets			Total Revenue		
		Adj. R^2	β	c	Adj. R^2	β	c	Adj. R^2	β	c	Adj. R^2	β	c
All	6529	0.334	0.799***	1.959	0.127	0.544***	-0.215	0.337	0.918***	-3.863	0.446	0.944***	-3.798
Basic Materials	635	0.499	0.978***	2.377	0.229	0.700***	-0.497	0.520	1.097***	-4.402	0.608	0.951***	-2.798
Consumer Cyclicals	1034	0.633	0.979***	0.921	0.230	0.534***	-0.154	0.508	0.940***	-4.089	0.569	0.988***	-4.458
Consumer Non-Cyclicals	481	0.569	0.824***	1.900	0.264	0.538***	0.076	0.538	0.915***	-3.516	0.545	0.878***	-3.133
Energy	420	0.344	0.691***	3.505	0.373	0.689***	-0.391	0.591	1.078***	-4.556	0.582	0.850***	-2.068
Financials	993	0.193	0.432***	2.720	0.195	0.614***	-1.673	0.263	0.609***	-1.939	0.272	0.613***	-1.461
Healthcare	659	0.433	1.018***	0.714	0.856	0.823***	-3.698	0.745	1.132***	-6.214	0.792	0.810***	-2.902
Industrials	1137	0.375	0.868***	1.590	0.166	0.546***	-0.060	0.473	1.013***	-4.611	0.470	1.000***	-4.331
Technology	742	0.570	0.990***	0.708	0.205	0.553***	-0.910	0.555	0.994***	-4.858	0.592	0.980***	-4.543
Telecommunications Services	153	0.504	0.862***	1.742	0.268	0.638***	-1.016	0.449	0.927***	-4.073	0.505	0.946***	-3.909
Utilities	275	0.238	0.829***	3.316	0.150	0.757***	-0.950	0.359	1.231***	-5.970	0.357	1.144***	-4.488

***$p < 0.001$.

might be a better explanatory variable than total revenue for most industries. For more than half of the industries scaling is superlinear. This feature, whether an industry scales sub- or superlinear, is generally consistent for employees, assets or revenue as explanatory variable.

Waste. The scaling of waste production shows a poor fit, with only a R^2 of 0.14 (Fig. 1). The other size variables did not show a better fit, with $R^2 = 0.10$ for employees, R^2=0.09 for assets and lastly, R^2=0.04 for market capitalisation. Thus, the analysis for waste shows that the data does not fit the model well at an aggregated level (Table 4). The *p*-values do, however, show that the relationship between all the size variables and waste is statistically significant at the 0.1% level. Once more, the fit improves when splitting the sample per industry. Thus, although waste does not appear to show universal scaling, it does appear to be industry-specific. Revenue has, on average, the highest adjusted $R^2 = 0.36$, implying that data fit the regression model with revenue as explanatory variable the best. Like Energy Use and Water Withdrawal, Waste shows superlinearity for most sectors and industries.

Univariate versus multivariate benchmarking. As shown by the literature for emissions, the larger the number of explanatory variables, the more accurate is the prediction[43–46]. In the same vein, the multidimensional determination of the size of the corporation, i.e. with more than one metric, can improve the fitting of the scaling. The improvement, tough negligible (from an R^2 of 0.443 to 0.465), is also confirmed by an AIC test we run over all estimations (see SF4). Nevertheless, the questions is whether the gain in accuracy compensates for the loss in interpretability. Furthermore, in multidimensional space the interpretation (and visualization) of scaling laws translate in a complex mathematical problem. If the goal of the benchmark is that of enabling a fast and transparent circulation of easily interpretable and actionable information, the regression based on only one, significant size variable is preferable. How much accuracy do we loose in availing of only one variable? For the whole sample of corporations and each sector separately, we performed a multivariate regression analysis with independent variables: Market Capitalisation (MC), Assets (ASS), Revenues (REV) and Employees (EMP). We, then, compared the observed value of CO_2e emissions with the fitted lines obtained by both the multivariate and the univariate analyses (see Table 1 in the main text) computing for each one the frequency of points locating above (below) such regression lines in both cases. In other terms, we compute the number of observations having positive (negative) deviations for the multi and univariate divided by the total number of observations. Over the entire sample, for 93% of corporations employing revenues as a size factor is enough informative to determine their benchmark in terms of emissions of CO_2e. Breaking down at sector level, revenue performs always better than any other size-factor, determining between 96% and 83% of companies' benchmark, with the only exception of Healthcare, where number of employees performs better (89% vs. 70%).

We further investigated the cardinality of *revenue* as an explanatory variable for emissions by performing a Path Analysis for all ten sectors. (In Path Analysis the first model is considered a simple linear regression; while, the second model is considered a multiple linear regression model. The tested assumption is that there are multiple independent variables that all affect the output variable rather than defining some independent variables as intermediates between the main independent variable and the dependent variable.) In all sectors employees, assets and market capitalization can be considered

Table 2 Energy use vs. company size.

		Employees			Market Capitalisation			Assets			Total Revenue		
Sector	***n***	**Adj. R^2**	**β**	**c**	**Adj. R^2**	**β**	**c**	**Adj. R^2**	**β**	**c**	**Adj. R^2**	**β**	**c**
All	2416	0.213	0.687***	3.687	0.074	0.437***	2.252	0.189	0.744***	−0.911	0.299	0.919***	−2.371
Basic Materials	373	0.421	0.966***	3.531	0.136	0.508***	2.508	0.475	1.104***	−3.401	0.485	1.068***	−2.827
Consumer Cyclicals	305	0.510	1.066***	1.689	0.206	0.628***	0.266	0.448	1.025***	−3.755	0.498	1.072***	−4.060
Consumer Non-Cyclicals	205	0.483	0.829***	3.115	0.224	0.566***	1.139	0.452	0.883***	−1.971	0.472	0.885***	−1.942
Energy	164	0.317	0.756***	4.421	0.355	0.787***	−0.231	0.549	1.195***	−4.721	0.539	1.000***	−2.494
Financials	305	0.099	0.325***	4.362	0.132	0.641***	−0.717	0.131	0.486***	0.484	0.130	0.438***	1.378
Healthcare	160	0.605	1.062***	1.662	0.312	0.701***	−1.067	0.530	0.901***	−2.823	0.499	0.836***	−1.950
Industrials	479	0.204	0.784***	3.174	0.077	0.432***	2.390	0.337	1.053***	−3.824	0.312	1.024***	−3.368
Technology	210	0.390	0.935***	1.994	0.159	0.509***	0.859	0.425	1.002***	−3.861	0.379	0.954***	−3.261
Telecommunications Services	91	0.590	0.869***	2.844	0.330	0.821***	−1.627	0.510	0.988***	−3.536	0.517	1.038***	−3.688
Utilities	124	0.072	0.415**	5.195	0.089	0.587	1.096	0.227	0.990***	−3.197	0.218	0.847***	−1.312

**$p < 0.01$, ***$p < 0.001$

endogenous variables to revenue, with the exception of healthcare and utilities, which shows a strong dependence to employees the former and assets the latter (see supplementary material, SM3).

Comparing the benchmark with ESG environment rating. Inspired by the concepts of Sectoral Decarbonization Approach (SDA) and Strategic Benchmarking (SB), we herein propose a benchmarking approach based on scaling analysis and self-reporting data. SDA allows companies to set sector-specific emissions targets according to output intensity indicators[32,33], while the theory of SB is a management practice and investigation methodology that applies to national and global corporations, within and across sectors, aimed at comparing the strategies of successful businesses[47,48]. As an example, we consider the case of insurance & brokers. We compare Allianz, Allianz NL, NN Group, ASR Netherlands, Assicurazioni Generali and AXA. Employees as an explanatory variable was found to have the highest goodness-of-fit with the data in this sector. Figure 2 shows that both Allianz Group and AXA are above the benchmark. This indicates that they emit more greenhouse gases than what would be expected on the basis of their size. At the same time, their competitors are below the benchmark, indicating a better environmental performance. Interestingly, however, Allianz Group has been scoring high in terms of ESG performance in numerous reputation (third-parties) indices, such as, for example: top 5% in the insurance industry for VIGEO EIRIS; 1st at subindustry level for SUSTAINALYTICS; 1st in institutional shareholder services for ISS QualityScore; Top 8% of sector for FTSE4 GOOD; Gold class (overall best in the sector globally) for DJSI; A+ for PRI and A- for CDP and AAA for MSCI[49].

If we widen the scope to all sectors the picture becomes even grimmer. In Fig. 3 we compare the 2018 environmental score provided by *Morningstar Sustainanalytics* for a sub-sample of 1104 global corporations and 9 sectors with the performance assessed with the proposed benchmark (only emissions). The Pearson correlation between the scores and the emissions performance is 0.04, with a *p-value* of 0.16. A possible explanation for the divergence might be that existing indices and ratings are not weighted for firm size, like scaling does or that emissions' level or intensity have a minder weight in the multiple evaluation criteria. However, our results are consistent with research by Rekker et al.([50]) who found that most ratings disregard mitigation goals. Furthermore, they confirm recent findings that "*ESG ratings have little to no relation to carbon intensity, even when considering only the environmental pillar of these ratings*"[51]. Has the Environment ESG score more in relation to the other impact categories? Not really. As we show in Table 5 Environmental-ESG score has virtually no correlation with any environmental impact factor. On the contrary, the herein proposed benchmark shows significant and high correlation across impacts. The same holds breaking down at sector level, with some exception. For example, emissions shows the highest correlation with the other impact categories (91-49%), in all sectors, except for Utilities and Basic Materials, where seems to be a poor predictor of waste and water footprint (see supplementary material, SM4).

Discussion

The sublinear scaling observed in most industries was in line with expectations[40]. More surprising and unravelling are the cases that scale superlinear. The property of superlinearity is inconsistent through impact categories and size factors, as it can change with the level of aggregation and shows the best fit at the highest granularity. Superlinearity leads to open-ended growth[41]. Thus, the environmental impact grows at an increasing pace when companies become larger. It is possible that superlinearity might be caused by economies of scale whereby cost savings increase with the level of production. In an economy of scale situation, large companies might be able to lower the price of their product or service as the size increases and a higher output would result in a higher environmental intensity. This theory is supported by the fact that the industries in which superlinearity was observed are highly competitive, e.g. airlines, oil & gas, and independent power producers. Another hypothesis points to the role of subsidies for fossil fuels and energy-intensive industries. Furthermore, the sub- or superlinear nature of scaling is important for setting the emissions and environment targets of corporations, because in the former case, the efficiency increases with the size, in the latter it decreases, meaning that bigger companies will be either facilitated or hindered in aligning their environmental-climate and economic-financial targets.

The concept of a global benchmark comes with a *caveat*. Some countries have more stringent policies than others, or more rigid climatic conditions, let alone the large gamut of costs of energy. We will refer to these kind of constraints as *the spatial embedding* of corporations (a problem sometimes referred to in the economic literature as that of *international benchmarking*[48] or that *location-based* accounting[52]). In order to assess the effect of the spatial embedding on the sample we computed the coefficients of variance (CV's) for the country of incorporation (the country

Table 3 Water withdrawal vs. company size.

Sector	n	Employees			Market Capitalisation			Assets			Total Revenue		
		Adj. R^2	β	c	Adj. R^2	β	c	Adj. R^2	β	c	Adj. R^2	β	c
All	2090	0.124	0.587***	4.119	0.061	0.449***	2.144	0.140	0.731***	−0.755	0.193	0.839***	−1.570
Basic Materials	365	0.253	0.888***	3.885	0.145	0.616***	1.538	0.350	1.113***	−3.443	0.349	1.048***	−2.578
Consumer Cyclicals	222	0.487	1.094***	1.470	0.168	0.581***	0.692	0.344	0.889***	−2.483	0.322	0.873***	−2.207
Consumer Non-Cyclicals	183	0.288	0.736***	3.595	0.142	0.510***	1.786	0.294	0.810***	−1.181	0.278	0.798***	−1.025
Energy	152	0.415	0.902***	3.683	0.311	0.735***	0.057	0.497	1.190***	−4.936	0.530	1.025***	−3.025
Financials	257	0.070	0.289***	4.670	0.054	0.463***	1.197	0.048	0.336***	2.201	0.062	0.329***	2.573
Healthcare	154	0.607	1.149***	1.329	0.281	0.720***	−1.243	0.547	0.999***	−3.754	0.548	0.968***	−3.160
Industrials	345	0.242	0.737***	2.886	0.113	0.441***	1.829	0.258	0.815***	−1.972	0.246	0.814***	−1.824
Technology	182	0.316	0.851***	2.344	0.049	0.311**	2.856	0.239	0.797***	−1.863	0.235	0.786***	−1.642
Telecommunications Services	71	0.756	1.264***	0.235	0.227	0.899***	−3.282	0.484	1.266***	−7.251	0.614	1.441***	−8.562
Utilities	169	0.088	0.745***	4.981	0.102	1.002***	1.931	0.142	1.272***	−5.117	0.154	1.222***	−3.991

**$p < 0.01$, ***$p < 0.001$

Table 4 Waste production vs. company size.

Sector	n	Employees			Market Capitalisation			Assets			Total Revenue		
		Adj. R^2	β	c	Adj. R^2	β	c	Adj. R^2	β	c	Adj. R^2	β	c
All	1767	0.103	0.604***	2.200	0.035	0.375***	1.026	0.084	0.631***	−1.605	0.135	0.767***	−2.733
Basic Materials	323	0.100	0.883***	2.301	0.077	0.680***	−0.669	0.130	1.041***	−4.343	0.085	0.800***	−1.834
Consumer Cyclicals	182	0.241	0.793***	1.102	0.111	0.494***	−0.203	0.230	0.725***	−2.602	0.293	0.832***	−3.549
Consumer Non-Cyclicals	150	0.457	0.906***	0.965	0.164	0.538***	−0.389	0.381	0.943***	−4.358	0.392	0.962***	−4.523
Energy	128	0.336	0.929***	1.421	0.209	0.643***	−1.122	0.294	0.997***	−5.042	0.281	0.865***	−3.528
Financials	183	0.003	0.119	3.395	0.012	0.313	0.783	−0.004	0.068	3.098	0.002	0.134	2.541
Healthcare	119	0.629	1.231***	−1.027	0.277	0.719***	−3.325	0.454	0.954***	−5.408	0.517	0.834***	−3.950
Industrials	353	0.162	0.758***	1.220	0.053	0.391***	0.712	0.197	0.902***	−4.429	0.258	1.023***	−5.431
Technology	142	0.250	0.824**	0.412	0.061	0.378***	0.221	0.297	0.994***	−5.765	0.251	0.922***	−4.982
Telecommunications Services	60	0.559	1.184***	−1.272	0.300	1.010***	−6.184	0.595	1.338***	−9.807	0.566	1.344***	−9.413
Utilities	127	0.164	0.832**	1.889	0.063	0.599***	−0.747	0.187	1.114***	−6.243	0.206	1.104***	−5.638

**$p < 0.01$, ***$p < 0.001$

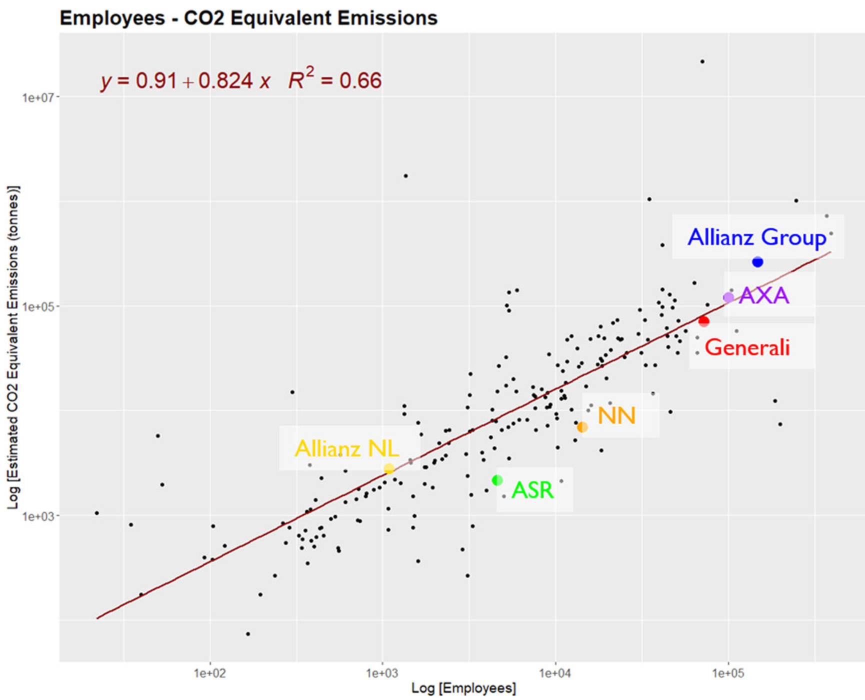

Fig. 2 Log-log scale plot of employees vs. estimated CO_2 equivalent emissions of insurance & brokers industry. Highlighted are the emissions of: Allianz, Allianz NL, NN Group, ASR Netherlands, Assicurazioni Generali and AXA as opposed to the number of employees, as was found to be a better explanatory variable of emission for this industry. Red line = linear regression, with the regression model statistics reported on the left top (including the R^2-value).

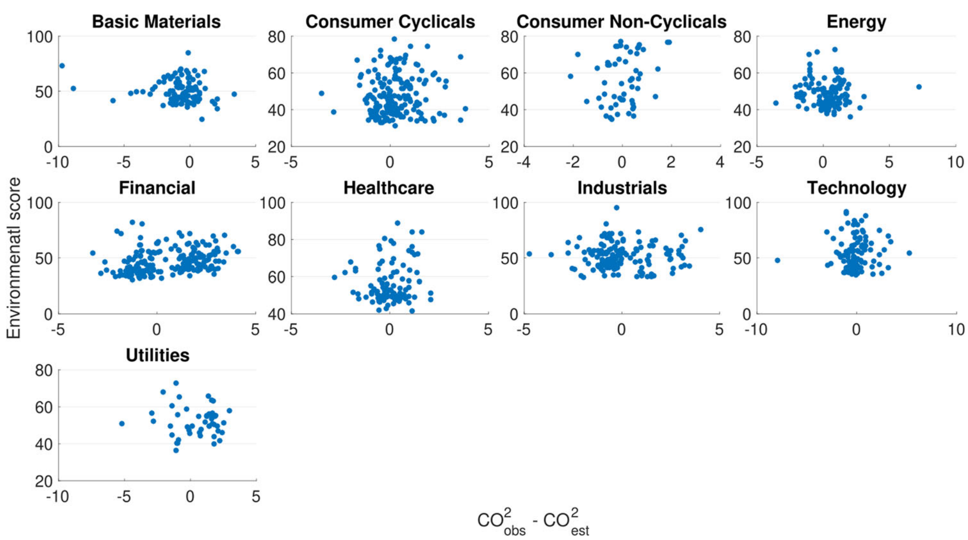

Fig. 3 Sustainalytics ESG ratings versus actual performance. In this plot, we compared Sustainalytics ESG ratings and environmental scores for the year 2018 to benchmark deviations of CO_2^{eq} ($y_{obs}-y_{est}$) for 1104 global corporations for 9 sectors. The Pearson correlation over the whole sample is 0.04, with a *p-value* of 0.16.

where the company is legally registered). Most of the countries lie within one standard deviation from the benchmark (see supplementary material, SM2, for more details). In fact, only 11 out of 76 countries are more than one standard deviation away from the benchmark (emissions). Implying that, in general, most countries are relatively close to the benchmark. Nevertheless, scaling corporate impacts over the country of incorporation implies that most activities are held in the same country, which is a strong assumption. Further research should investigate how the transnational dispersion of production plants shape the environmental footprint of global corporations.

It is also worthy to remark that size-dependent and sector-specific benchmarks like the one here proposed is agnostic about the absolute impact of the economic activity. That is to say, a corporation may score very well (well above the benchmark) and yet having a significant environmental impact.

The problem of interpreting deviations from the fit is recurrent in scaling analysis. The study of scaling laws in cities, another prominent form of social organization, shows that deviations can depend on the definition of urban area, the granularity of data or the functional taxonomy (i.e. the definition of activity)[39,53]. Seemingly, we may assume that deviations (and a better fit) can be

Table 5 Pearson correlation matrix between environmental size-depend impacts measured as deviation from the benchmark and the Environmental score according to the Sustainalytics ESG rating for a sample of $N = 256$ corporations; in italics impacts mutual correlations excluding ESG rating ($N = 1616$).

	ESG	CO_2e	*Energy*	*Water*	*Waste*
ESG	1	**-0.08**	**-0.07**	**0.03**	**0.01**
CO_2e		1	**0.89*****	**0.65*****	**0.49*****
Energy	*NA*	*0.83****	1	**0.68*****	**0.53*****
Water	*NA*	*0.66****	*0.63****	1	**0.64*****
Waste	*NA*	*0.55****	*0.52****	*0.60****	1

In the Supplementary Material (SM4) sectors-specific cross-correlations are provided.
***$p < 0.001$.
In bold correlations between ESG and environmental impact (sample = 256); in italics correlation between different impact categories (sample = 1616).

explained by a more in-depth analysis of featuring peculiarities of each sector/industry/country and on the *system boundaries*, that is, on the administrative contour of a corporation with respect to subsidiaries and parents; besides, obviously, using a more refined statistical approach to deal with heteroskedasticity and other possible sources of bias[39,54]. Lastly, in the Supplementary Material (SM2) we addressed the vexed question of the reliability of self-reporting data (sometimes referred to as *sustainable materiality*) and ESG rating providers[55,56]. We include an extensive error analysis performed comparing different databases and different years of the same database to show that despite some major, localized inconsistencies, our results are generally unaffected by discrepancies in the reporting source. However, for a more extensive investigation on the consistency and reliability of different ESG databases, we suggest the works by Brander et al.[52] and Busch et al.[57]. The success of scaling analysis for organisms built on a theoretical model that could explain the mechanism and predict the exponents. An efficient, fractal-like, transport network supports the transfer of nutrients across the tissues and it was demonstrated that this network scales with a power of 3/4 to the supported volume[37,38]. Similarly, the observed scaling laws in corporations were suggested by West to be caused by a supporting *social network* of stakeholders or employees[22,40]. We are still far from a fully-fledged model, but the notion that some industries show a better scaling for employees rather than revenue hints to relative less constraining role of the supply network. Here, the supporting network might be social rather than *economic* and the corporate metabolism might be determined by the behaviors of employees and good practices rather than by the binding *energy imperatives* of the featuring economic process.

Conclusions

Scaling has shown to be a promising approach for assessing the environmental impact of companies based on few simple metrics, but conspicuous and available data. The results from the scaling analysis showed that there is a significant relationship ($p < 0.001$) between the environmental impact variables and size. In other words, changes in a size variable result in changes in the environmental impact variables. A significant relationship and goodness-of-fit was frequently observed, globally and for every sector. In addition, the results proved to be robust, as the data from previous years show similar results. Typically the scaling of sectors/industries was shown to be sublinear, i.e. the environmental impact of companies increases at a slower pace than the size of the company. Nevertheless, there are also industries that scale superlinearly, which might be possibly due to economies of scale. The implication for the policy maker of these findings for setting environmental benchmarks and targets is threefold: (1) not only the sector, but also the size must be considered in benchmarking; (2) the relationship between size and impact is non-linear (3) when the sector scale sublinearly the bigger the company the easier it will be for the company to reduce its environmental impact. For the corporate stakeholders, this benchmark could represent an implementable and interpretable solution to the problem of a science-based benchmark.

It is worth noting that the hereby proposed methodology relies heavily on a vast and open-access database whereupon companies or regulators can estimate the current, sector specific benchmark. Ultimately that means that the more data is available and accessible, the higher the accuracy of the assessment. In the supplementary material (SM2), we report the needed information to asses the emissions of single companies as compared to the sector's benchmark. It is thus recommendable for international (and, in the future, national/regional) corporations to have access to shared information to set their ESG goals more accurately, on the one hand, and to enhance the transparency and accessibility of their data, on the other. Hence, the development of a global and local repository on information in relation to corporate metabolism should be the goal of the policymaker in order to progress toward the much coveted "corporate stewardship" on the path toward sustainability[12].

Methods and data

Data. This research focuses on publicly traded companies from all over the world. Companies, global operating companies in particular, typically have complex organisational structures including sophisticated supply chains. Thus, while goods might be sold in one country, the environmental impact might be caused in a different country.

For the analysis, Thomson Reuters EIKON (formerly Datastream) is used to collect the data. EIKON is a set of software products provided by Refenitiv[42] for analysing financial markets. It covers 99% of the global market cap, across more than 150 countries and 133 TRBC (Thomson Reuters Business Classification) industries[4]. Thomson Reuters acquires information from annual reports, corporate sustainability reports, nongovernmental organisations, and news sources for large, publicly traded companies at annual frequency. It is one of several providers that measure firms ESG performance. Differences with other providers, such as Systainalytics and Bloomberg, originate from which ESG choices are considered by each data provider and how they are weighted. The data was collected by using the Screener App in EIKON. With this tool you can identify companies that meet certain criteria. The app also allows, besides the financially related data, to screen ESG data. In total there are 658 ESG data items, of which 121 are on environmental issues. Figure 4 shows the spatial distribution of the reporting companies.

The data is from 2018 and the initial sample includes 7587 companies from 81 countries and 133 TRBC industries (Fig. 4). However, in order to analyse data, companies with missing or zero values were removed from the dataset and industries with less than 10 companies were excluded. An overview of the

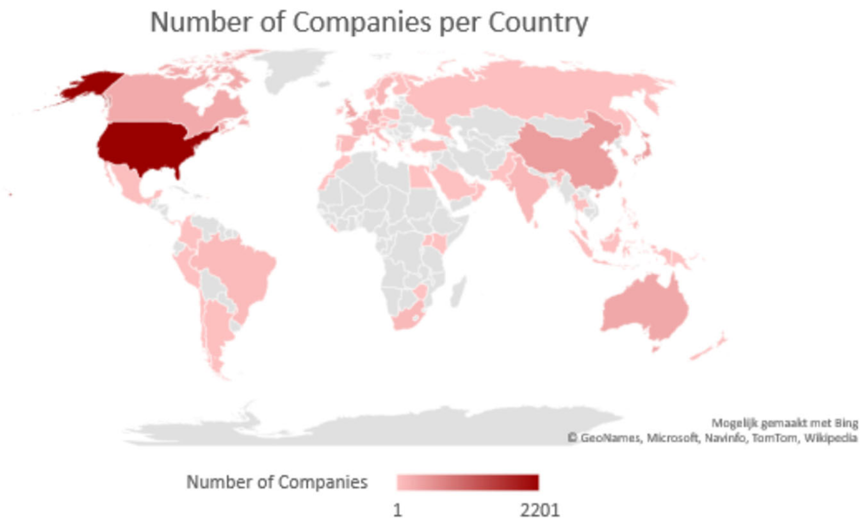

Fig. 4 World distribution of the studied corporations. The World map shows the number of companies per country of incorporation (the legal address of the company and where it pays the corporate taxes) for the estimated CO_2 equivalent emissions sample. Original map generated with *Microsoft Bing Maps Platform API*.

Table 6 Indicators of environmental impact.

	Estimated CO_2 Eq.	Energy Use	Water Withdrawal	Waste
Total of environmental impact indicator	14,573 Mt	104,734 PJ	451 billion m3	19,068 Mt
Number of companies	6529	2416	2090	1767
Number of Countries	76	66	63	61
Number of Industries	123	91	79	73
Total Number of Employees (x1,000,000)	124	75	68	54
Total Revenue (billion €)	41,497	25,679	23,769	19,739
Total Assets (billion €)	97,774	58,476	53,611	430,176
Total Market Capitalisation (billion €)	58,785	33,209	30,126	220,175

samples used for the analyses is shown in Table 6 per environmental impact variable analysed. As a comparison, the global GDP in 2018 was 75 trillion € and the annual global CO_2 equivalent emissions were 51.8 gigatonnes. Meaning that the dataset covers 28% of the global emissions. Likewise, with 104,734 PJ, the Energy Use sample covers 18% of the global direct primary energy consumption[58]. Compared to the global freshwater use, the Water Withdrawal sample encompasses 11%.

Environmental Impact indicators, definition. **Estimated CO_2equivalents emission** The following gases are relevant: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCS), perfluorinated compound (PFCS), sulfur hexafluoride (SF6), nitrogen trifluoride (NF3). Total CO_2 emission = direct (scope1) + indirect (scope 2)Scope 1: direct emissions from sources that are owned or controlled by the company Scope 2: indirect emissions from consumption of purchased electricity, heat or steam which occur at the facility where electricity, steam or heat is generated.

Energy use The total amount of energy that has been consumed within the boundaries of the company's operations. Total direct and indirect energy consumption: Total energy use is total direct energy consumption plus indirect energy consumption. Purchased energy and produced energy are included in total energy use. For utilities, transmission/ grid loss as part of its business activities is considered as the total energy consumed. For utilities, raw materials such as coal, gas or nuclear used in the production of energy are not considered under total energy use.

Total water withdrawal The total volume of water withdrawn from any water source that was either withdrawn directly by the reporting organization or through intermediaries such as water utilities. Different sources of water like well, town/utility/ municipal water, river water, surface water, etc. are considered.

Total amount of waste produced Total waste is non-hazardous waste plus hazardous waste. Only solid waste is taken into consideration. For sectors like mining, oil & gas, waste generation like tailings, waste rock, coal and fly ash, etc. are also considered.

Methods

Allometry was first introduced in 1936 to describe the discrepancy between the growth rate of body parts in organisms[35]. Almost all physiological characteristics scale with body mass (M) according to a power law: $Y = Y_0 M^{\beta}$, where Y can denote the biological variable (e.g. energy consumption) and the exponent reflects the general dynamic rule at play[37]. The research into using scaling as a tool for revealing underlying dynamics and structure has led to a unified quantitative picture of the organisation, structure, and dynamics of organisms. Allometric scaling has been explained by means of network theory whereby organisms were modelled as transportation networks (of metabolites and nutrients) maximizing their efficiency[38]. Similar to organisms, social organisations have some kind of metabolism as well. In order to sustain themselves there is a set of flows of materials and energy, suggesting that they might have similar scaling dynamics as organisms.

The scaling laws has also been successfully applied to cities by Bettencourt, one of the leading scholar on scaling analysis[41,54]. He studied if there is quantitative and predictive evidence that support the implications that social organisations are extensions of biology, and proved that this is indeed the case. Companies can also be approached as social system, just like cities; West showed how revenues of companies follow scaling laws, suggesting an underlying (social or economic) network could be the reason[40,59]. The total revenue (or sales) can be thought of as the metabolic trait of the company while the expenses can be thought of as the maintenance costs.

Regardless of their industry, all companies cannot produce goods or provide services without creating complex organisational structures. It is essential that these structures are adaptive if it is going to survive in a competitive market. Producing goods or providing services requires the integration of energy, resources and capital - the metabolism of a company. With $N(t)$ as a measure of the company's size at time t, the power law scaling takes the form

$$Y(t) = Y_0 N(t)^{\beta} \tag{1}$$

Where Y denotes the environmental impact variable (CO_2 equivalent emissions, energy use, water withdrawal or waste). Y_0 is a normalisation constant and the exponent which reflects general dynamic rules across the companies. When plotted on a log-log scale, these scaling relationships are linear:

$$\ln Y(t) = \beta \ln N(t) + \ln Y_0 \tag{2}$$

Consequently these relationships can be described using the simple linear equation:

$$y = \beta x + \gamma \tag{3}$$

In its linear form, the constants in the scaling equations can be determined by performing a regression analysis method, e.g. a least-squares regression which is used in this research. After combining the samples from the different continents, the regression analysis was performed using R Studio (RStudio Team, 2020). For every dependent variable (= the environmental indicator) a linear regression model was fitted using the measures for firm size, i.e. assets, employees, market capitalisation and total revenue, as independent variables. The scaling was considered to be superlinear when β>1.02 and sublinear whenβ <0.98. In the other cases the scaling was considered to be approximately linear between 0.98 and 1.02. A sublinear scaling is typical of a phenomenon featured by a stabilizing growth path, which means growth that tends to a steady state. On the contrary, superlinear features unbounded growth that tends to instability ([37,40]).

Data availability

The data that support the findings of this study are available from Thomson Reuters EIKON but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are, however, available from the authors upon request and with permission of Thomson Reuters EIKON. All data generated during this study are included in this published article as Supplementary Data, available at: https://doi.org/10.6084/m9.figshare.24648141.v1.

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Author contributions

R.B. and R.M. performed the analysis and wrote the manuscript; F.R. and Y.S. supervised the analysis; F.R. designed the analysis and wrote the manuscript; K.H. contributed to the writing the manuscript; all authors contributed in reviewing the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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