HARVARD BUSINESS SCHOOL
Impact-Weighted Accounts

Corporate Environmental Impact: Measurement, Data and Information

Executive Summary

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Overview

Interest in measuring and analyzing environmental impact has increased significantly as organizations have seen their customer relations, industry, and organizational competitiveness affected by their environmental impacts. However, there are still challenges that prevent full incorporation of environmental data in business decisions.

For corporate managers, the main challenge is understanding how different environmental impacts can be measured, compared, and integrated into the decision-making process to allow for more seamless management of risk, return, and impact, as well as more efficient, sustainable allocation of resources.

For investors, the challenge lies in measuring environmental impacts across many companies in a transparent, comparable and reliable way so that the results can be benchmarked and assessed across the market and within industrial classifications.

To address these challenges, Impact-Weighted Accounts at Harvard Business School has developed a methodology using several established academic resources to calculate monetized measures of environmental impacts from operations of organizations using publically available data.

We measure impacts on “safeguard subjects” (Steen and Palander 2016) which are resources that are critical for human health and well-being. Each safeguard subject is made up of multiple impact categories and indicators for measuring the current state of each safeguard subject (Life Cycle Initiative 2016; Steen and Palander 2016). The benefit of using these for grouping impacts is that they provide clear detail on which stakeholders are experiencing the impact and what that impact is. Further, there are clear indicators for evaluating the status of each. For this paper, we work with eight safeguard subjects: Human Health (Working Capacity), Crop Production Capacity, Meat Production Capacity, Fish Production Capacity, Wood Production Capacity, Drinking Water & Irrigation Water (Water Production Capacity), Abiotic Resources, and Biodiversity.

Using the methodology and data-sources described below, we were able to calculate total environmental impact for over 2,500 organizations with data going back to 2010, broken out by the safeguard subjects. In years 2018 and 2017, the number of companies reporting the required level of information is closer to 1,800. In order to compare organizations of different sizes, which would reasonably be expected to have different absolute environmental impacts, we express our calculations for total organizational environmental impact as a percentage of sales and operating income (a process referred to as scaling) as proxies for organization size (henceforth defined as *environmental intensity*). This provides an estimate for environmental damage per unit of sales or operating income. Our key insights are the following. First, we document that the average environmental intensity scaled by sales for our sample, assuming a zero discount rate, is 11.6%, but the median is only 1.9%. For several industries, such as utilities, construction materials, marine and airlines, the level of environmental impact is so large that it is equal to more than 25% of revenues. Similarly, we discover that the average environmental intensity scaled by operating income, assuming a zero discount rate, is 91.7% and the median is 19.4%. A handful of industries have such a high level of environmental impact that it is equivalent to over 150% of their operating income. Pricing of those environmental externalities would lead to significant value erosion for these firms.

Next, we sought to explain the drivers of variation in environmental intensity across organizations. Our evidence suggested that two primary drivers, industry association and organizational specific factors, explained the majority of the variation for both impact scaled by sales and operating income. Broadly, specific industries are poorly positioned if their environmental intensity are priced and are, therefore, exposed to significant levels of regulatory risk. We found that close to 60% of the variation in environmental intensity is driven by industry membership. However, firms within an industry have significantly different profiles, with approximately 30% of variation related to firm specific factors, highlighting the importance of divergent strategies.

We also examined the relation between environmental intensity and established environmental ratings from data providers. We complemented our data with environmental ratings from three of the main data providers, MSCI, RobecoSAM, and Sustainalytics. Our calculated environmental intensity exhibits negative yet moderate correlation to the ratings, consistent with firms that have greater adverse environmental impact receiving lower ratings, but the scale of the ratings were inconsistent in magnitude with our calculated environmental impact. In fairness to the ratings providers, they are not necessarily measuring impact. Rather, they intend to integrate multiple signals of how well a company is managing environment-related risks and opportunities. Thus, one would expect somewhat low correlations and should not necessarily be alarmed by the absence of high correlations. We viewed our results to be informative as to the magnitude of those correlations and whether the ratings can also be interpreted as evidence not only of environmental management, but also of environmental impact.

Our overall conclusion is that although ratings may well provide important insights to the management of environmental risks and opportunities, they are unlikely to provide insights into the impact that an organization has on the environment and, therefore, users should use them with caution in selecting and managing investment products marketed as providing positive impact.

Finally, we asked the question of whether market prices reflect environmental intensity. We estimated the relation between equity valuation multiples and environmental impact and generated three insights: First, there is a moderate yet significant relationship between environmental impact and valuation multiples. The estimates suggest that a firm with double the environmental intensity has 2.3% lower Tobin's Q and 4.7% lower price to book value of equity. Second, the relation persists after accounting for environmental ratings, which we find not to be related to valuation multiples. Third, we identify the industries, such as electronic equipment, textiles and apparel, construction materials, and chemicals, in which the relation between valuation multiples and environmental impact is the strongest.

A final interesting finding emerges when examining whether environmental intensity is reflected in stock valuations according to industry. For most industries, we find that environmental intensity is associated with lower market valuation, lower returns, and higher risk. However, while environmental intensity is priced in several industries with large environmental impact such as construction materials or chemicals, it is notably not reflected in some other industries with similarly large and visible environmental impacts, such as those in the Utilities sector. A potential explanation is that the industry-level business model is overwhelming any firm-level differences within those industries, leading to no differential pricing of environmental intensity across firms.

Overall, our first main conclusion is that measurement of environmental impact from operations is feasible for many companies in the economy on the basis of publicly disclosed data. Our paper provides a methodology how one could go about constructing those impact measurements. Our second main conclusion is that these measurements contain information that is different than that contained in environmental ratings widely used by investors and other stakeholders, and that this information is value relevant.

Technical Appendix: Data Sources & Methodology

We note that the following represents an abridged version of the full methodology developed in the working paper of the same title. Some details have been removed for conciseness.

Our sample is derived from the universe of organizations within the Bloomberg ESG Index, the set of organizations within the Bloomberg database that has reported some environmental data. We collected data only for organizations with a market capitalization of greater than 100 million USD, as ESG reporting is most common in larger organizations. We expanded the quantity and verified the quality of the environmental data in our sample by adding data from Thomson Reuters's Asset4 ESG database.

We noted numerous instances of errors in our collected data, such as incorrectly scaled values or reported values that did not match organizations' sustainability reports. Therefore, we conducted an analysis of values reported by Thomson Reuters and Bloomberg. We created two separate methodologies to confirm the accuracy of the data, one for observations where data is available from both providers and one for observations that have data from only one provider.

Of the 19,914 observations in our sample, 14,285 were missing NOx data, 17,018 were missing VOC data, 14,571 were missing SOx data, 7,738 were missing water withdrawal data, and 14,380 were missing water discharge data. We imputed data for these missing values using industry-country emissions data from Exiobase, a global database of industry input and output requirements. To adjust the industry-level values from Exiobase to organization-level values, each Exiobase value was scaled by the ratio of organization revenue in a given year to total industry output in a given year, up to 2016, the latest year for Exiobase data. This methodology, while imperfect, was an attempt to estimate the missing organization-level emissions by attributing a pro-rata portion of industry totals to an organization, thereby providing comparability among organizations and industries.

To ensure robustness and reliability of our results, we restricted our sample to observations that have less than 20% imputed contribution to environmental impact. We found the average imputed contribution to be less than 10%. This restriction produced a final sample of 13,228 organization-year observations.

In the case of 4,727 firm-year observations, water withdrawal data was available but water discharge data was missing. The water withdrawal and consumption data within Exiobase relates specifically to companies operating in industries relating to Agriculture, Livestock, Manufacturing, and Electricity, but this is far from exhaustive. To ensure that water use was being consistently and comparably measured, we developed and applied a method of imputing the missing data for water discharge when water withdrawal data was available.

The EPS water monetization factors are on a global level and do not account for local scarcity. Therefore, we supplemented the EPS monetization coefficients with two additional data sources: the AWARE Model, which provides conversion factors for the absolute amount of available fresh water remaining in each country in terms of global-equivalent cubic meters (Lee et al. 2018) and water costs from Waterfund, which posits that the best representation of the global average price of water is the sum of all economic costs of supplying water. Therefore, the environmental impact of water is calculated as the sum of two components: water production and delivery cost and wastewater treatment cost. Water production and delivery cost scales according to water consumption and by water scarcity. Wastewater treatment cost is not affected by water scarcity and only scales according to water consumption.

$$(1)\ Environmental\ Impact\ of\ Water_{i,t} = \left(Net\ Water\ Consumed_{i,t} * AWARE\ Factor_{j,t} * Water\ Production\ \&\ Delivery\ Unit\ Cost_j\right) + \left(Net\ Water\ Consumed_{i,t} * Wastewater\ Treatment\ Unit\ Cost_j\right)$$

To transform the direct emissions of an organization's operations into their monetized impacts, we multiplied the monetization coefficients in the Environmental Priority Strategies (EPS) database by the reported (or imputed) emissions of an organization. Equation 1 describes the calculation of environmental impact of emissions for organization *i* in year *t*.

$$(2)\ Environmental\ Impact\ of\ Emissions_{i,t} = \sum(Emissions\ Volume_{e,i,t} * EPS\ Monetary\ Coefficient_e)$$

Specifically, organization's reported (or imputed) values for GHG[1], SOx, NOx, and VOC emissions are separately multiplied by the respective EPS monetary coefficients. The resulting four products are summed to produce the environmental impact of emissions.

Finally, we calculated the environmental impact of an organization *i* in year *t* as the sum of the environmental impact of emissions and the environmental impact of water.

$$(3)\ Environmental\ Impact_{i,t} = Environmental\ Impact\ of\ Emissions_{i.t} + Environmental\ Impact\ of\ Water_{i,t}$$

The default discount rate is 0% given the consideration for intergenerational equity but we conducted a sensitivity analysis of this assumption by also using a 3% discount rate.

[1] GHG emissions are reduced by carbon offsets.

Selected Tables

Table 1: Summary Statistics for Environmental Intensity

Environmental Intensity	Mean	Median	Q3	Q1
Env Imp / Sales 0%	11.6%	1.9%	8.8%	0.6%
Env Imp / Sales 3%	6.6%	0.8%	3.8%	0.2%
Env Imp / Op Inc 0%	91.7%	19.4%	86.8%	4.7%
Env Imp / Op Inc 3%	56.2%	8.1%	37.4%	2.0%

Environmental intensity is the product of the function that interacts firm level emissions and water data, either reported from Bloomberg or Thompson Reuters or imputed using Exiobase data, with EPS and AWARE factors, scaled by revenue or operating income. Discount rates are calculated by discounting EPS factors.

Table 2: Correlation Matrix of Environmental Intensity and Ratings

Variable	Env Imp / Sales 0%	Env Imp / Sales 3%	Env Imp / Op Inc 0%	Env Imp / Op Inc 3%	E Rating M	E Rating RS
Env Imp / Sales 0%	1.000					
Env Imp / Sales 3%	0.980	1.000				
Env Imp / Op Inc 0%	0.872	0.822	1.000			
Env Imp / Op Inc 3%	0.894	0.870	0.984	1.000		
E Rating M	-0.248	-0.254	-0.233	-0.247	1.000	
E Rating RS	-0.148	-0.145	-0.125	-0.126	0.306	1.000
E Rating S	-0.260	-0.249	-0.230	-0.226	0.371	0.463

Table 2 is the univariate correlation matrix for the environmental intensity scaled by sales and operating income (0% discount rate), environmental intensity scaled by sales and operating income (3% discount rate), MSCI environment rating, RobecoSAM environment rating, and Sustainalytics environment rating. Across all tables hereafter, MSCI, RobecoSAM and Sustainalytics will be simplified using the first letter of their names – M, RS, and S, respectively.

Table 3: Market Pricing of Environmental Intensity

Dependent Variable	Tobin's Q				Price to Book Value of Equity			
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	0.050	0.371	-0.030	0.498	0.262	0.011	0.246	0.005
Env Imp / Sales 0%	-0.025	0.010			-0.050	0.000		
Env Imp / Op Inc 0%			-0.014	0.001			-0.078	0.000
ROA	3.812	0.000	4.765	0.000				
ROE					1.776	0.000	2.075	0.000
Leverage					0.712	0.000	0.614	0.000
N	13,050		12,317		12,880		12,158	

Table 3 describes OLS models that regress independent variables (environmental intensity) on dependent variables, Tobin's Q and Price to Book Value of Equity. Tobin's Q is a measure of market value over the replacement value of assets. ROA is return on assets. ROE is return on equity. All models include year, country, and industry effects. Both dependent variables and the independent variables are log-transformed. N is the number of observations. Observations are firm-year pairs.

Table 4: Financial Materiality of Environmental Intensity

Dependent Variable	Sharpe ratio		Stock return		Volatility		Beta	
Panel A: E. Impact Scaled by Sales								
Variable	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	-0.216	0.055	-7.644	0.027	20.294	0.000	0.859	0.000
Env Imp / Sales 0%	-0.045	0.001	-0.850	0.034	0.661	0.000	0.039	0.014
N	12,375		12,880		12,379		11,311	
Panel B: E. Impact Scaled by Operating Income								
Variable	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	-0.319	0.000	-11.353	0.000	19.630	0.000	0.838	0.000
Env Imp / Op Inc 0%	-0.070	0.000	-1.520	0.000	0.791	0.000	0.048	0.000
N	11,681		12,150		11,684		10,656	
Panel C: Environmental Impact Scaled by Sales with E. Rating Added								
Variable	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	-0.173	0.204	-4.708	0.270	24.277	0.000	0.852	0.000
Env Imp / Sales 0%	-0.039	0.009	-0.724	0.099	0.375	0.043	0.035	0.059
Env Rating	0.002	0.742	0.016	0.931	-0.515	0.000	0.000	0.944
N	9,375		9,746		9,375		8,528	
Panel D: E. Impact Scaled by Operating Income with E. Rating Added								
Variable	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	-0.223	0.038	-6.569	0.010	23.933	0.000	0.829	0.000
Env Imp / Op Inc 0%	-0.061	0.000	-1.266	0.000	0.695	0.000	0.050	0.000
Env Rating	-0.004	0.556	-0.196	0.292	-0.457	0.000	0.001	0.872
N	8,950		9,299		8,950		8,144	

Table 4 describes OLS models that regress independent variable, log-transformed environmental intensity, on dependent variables, Sharpe ratio, stock return, stock price volatility, and market beta. Sharpe ratio is defined as stock return over the calendar year divided by stock price volatility over the calendar year. Market beta is calculated as the relationship between firm stock returns and country market returns using monthly data over the past 3 years. All models also include year, industry, and country fixed effects. Specifications for the environmental intensity calculated using a 0% discount rate are included. Panels C and D also include control for the average rating across MSCI, RobecoSAM and Sustainalytics (denoted as Env Rating).

References

Bernick, L., Bullock, S., Burks, B., Chlebeck, E., Hobson, D., and Tenuta, E., 2017. Smart Water Management for Business Growth: Integrating Water Risk into Business Decision Making.

Kotsantonis, S. and Serafeim, G., 2019. Four Things No One Will Tell You About ESG Data. *Journal of Applied Corporate Finance*, *31*(2), pp.50-58.

Lee, J.S., Lee, M.H., Chun, Y.Y. and Lee, K.M., 2018. Uncertainty Analysis of the Water Scarcity Footprint Based on the AWARE Model Considering Temporal Variations. *Water*, *10*(3), p.341.

Life Cycle Initiative, 2016. Global guidance for life cycle impact assessment indicators. *United Nations Environment Programme*.

Schmidt, J.H., Merciai, S., Delahaye, R., Vuik, J., Heijungs, R., de Koning, A. and Sahoo, A., 2014. Recommendation of terminology, classification, framework of waste accounts and MFA, and data collection guideline. *CREEA*.

Sotos, M., 2015. GHG Protocol Scope 2 Guidance. An amendment to the GHG protocol corporate Standard. *World Resources Institute*.

Steen, B. and Palander, S., 2016. A selection of safeguard subjects and state indicators for sustainability assessments. *The International Journal of Life Cycle Assessment*, *21*(6), pp.861-874.

Steen, B., 1999. A systematic approach to environmental priority strategies in product development (EPS): version 2000-general system characteristics (p. 67). Gothenburg, Sweden: Centre for Environmental Assessment of Products and Material Systems.

Turner, S.W., Hejazi, M., Yonkofski, C., Kim, S.H. and Kyle, P., 2019. Influence of Groundwater Extraction Costs and Resource Depletion Limits on Simulated Global Nonrenewable Water Withdrawals Over the Twenty-First Century. *Earth's Future*, *7*(2), pp.123-135.