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Corporate Environmental Impact: Measurement, Data, and Information

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Harvard Business School

Impact-Weighted Accounts Project Research Report

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Abstract

As an organization's environmental impact has become a central societal consideration, thereby affecting industry and organizational competitiveness, interest in measuring and analyzing environmental impact has increased. We develop a methodology to derive comparable and scalable monetized environmental impact estimates by applying characterization pathways and monetization factors to organization level environmental outputs, including carbon emissions, water use, and other emission types. The median environmental impact as a percentage of an organization's sales (operating income), referred to as *environmental intensity*, is 2% (22%) suggesting a significant level of 'hidden liabilities' and potential for value erosion if environmental impacts are priced. About 60% of the variation in environmental intensity is driven by industry membership, while the rest can be attributed to firm specific factors or to country and more granular industry classifications. Environmental intensity exhibits moderate correlation with various environmental ratings across firms and industries and no correlation across firms within industries. Firms with higher environmental intensity exhibit lower corporate market valuation, consistent with investors viewing environmental impacts as financially material and pricing them in some but not all industries. We document the dynamic materiality of environmental intensity, where the relation between environmental intensity and corporation valuation has become stronger in recent years.

Keywords: *environment, impact, measurement, environmental ratings, corporate valuation, financial materiality*

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1. Introduction

As an organization's environmental impact has become a central societal consideration, thereby affecting industry and organizational competitiveness, interest in measuring and analyzing environmental impact has increased.[1] For example, in recent years an increasing number of regulations seek to limit harmful pollutants, such as tailpipe emissions, that have forced automobile manufacturers to adapt through product development in order to remain competitive. Large corporate buyers, such as Walmart, have raised the bar for their suppliers, seeking to reduce carbon emissions in their supply chain, thereby forcing them to innovate. Banks are now offering loans to corporations at preferred rates if they can demonstrate improvements in their environmental impact.

Against this backdrop, an increasing number of companies and investors are measuring and managing their environmental impact, and numerous organizations have emerged to provide guidance to various producers and consumers of information, including the Sustainability Accounting Standards Board (SASB), the Global Reporting Initiative (GRI), The Task Force for Climate-related Financial Disclosures (TCFD), and the Corporate Reporting Dialogue. These organizations have developed environmental reporting standards for calculation and disclosure of environmental metrics.[2] Additionally, there has been significant documentation of the process for scoping, gathering data, converting the company level results to impacts, and selecting prices by, among others, the Capitals Coalition, ISO 14007 and 14008 Protocols, and the Impact Institute.[3]

Despite these numerous efforts, there are still challenges that prevent full incorporation of environmental data in business decisions. For corporate managers, the main challenge is to understand how different environmental impacts can be measured, compared, and integrated into the decision-making process to allow for better, more seamless management of risk, return, and impact, as well as more efficient, sustainable allocation of resources. From an investor perspective, 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.

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[1] Impact is defined as the change in an outcome. An outcome is the result of an action or event which is an aspect of social, environmental or economic well-being.

[2] A 2019 literature review of existing valuation methodologies provides a robust, though not exhaustive list of 31 sustainability and environmental thought leadership efforts, which provide critical guidance on process, scope, sensitivity testing, and pathways by which environmental impacts may be estimated (Oxford Analytica Foundation, 2019).

[3] More information about the Natural Capital Protocol is available at https://naturalcapitalcoalition.org/category/protocol-case-studies/. Information about the ISO Protocols is available at https://www.iso.org/standard/43243.html. Impact Institute's methodology is available at https://www.impactinstitute.com/ipl-assessment-methodology/.

In this paper, we develop a methodology using several established academic resources that allow us to measure an organization's environmental impact from operations. To achieve this, we use characterization pathways[4] and monetization factors[5] from the Environmental Priority Strategies (EPS) Database, Available WAter REmaining (AWARE) Model, and Waterfund, along with organization level data of environmental outputs,[6] such as carbon emissions, nitrous oxide, sulfur oxide, VOC, PM 2.5, and water withdrawal and discharge, sourced from Bloomberg and Thomson Reuters. Importantly, given disagreement in the scientific literature, we assess the sensitivity of our measurements to alternative discount rates. We also go to great lengths to reconcile and clean environmental output raw data as we find significant data inconsistencies and errors.

In order to compare organizations of different sizes, which would reasonably be expected to have different absolute environmental impacts, we scale our calculations for total organizational environmental impact by sales and operating income as proxies for organization size (henceforth defined as *environmental intensity*). This provides an estimate for environmental damage per unit of sales or operating income. [7] 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 11.8%, but the median is only 2.0%. For several industries, such as utilities, construction materials, 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 117.4% and the median is 21.5%. 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 seek to explain what drives variation in environmental intensity across organizations. For the intensity scaled by sales, we find that industry membership explains over 60% of the variation while country effects explain only 5-10%. Including subindustry effects provides an additional explanatory power of about 5% over and above industry effects. The environmental intensity scaled by operating income demonstrates a similar trend. About 30% of the variation can be attributed to firm specific effects suggesting that an organization's unique strategy, asset composition, operations and competitive positioning are

[4] Characterization Pathways are scientifically-based methodologies to transform outputs into impacts.
[5] Provide conversions from impacts denominated in the standard terms of impact, such as quality adjusted life years, into monetary values (usually $/kg emission or input).
[6] Outputs are the direct results of an organization's operations.
[7] A measure of the efficiency of resource use or emissions (e.g. water, energy, materials) needed for the production, processing and disposal of a unit of good or service, or for the completion of a process or activity; it is expressed in this analysis as unit under analysis/revenue or operating income.

significant factors. For example, the environmental intensity scaled by revenue (operating income) for an airline at the 75th percentile of the distribution is 32% (834%) while an airline at the 25th percentile of the distribution has an environmental intensity of 21% (232%). Therefore, we observe significant differences in their environmental intensity across firms in each industry. Collectively, our evidence suggests that specific industries are poorly positioned if their environmental intensity are priced and therefore exposed to significant levels of regulatory risk. However, within each industry, firms have significantly different profiles, highlighting the importance of divergent strategies.

We then examine the relation between environmental intensity and established environmental ratings from data providers. We complement our data with environmental ratings from three of the main data providers, MSCI, RobecoSAM, and Sustainalytics. These data providers are not necessarily measuring impact. Rather, they intend to integrate multiple signals of how well a company is managing environmental related risks and opportunities. Thus, one would expect somewhat low correlations and should not necessarily be alarmed by the absence of high correlations. We view 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. The answer is no, as reflected by the relatively low, albeit significant, correlations that range from 0.13 to 0.26. After controlling for industry and country membership, the correlation estimates are reduced by around 65%, suggesting that within an industry, environmental ratings are almost completely uncorrelated with estimates of environmental intensity.

Finally, we ask the question of whether market prices reflect environmental intensity. We estimate the relation between equity valuation multiples, stock returns, volatility, and environmental impact and generate several insights: First, there is a moderate yet significant relationship between environmental intensity and valuation multiples. Second, environmental intensity has become more material over time. Third, we identify the industries, such as building products, and textiles and apparel, in which the relation between valuation multiples and environmental impact is the strongest and industries such as oil and gas and utilities that the relation has become stronger over time. We infer that environmental impact is a financially material signal across many industries and is becoming increasingly material in recent years.

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

The remainder of the paper proceeds as follows. Section 2 describes our data sources. Section 3 describes our methodology for calculating environmental impact. Section 4 presents the results of our analyses. Section 5 discusses additional analyses and section 6, caveats. Section 7 concludes the paper.

2. Data Sources

2.1 Bloomberg and Thomson Reuters (ASSET4) Databases

We acquire organization-level emissions and water use data from both Bloomberg and Thomson Reuters for years 2010 to 2019. Specifically, we collect data on four emissions variables and two water use variables. Total greenhouse gas emissions (GHG total)[8] are the total scope 1[9] and scope 2 emissions[10] of an organization in a reporting year for the organization's country of domicile (Sotos. 2015).[11] Nitrogen oxide (NOx), sulfur dioxide (SOx), and volatile organic compounds (VOC) are three additional emissions types collected at the organization level. The two water use variables include water withdrawal and water discharge.[12] We also collect data on carbon offsets, voluntary purchases of carbon credits and certificates to compensate for emissions.

2.2 Exiobase

While reporting of ESG data has improved significantly over the last decade, particularly data related to environmental variables, data availability is still a concern and a challenge for empirical analysis. When data points are not available from Bloomberg or Thomson Reuters, we impute missing values using data from Exiobase. Exiobase provides a global environmentally extended multi-regional input-output table as a baseline for supply chain analysis, and estimates emissions and resource extractions by industry (Schmidt et al. 2014).[13] Specifically, we utilize the Factors of Production tables from Exiobase. These tables are input-output tables that map inputs and outputs for a given industry in a country. We also use the total

[8] A Bloomberg data point which includes Scope 1 and Scope 2 emissions (see below) of the seven gases covered by the UNFCCC: carbon dioxide (CO_2); methane (CH_4); nitrous oxide (N_2O); hydrofluorocarbons (HFCs); perfluorocarbons (PFCs); sulphur hexafluoride (SF_6), and nitrogen triflouride (NF_3)

[9] Defined by the GHG Protocol as direct emissions that occur from sources owned or controlled by the company

[10] Defined by the GHG Protocol indirect emissions from the generation of purchased energy including the emissions resulting from the production of grid electricity

[11] Greenhouse gases are defined by the GHG Protocol as the seven gases covered by the UNFCCC: carbon dioxide (CO_2); methane (CH_4); nitrous oxide (N_2O); hydrofluorocarbons (HFCs); perfluorocarbons (PFCs); sulphur hexafluoride (SF_6), and nitrogen triflouride (NF_3)

[12] Water withdrawal is the total amount of water diverted from any source for use by the organization. Water discharge refers to the total amount of liquid waste and process water discharged by the organization. We define net water consumed as water withdrawal minus water discharged. Exhibit 3 provides additional descriptive information for these variables.

[13] Exiobase provides data from 44 countries and 5 rest of the world regions, as well as 164 industries, 417 emission categories, and over 1000 emission, material, and resources categories. Exiobase tables were accessed through the Pymrio Python Package on Github. Industry Factors of Production were sourced from the F Table of Exiobase and Industry Output was Sourced from the X Table, Inter-industry coefficients (direct requirements matrix) sourced from the A Table.

industry output table, which provides a total monetary production by industry and by country. Lastly, we use the inter-industry coefficients table, which shows inter-industry purchases to map upstream impacts, such as Scope 2 emissions from power purchases. These imputations could contain large measurement errors as they rely on several assumptions (Kotsantonis and Serafeim 2019).

2.3 The EPS Database

The Environmental Priority Strategies (EPS) database provides publicly available, scientifically-based methodology to transform the direct results of an organization's operations, referred to as outputs, such as emissions, into their impacts, referred to as characterization pathways. The database also provides a comprehensive set of conversions from impacts denominated in the standard terms of impact, such as quality adjusted life years, into specific monetary values (usually $/kg emission or input) referred to as monetization factors. The impacts covered are defined as "safeguard subjects" (Steen and Palander 2016). Each safeguard subject[14] is made up of multiple impact categories and indicators, called state indicators,[15] for measuring the current state of each safeguard subject (Life Cycle Initiative 2016; Steen and Palander 2016).[16] Steen and Palander (2016) provide extensive detail on the selection of the safeguard subjects and state indicators. 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.

The EPS database also provides uncertainty estimates,[17] a factor by which the median value may be multiplied or divided to find the values representing one standard deviation higher or lower values in line with guidance from the ISO. The default monetization factor methodology is based on willingness-to-pay[18] (WTP) for one indicator unit, and global variations are captured in the uncertainty factor. Absent an observable market for the good, the methodology uses a number of approaches including Contingent

[14] Resources that are critical for human health and well-being. Each safeguard subject is made up of multiple impact categories.

[15] Indicators which provide a measure of the current state of each safeguard subject.

[16] These broadly align with the end-point indicators in the UN Life Cycle Impact Analysis Indicators (UN LCIA) and the International Organization for Standardization (ISO), a recognized international multi-stakeholder standard setting organization, 14000 series, though there are some differences.

[17] A factor by which the median value may be multiplied or divided to find the values representing one standard deviation higher or lower values.

[18] A monetary measure for the willingness to restore changes in the safeguard subjects. The WTP in the EPS is measured in today's OECD population and applied to all those who are affected by a change.

Valuation Method[19] (CVM), and hedonic pricing[20] (Steen 1999). The default discount rate for EPS is 0% given the consideration for intergenerational equity. We conduct a sensitivity analysis of this assumption in the results section of this paper by also using a 3% discount rate.

2.4 The AWARE Model

The Availability WAter REmaining (AWARE) model provides supplemental water monetization factors, allowing us to account for the effect of local water scarcity. While many environmental impacts may have localized impacts, such as the health implications of PM 2.5 pollution, these impacts can be consistently estimated using the same characterization pathways globally, given that the pathways of impact are dictated by the laws of chemical interactions and their interactions with biological systems such as the human body.[21] However, water scarcity varies significantly among geographical locations based on resource availability, as well as agricultural, industrial, and human needs. Moreover, unlike other commodities with well-defined global markets, inter-regional transfers of water are logistically challenging and expensive.

Water consumption in one area has highly variable implications for human well-being. In order to better incorporate the nuances of local water scarcity and availability based on various human and ecosystem demands while also enabling comparisons at a corporate level, a more robust model is needed. EPS water monetization factors are on a global level and do not account for local scarcity. Therefore, we incorporate data from 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). In other words, the AWARE factors represent the available water remaining per unit of surface in a given watershed relative to the world average after human and aquatic ecosystem demands have been met.[22] The underlying assumptions of this model are described in Exhibit 1. By integrating controls for local water scarcity, the AWARE model provides a more accurate comparison of water use across countries with different levels of water scarcity. The scaling provided by the model also allows for the use of a global price once the local water use is converted to a global equivalent value by multiplying it with the AWARE factor.

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[19] In contingent valuation, the good to be valued is presented in its entirety (as a bundle of its attributes). The respondents are asked for their WTP to avoid a deterioration in quality or quantity of the good or to secure an improvement. Alternatively, they are asked for their WTA to tolerate a deterioration or to forgo an improvement. For more information see ISO 14008 Protocol.

[20] The starting point for the hedonic pricing method is the observation that market goods have different attributes, each of which influences the price of the good to a greater or lesser extent. The hedonic pricing method uses statistical methods to isolate the implicit "price" of each of these characteristics. For more information see ISO 14008 Protocol.

[21] This is not to ignore that some of the impacts, such as the health impact from air-pollution, are very local, however, given the ubiquity of laws of chemistry and the known ranges of biological systems, the same pathway can be used to estimate even local impacts around the world.

[22] AWARE Factors- conversion factors for the absolute amount of available fresh water remaining in each country in terms of global-equivalent cubic meters, defined as the world average after human and aquatic ecosystem demands have been met.

2.5 Waterfund's Global Water Price

A key challenge in identifying the price of water is that there is often little correlation between the actual price paid and its availability (Bernick et al. 2017*)*. A global water price is sourced from Waterfund, which has developed a comprehensive measure of water cost for 19 locations globally. The Waterfund dataset provides two broad sub-categories, water production and delivery and wastewater treatment, each of which has components of operating expenses, depreciation, and non-operating expenses. This helps to provide a key measure of the hidden "economic costs of water," which are not properly incorporated into the price that companies pay for water. Waterfund's data does not provide an estimate for the raw cost of extracting water, however, as water itself is viewed as a human right and research on this has been surprisingly sparse.[23] Even absent the raw cost of water, the Waterfund price represents a significantly more economically representative cost of water compared to the current prices in many countries.

2.6 Accounting and Stock Market Data

Financial data was collected from Worldscope and converted to USD using year end exchange rates. In addition to using raw sales data as provided by Worldscope, we calculate return on assets (ROA), return on equity (ROE), Tobin's Q, price to book value of equity, and leverage. All stock market data, such as total investment return, volatility, and market beta are also sources from Worldscope.

3. Methodology

3.1 Sample Selection

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 collect data only for organizations with a market capitalization of greater than 100 million USD, as ESG reporting is most common in larger organizations. This restriction captures the vast majority of the Bloomberg ESG Index and produces a sample of 9,714 unique organizations. We collect data on these 9,714 organizations from 2010 to 2019, resulting in 97,140 organization-year observations. Of these 97,140 observations, only 18,202 have GHG total data from Bloomberg. By adding data from Thomson Reuters's Asset4 ESG database, we expand the quantity of the environmental data in our sample.

We note numerous instances of errors in our collected data, such as incorrectly scaled values or reported values that do not match organizations' sustainability reports. Therefore, we implement a methodology of removing obvious outliers reported by Thomson Reuters and Bloomberg. First, we observe

[23] Turner et al. (2019) estimated the 2017 global price of groundwater to be on average $0.096/m^3, however, this does not include estimates for surface water cost or other high capital costs of the required infrastructure for abstracting, transferring, storing, and treating water. Moreover, the percentages of water sourced from groundwater versus surface water are neither consistent across different water utility agencies nor readily quantified by them.

there are a substantial number of organizations with data covered by one provider and not the other. Employing both databases, we collect data from 2010 to 2019, resulting in 24,276 organization-year observations that have data for total greenhouse gas emissions.

To minimize concerns about the quality of the environmental data, we create a methodology to attempt to confirm their accuracy. For all values within our dataset, we attempt to assess the accuracy of a value by comparing it to other values within a specific organization's time series. We hypothesize that the emissions (or water withdrawal/discharge) intensity of an organization is a function of many organization specific factors (e.g. technology, capital expenditures, etc.) that in the short-term are primarily fixed. Therefore, in the absence of mergers and acquisitions or significant changes to the dynamics of organization operations, the year-over-year change in organization emissions intensity should be moderate. We calculate a lagged variable that is the difference of the intensity value in year *t* and the intensity value in year *t-1* divided by the intensity value in year *t-1*. We disregard values where year-over-year change is greater than 50% or less than -50%. However, there are reasons intensity values could experience significant year-over-year changes, such as a merger or acquisition, development of new technology, or large changes to organization operations. In order to observe if a change in intensity is sustained into future years, we create a leading value, which is the lagged year-over-year change value calculated for year *t+1*. If the lagged year-over-year variable notes a greater than 50% increase or decrease, but the leading year-over-year variable notes that the increase is sustained in the next year, we assume that some operational or technological change has occurred and, as such, assume the value that experienced a large year-over-year intensity jump or drop to be accurate.

GHG total is deemed the most financially material emission type per the EPS monetization factors. Therefore, we restrict our sample to observations that have reported GHG total data from either Bloomberg or Thomson Reuters. Restricting on observations that have GHG total data produces a final sample of 24,276 organization-year observations. Table 1 describes summary statistics for this sample.

Table 1: Summary Statistics of Sample

	Obs.	Mean	Median	S.D.	Min	Max
GHG total	24,276	4,009,194	197,780	19,100,000	0	676,000,000
Water withdrawal	16,056	378,000,000	2,380,000	8,990,000,000	0	775,000,000,000
Water discharged	7,226	212,000,000	3,724,955	1,850,000,000	0	70,500,000,000
Water discharged (imputed)	16,263	185,000,000	1,543,031	2,320,000,000	0	215,000,000,000
SOx	6,395	32,284	221	375,625	0	18,600,000
NOx	7,223	29,918	800	344,864	0	10,100,000
VOC	3,716	520,062	330	14,300,000	0	638,000,000
Carbon offsets	2,331	1,117,707	11,000	9,055,419	0	243,000,000

Table 1 describes the summary statistics for our sample. All observations have non-missing values for GHG total. Water discharged contains only data reported by Bloomberg or Thomson Reuters. For observations missing water discharged, we impute values by multiplying water withdrawal by the industry-year median water discharged-water withdrawal ratio. Water discharged (imputed) is the final variable which includes reported water discharged data and the data we impute. All emissions variables have units of metric tonnes. GHG total and Carbon offsets are in CO2-equivalent metric tonnes. Water withdrawal, water discharged, and water discharged (imputed) are in cubic meters. Observations are firm-year pairs.

3.2 Imputation of missing values

Of the 24,276 observations in our sample, 17,053 are missing NOx data, 20,560 are missing VOC data, 17,881 are missing SOx data, 8,220 are missing water withdrawal data, and 17,050 are missing water discharge data. We impute data for these missing values using industry-country emissions data from Exiobase (F Table – Factors of Production).

Global Industry Classification System (GICS) data is sourced from Bloomberg and mapped to our organization reported emissions data. However, Exiobase uses the Nomenclature of Economic Activities (NACE) industry classification to define industry classifications, requiring a mapping from NACE to GICS codes.[24] To adjust the industry-level values from Exiobase to organization-level values, each Exiobase value is scaled by the ratio of organization revenue in a given year to total industry output in a given year, up to year 2016, the latest year for Exiobase data.[25] Industry output is sourced from the Exiobase industry output dataset for the organization's domicile country as listed in Bloomberg. As with water, given lack of information available, the domicile country for the organization is used to select the industry level information in the Exiobase data.[26] This methodology is an attempt to estimate the missing organization-level emissions by attributing a pro-rata portion of industry totals to an organization. While imperfect, this step is necessary to provide comparability among organizations and industries, and unless otherwise

[24] NACE industries are converted to International Standard Industrial Classification Revision 3.1 (ISIC) classifications and then to ISIC 4 using concordance tables from the United Nations, available at https://unstats.un.org/unsd/classifications/econ/ (Schmidt *et al 2012)*. These are then mapped to the 2012 North American Industry Classification System (NAICS) using a concordance table from the United States Census Bureau, available at https://www.census.gov/eos/www/naics/concordances/concordances.html. Lastly, these are mapped to GICS codes from Bloomberg, available at https://sites.google.com/site/alisonweingarden/links/industries. For those that do not match directly, GICS sub-industry codes are hand mapped to NAICS codes.

[25] Where the industry revenue was not quantified by Exiobase, as was the case for a small minority of industries given data availability, the above-described pro-rata allocation methodology was not done to the inputs from the Factors of Production Table. Instead, the full industry level factors of production were used, which is equivalent to multiplying by 100% instead of some percentage of company level revenue to industry output. This occurs in 8120 out of 71883 industry-country observations.

[26] Review of the Exiobase and economic activity calculation methodology suggests that the challenge of attributing economic activities by domicile is a pervasive issue. The Exiobase uses GDP among its macro inputs for estimation of economic activity in a region. Guidance from the OECD indicates that foreign subsidiaries of a multi-national organization should be treated as resident in their countries of location rather than in the countries of their parent organization. However, artificial transfer pricing, tax incentives, transfer of intellectual property, consolidated accounting, reporting, and billing practices, among others, can result in a difference between where transactions are reported and where they actually occur (Landefeld, et al. 2011). Thus calls into question the use of the domicile country to select Exiobase industry factors. However, the relatively small contribution of country level effects, as we document in the paper, indicates that this does not play a substantial role in our sample, given the restriction on the maximum allowable level of the environmental impact valuation derived from the imputation methodology.

disclosed, we believe it is fair to assume that organizations' production requirements are similar to the standard production requirements of a given industry within a given country.[27]

For 8,830 firm-year observations, water withdrawal data is available but water discharge data is missing. The water withdrawal and consumption data within Exiobase is specifically for companies operating in industries relating to Agriculture, Livestock, Manufacturing, and Electricity, but this is far from exhaustive. To ensure that water use is being consistently and comparably measured, we develop a method of imputing the missing data for water discharge when water withdrawal data is available. We first determine the best predictor of water discharge: The correlation of water withdrawal to water discharged is 0.8222 compared to the correlation of 0.0003 between water discharged data and sales. Thus, within a given GICS industry-year, we calculate the median ratio of water discharged to water withdrawal using all firms with available water discharge and water withdrawal data. We then impute the missing water discharge for a firm by multiplying its water withdrawal with the industry-year median water discharge-water withdrawal ratio value. Net water consumed is calculated as water withdrawal less water discharged. In order to ensure the imputation process does not produce water discharge data points that create negative net water consumed values, we constrain the maximum imputed water discharge value to be no greater than the firm's water withdrawal value.

3.3 Environmental Impact of Water

The environmental impact of water is calculated using Waterfund's global average water price and AWARE factors, as opposed to EPS factors used for monetization of emissions variables. Equation 1 defines the environmental impact of water.

$$(1)\ Environmental\ Impact\ of\ Water_{i,t} = Water\ Production\ \&\ Delivery\ Cost_{i,t} + Wastewater\ Treatment\ Cost_{i,t}$$

$$(2)\ Environmental\ Impact\ of\ Water_{i,t} = \left(Net\ Water\ Consumed_{i,t} * \ AWARE\ Factor_{j,t} * Water\ Production\ \&\ Delivery\ Unit\ Cost_{j}\right) + (Net\ Water\ Consumed_{i,t} * Wastewater\ Treatment\ Unit\ Cost_{j})$$

Waterfund posits 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 costs: water production and delivery and wastewater treatment. Water production and delivery costs scale by water consumption and by water scarcity. Wastewater treatment costs are not affected by water scarcity and only scale by water consumption. Equation 2 describes the breakdown of these two costs.

[27] There are some challenges associated with using organization-level revenue. Organization revenue can be distorted by complex tax structures which seek to domicile profits in low-tax jurisdictions. Further, this can impact the calculation of national accounts which are used as a key source of reconciling this Exiobase data (Lequiller and Blades 2014).

Water production and delivery costs, for organization *i* in year *t*, are the product of net water consumed, for organization *i* in year *t*, the AWARE factor and the water production and delivery unit cost, both defined for country *j* (time invariant factors). The AWARE factor is a measure of water scarcity, relative to a global average. Because both the AWARE factor and water production and delivery unit costs are measured at a country level, an important assumption of our model is that water is withdrawn from an organization's country of domicile. Given many organizations have operations outside of their country of domicile, our model could be applying incorrect AWARE factors and water unit costs to net water consumption. Increased geographic granularity in water disclosure data would improve the accuracy of our model's calculations. Wastewater treatment costs, for organization *i* in year *t*, are the product of net water consumption and the AWARE factor. Waterfund defines the wastewater processing cost as the sum of expenses incurred by water utilities to both treat the byproduct of water production and to provide specifically the recycled water to organizations. Thus, we conclude that this cost component intuitively does not depend on water scarcity, so the AWARE factor is not applied to it.

3.4 Environmental Impact Calculation

To calculate the environmental impact of emissions, we multiply EPS monetary coefficients by the reported (or imputed) emissions of an organization. Equation 3 describes the calculation of environmental impact of emissions for organization *i* in year *t*.

$$(3)\quad Environmental\ Impact\ of\ Emissions_{i,t} = \sum(Emissions\ Volume_{e,i,t} * EPS\ Monetary\ Coefficient_e)$$

The environmental impact of emissions for organization *i* in year *t* is the sum of each emissions type *e* multiplied by the respective EPS monetary coefficient for emissions type *e*. Specifically, organization's reported (or imputed) values for GHG[28], 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 calculate 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.

$$(4)\quad Environmental\ Impact_{i,t} = Environmental\ Impact\ of\ Emissions_{i.t} + Environmental\ Impact\ of\ Water_{i,t}$$

3.5 Robustness of Imputations

A potential source of error in our calculated value of environmental impact stems from the use of imputed data. To understand the extent of this potential error we conduct a decomposition analysis and determine what proportion of environmental impact is being determined by data reported by Bloomberg or

[28] GHG emissions are reduced by carbon offsets.

Thomson Reuters and what proportion is based on imputations using Exiobase data. We deconstruct environmental impact into its component pieces – each emissions type (net water consumption) multiplied by the respective EPS monetary coefficients (AWARE factors and Waterfund factors) – and calculate the percent contribution of each component to total environmental impact. Next, we determine the source of data for each environmental impact component, either reported from a data provider (Bloomberg or Thompson Reuters) or imputed using Exiobase data. For example, if VOC data is imputed for an observation, we define that observation's VOC environmental impact component as imputed. The percent contribution of all environmental impact components based on imputed data is the imputed contribution to environmental impact. For example, if VOC and SOx data are imputed and contribute 5% and 7% respectively to environmental impact, the total imputed contribution would be 12%.

To ensure robustness and reliability of our results, we restrict our sample to observations that have less than 25% imputed contribution to environmental impact. We find the average imputed contribution is less than 10%. This restriction produces a final sample of 14,805 organization-year observations.

3.6 Discount Factor Analysis

The EPS methodology assumes a 0% discount rate for purposes of intergenerational equity. There is a strong argument against discounting, given that in the social context, the time component does not represent the creation of wealth but rather involves re-distribution of resources between generations (Rabl 1996). Nevertheless, discounting the impacts with longer impact horizon causes a meaningful change in the cost of these emissions, and thus, it is important to sensitivity test the 0% discount rate.

We apply a uniform discount rate procedure over time; the long term growth rate of the world from 1913-2012, which is approximately 3% for the sake of conservatism (Piketty 2014).[29] A key issue with this discounting methodology, aside from the inter-generational ethics, is that it assumes that impacts are spread evenly over the course of the expected impact horizon, when in actuality, impacts are likely clustered or more heavily weighted to the end of the horizon when the cumulative effect is highest.

To discount the EPS Factors, we first modify the characterization pathway factor to isolate the yearly effect. Each characterization pathway factor is divided by the time horizon estimate (detailed in Exhibit 2). Next the cumulative cost of the impact with discounting is calculated using a present value calculation of the EPS State Indicator Value ($/unit), the discount rate, and the time horizon. Lastly, the impact value was re-calculated by multiplying the new Environmental Impact Factor by the present value of the Indicator Value.

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[29] This differs from Rabl's two-part discounting procedure, in which the conventional discount rate is used for the horizon t_{short} (about 30 years) and t_{long} uses the long-term growth rate of the economy, in terms of GNP per capita.

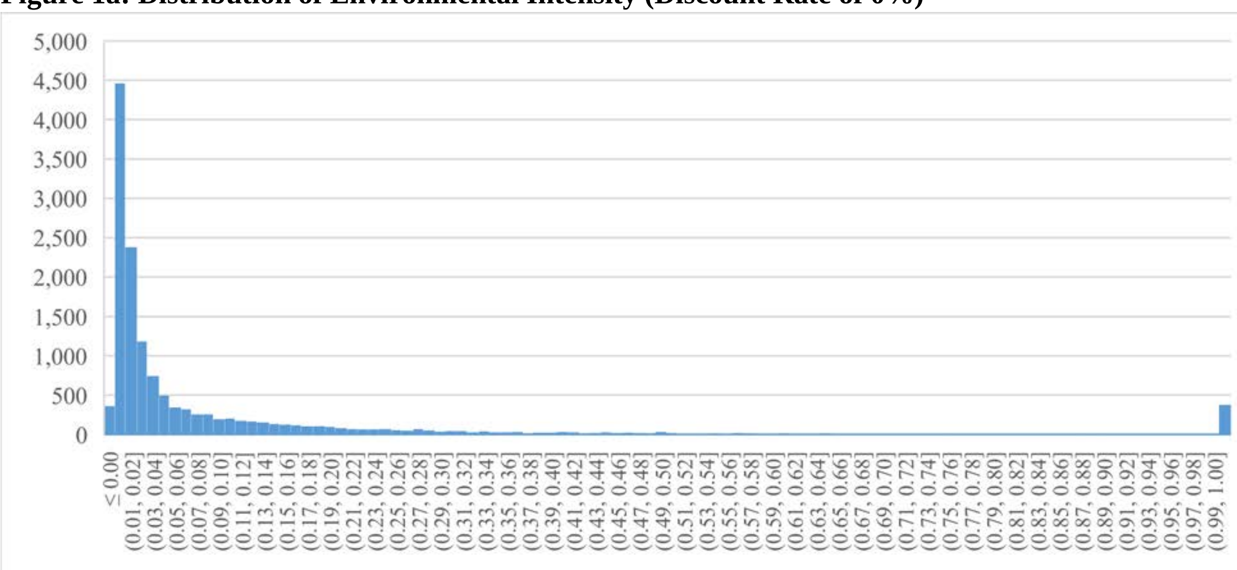
4. Results

4.1 Environmental Impact Statistics

To make environmental impact a comparable value across firms, we define *environmental intensity* as environmental impact scaled by sales or operating income. Figure 1a shows distribution of the sample's environmental intensity. The average intensity value scaled by sales, when the discount rate is zero, stands at 11.8%. The median is much lower than the mean at 2.0% and the third quartile of the distribution at 9.4%. This means that a minority of firms have very large values bringing the average up, as depicted in Figure 1a. As expected, environmental intensity is lower when discount rate is 3%. The average stands at 5.4% with the median of 0.8% and the third quartile at 4.0%.

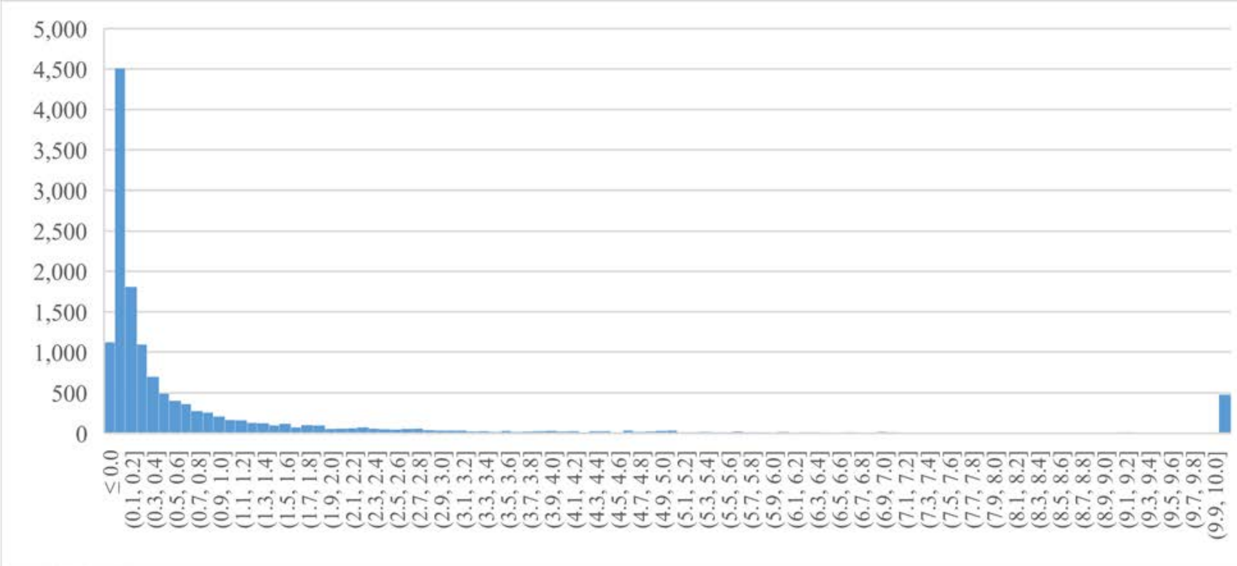
The environmental intensity values scaled by operating income demonstrate even greater variability, as demonstrated in Figure 1b. The average value, when the discount rate is zero, is 117.4%, with the median of 21.5% and the third quartile of the distribution at 92.1%. Therefore, similar to the environmental intensity scaled by sales, a small number of firms with large values pull the average up. The environmental intensity scaled by operating income is also lower when the discount rate is 3%. The average stands at 62.2% with the median of 8.8% and the third quartile at 39.2%.

Figure 1a: Distribution of Environmental Intensity (Discount Rate of 0%)



The vertical axis of Figure 1a displays the number of firm-year observations that belongs to each bin of the histogram. Each bin width is 0.01, representing environmental intensity (scaled by sales) of 1%.

Figure 1b: Distribution of Environmental Intensity (Operating Income, Discount Rate of 0%)



The vertical axis of Figure 1b displays the number of firm-year observations that belongs to each bin of the histogram. Each bin width is 0.1, representing environmental intensity (scaled by operating income) of 10%.

Table 2 shows the estimated adjusted R-squared, a measure of the explanatory power of the independent variables, from five different models where the environmental intensity is the dependent variable. We discuss only the results for the intensity scaled by sales as scaling by operating income yields similar inferences. The results are practically identical for the 3% discount rate, so for the sake of brevity, we show only the 0% discount rate analysis. The first model only includes year fixed effects. The explanatory power of the model is less than 1%, suggesting that environmental intensity for the sample has not changed systematically across years. The second model adds industry effects using the GICS classification. The explanatory power jumps to about 61%, suggesting that industry membership is a major determinant of variation in environmental intensity across companies. Adding in country effects in the third model raises the explanatory power to about 67%, suggesting that country membership also explains some of the variation, but the percentage is small relative to industry membership. The fourth model removes industry effects to understand if the limited explanatory power from country effects is only because we first included industry effects. This is not the case as the explanatory power of the model declines to about 11%, far below that of the industry effects model that stands at roughly 61%. The last model replaces industry with subindustry effects. The explanatory power increases from 67% to 72%, suggesting that even within industries, environmental intensity varies across subindustries, but the increase in power is less pronounced. Moreover, given that we have 155 sub-industries (instead of 67 industries), the number of firms within many sub industries is limited, leading some of the subindustry fixed effects to serve a similar function as firm fixed effects. Therefore, for the rest of the paper, we focus our attention on industries rather than subindustries.

Table 2: Sources of Variation in Environmental Intensity

Environmental Intensity	Year effects	+ Industry effects	+ Industry, Country effects	+ Country effects	+ Subindustry, Country effects
Env Imp / Sales 0%	0.12%	60.97%	66.52%	11.22%	71.55%
Env Imp / Op Inc 0%	-0.01%	55.74%	61.04%	11.10%	65.92%

Table 2 describes the adjusted R-squared of an OLS model that regresses a variety of fixed effects on environmental intensity as the dependent variable. Environmental intensity is created from the 0% discount rate. All models include year fixed effects. Column 1 only controls for year fixed effects. Column 2 adds industry effects. Column 3 adds industry and country effects. Column 4 adds only country effects. Column 5 adds subindustry and country effects.

Our findings above, which point to the importance of industry in driving environmental intensity, lead us to further investigate how industry-specific distributions of environmental impact differ. Figure 2a helps visualize the average, as well as the ratio between first and third quartiles for environmental intensity, for each industry. Both axes are log-transformed to aid visually inspecting the relative positioning of industries given that some industries have orders of magnitude larger environmental intensity than others. Not surprisingly, industries in the utility sector and resources (metals and mining, as well as oil and gas) score very high. Construction materials, airlines, paper and forest products, and chemicals are other industries with very high environmental intensity. Perhaps more surprising is the large variation across companies within the same industry. The differences between first and third quartile statistics are informative here. For example, in metals and mining, the firm in the third quartile has an environmental intensity of more than 4 times the firm in the first quartile. In an industry where asset mix and business lines is even more homogeneous, such as airlines, we still observe a sizeable spread of 32% versus 21% in the third and first quartiles respectively.[30]

The graphic comparison of industry-specific distributions of median environmental intensity values scaled by sales and operating income points to another interesting note: Figures 2a and 2b demonstrate which industries tend to have lower profit margins than others, as environmental intensity values scaled by operating income for some industries are affected much more severely than they are when scaled by revenue. For instance, air freight and logistics industry shows a clear distinction between the two environmental intensity values when it is calculated on a profit-basis as opposed to revenue-basis. Despite having a relatively low median environmental intensity value of 1.5% when scaled by sales, the median intensity value of air freight and logistics industry spikes up to 27.6% when scaled by profit. Likewise,

[30] The large spread in air freight and logistics industry is driven by a few observations having very high water withdrawal numbers while most of the industry having relatively high nitrous oxide which reduce the global warming potential of the other emissions.

other industries with low profit margins such as construction and engineering, food and staples retailing, and automobiles display an analogous trend.

As expected, in most of the cases, the distribution of environmental intensity shifts lower when discount rate is set at 3%. However, the degree of the change is not uniform across industries, as the effect of the discount rate is different across environmental impacts, and therefore, the overall effect depends on the composition of impacts across different industries. In general, industries in which carbon emissions dominate their environmental impact composition would experience a sharper decrease in environmental intensity after applying the 3% discount rate. In contrast, environmental impact from water withdrawals and other emissions are impacted less as their impacts are both short-term and long-term. Using SOx as an example, the effect on human health from secondary particles and direct exposure is estimated over the next year, while for the climate change pathways, it accumulates over 85 years according to EPS. Exhibit 2 provides detail on the time frames for each output type.

Figure 2a: Environmental Intensity (Sales) by Industry

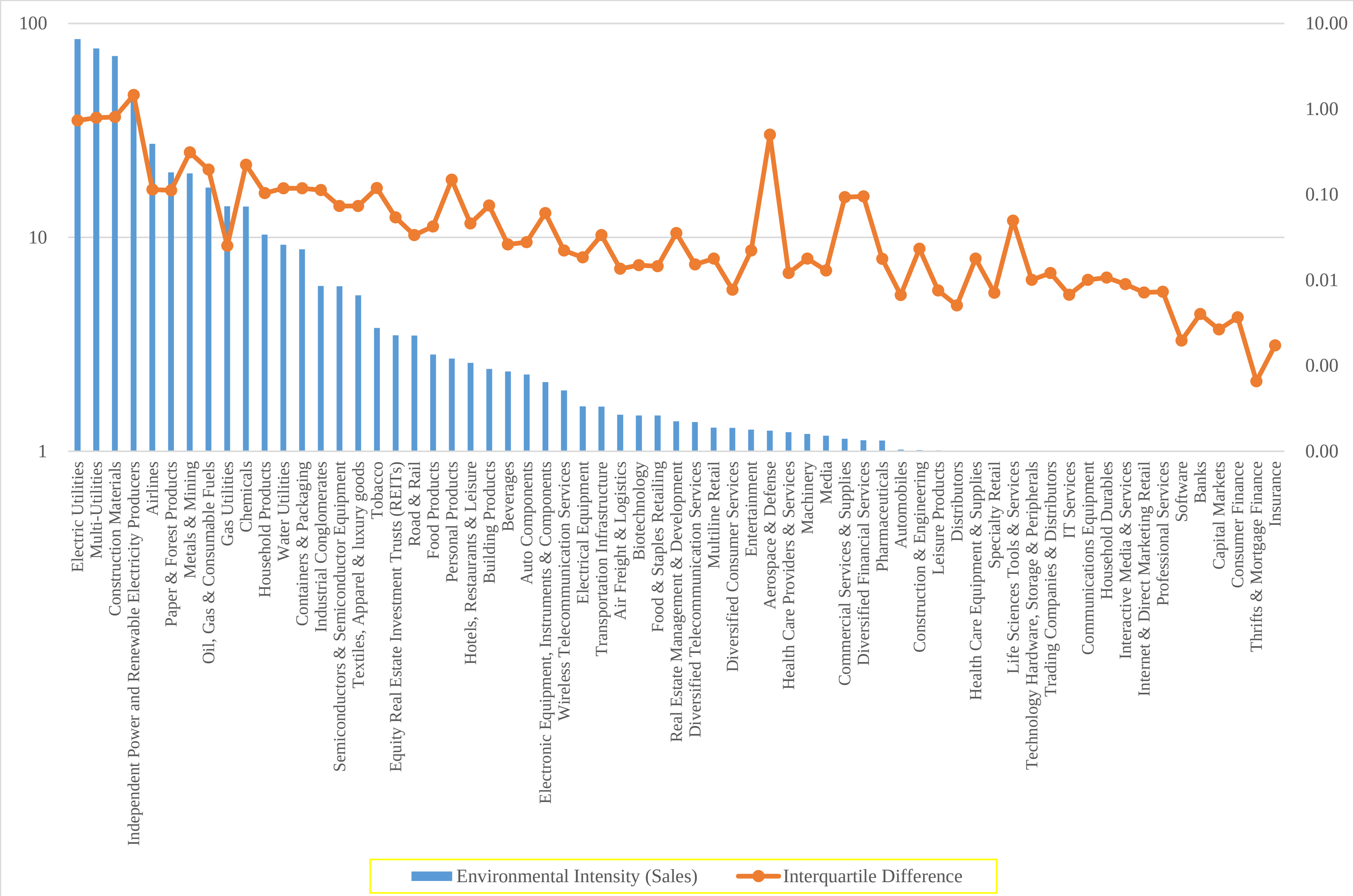


Figure 2a graphs distribution of environmental intensity by GICS industry. Environmental Intensity (Sales) indicates log-transformed environmental intensity. Interquartile Difference is log-transformed difference between the third and first quartile of the distribution of environmental intensity across firm-year observations in each industry.

Figure 2b: Environmental Intensity (Scaled by Operating Income) by Industry

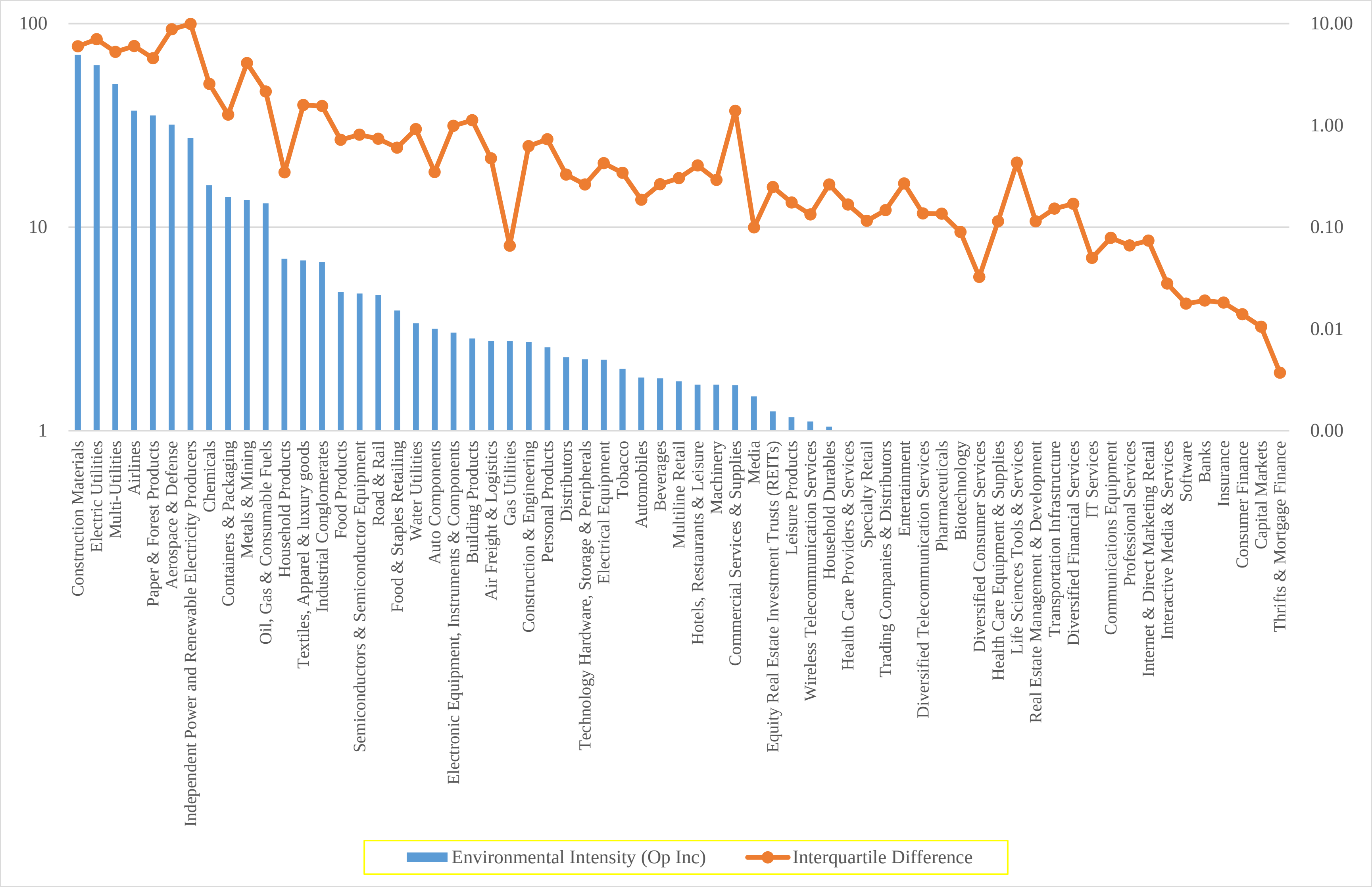
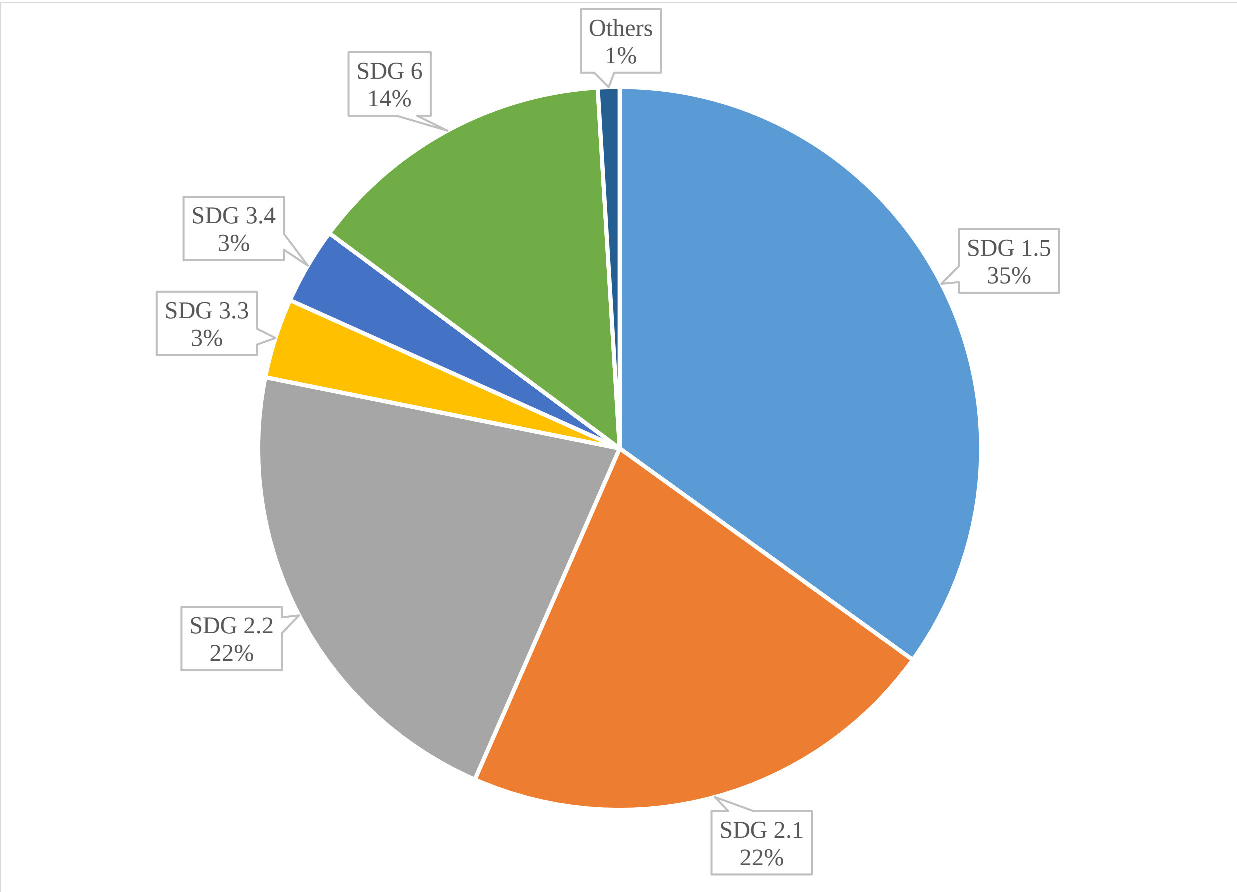


Figure 2b graphs distribution of environmental intensity (scaled by operating income) by GICS industry. Environmental Intensity (Op Inc) indicates log-transformed environmental intensity scaled by operating income. Interquartile Difference highlights log-transformed difference between the third and first quartile of the distribution of environmental intensity scaled by operating income across firm-year observations in each industry.

4.2 Sustainable Development Goals

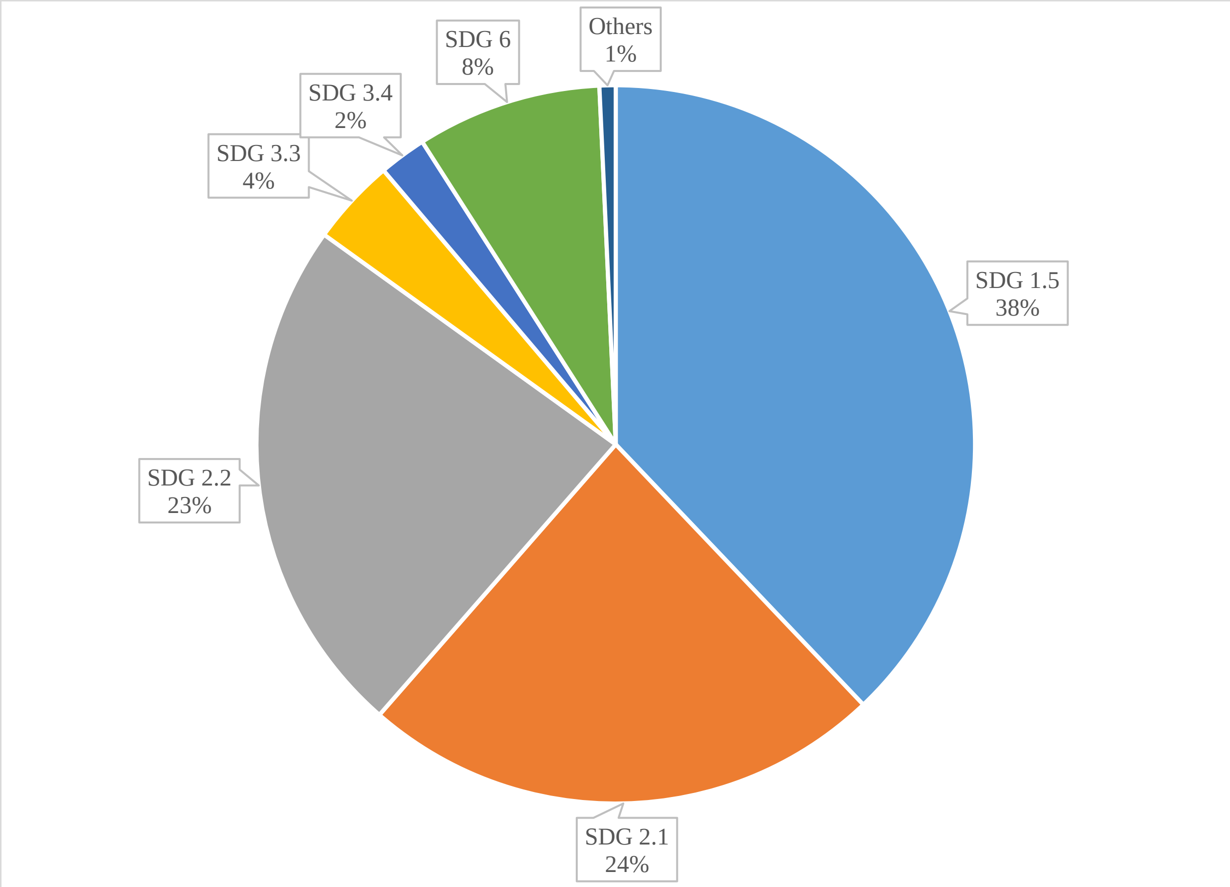
Utilizing the characterization pathways, safeguard subjects, and monetary conversion factors from the EPS database as previously mentioned in Section 2.3, we also delineate each emissions' impacts in terms of United Nations Sustainable Development Goals (SDGs). In total, we map each emission's characterization pathways to 17 relevant SDG targets[31]. Figures 3a and 3b depict the relative allocation of our sample's environmental impact to each SDG target for 0% and 3% discount rates respectively. We discover that the vast majority of corporate environmental impact is tied to four main SDG targets: SDG 1.5, which relates to poverty, SDG 2.1 and SDG 2.2, both of which concern ending hunger and malnutrition, and SDG 6, which relates to clean water and sanitation. As demonstrated by the graphic differences in the relative proportion of impacts that belong to each SDG target under 0% and 3% discount rates, we note once again that discount rates affect each emission's environmental impact differently, thereby resulting in asymmetrical degree of changes across the SDG targets.

Figure 3a: SDG Targets (0% Discount Rate)



[31] The list of 17 relevant SDG targets and their specific descriptions are included in Exhibit 4 of the Appendix. More details about SDG targets can also be found in the official UN website: https://sdgs.un.org/goals

Figure 3b: SDG Targets (3% Discount Rate)



4.3 Environmental Impact and Ratings

Next, we seek to understand the relationship between our calculated environmental intensity and widely used ratings that intend to measure how well a company is managing environment-related risks and opportunities. To do so, we obtain data from three ratings providers: MSCI, RobecoSAM, and Sustainalytics. For Sustainalytics, we have access only to US data, while for the other two providers, our sample includes both US and non-US firms. Given RobecoSAM coverage is more limited than the two providers, we obtain the largest sample for MSCI. The relation between the natural logarithm of environmental intensity and the ratings is negative, consistent with the idea that firms that have greater adverse environmental intensity receive lower ratings.[32] But the correlations are moderate, ranging from -0.13 to -0.26.

Environmental intensity values scaled by sales and operating income calculated using 0% and 3% discount rates have a correlation of 0.98, and as a result, correlations with the environmental ratings are extremely similar. When we examine the univariate correlations separately for each industry, the two

[32] We log transform the environmental intensity to decrease the skewness of the distribution that we documented in Section 4.1.

environmental intensity estimates under the two discount rate scenarios are very highly correlated. The lowest correlation is 0.80 in the Paper and Forest Products industry. In all other industries, the correlation values are above 0.90, with 57 out of 67 industries above 0.95. Given this finding, for the remainder of our analysis, we use the 0% discount rate estimate and identify any differences in results when using the 3% discount rate to simplify the exposition of the paper.[33]

Given that investors and analysts also use the ratings to compare firms within industries, we are interested in understanding how well ratings reflect environmental intensity (scaled by sales) within each industry. Table 3 presents the estimated coefficient and p-value on the environmental rating variable for models where the natural logarithm of the environmental intensity is the dependent variable. The first row presents estimates from a model based on variation across the whole market, while the second model includes industry and country fixed effects, thereby estimating the coefficient based on within industry and country variation. The coefficients decline sharply, suggesting that the ratings are not differentiating across firms within an industry on the impact dimension. Moreover, they lose statistical significance. The only exception is the MSCI rating, which still exhibits a significant coefficient, but the magnitude of it has now decreased by 65%.

Table 3: Estimates of Correlation between Environmental Intensity and Ratings

Independent Variable	E Rating M		E Rating RS		E Rating S	
Specification	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Across market	-0.151	0.000	-0.071	0.000	-0.328	0.000
Within industry, country	-0.052	0.000	-0.003	0.719	-0.039	0.183
Reduction in coefficient	65%		96%		88%	

Table 3 describes the OLS results of regressing environmental ratings on environmental intensity scaled by sales for 0% discount rate. MSCI, RobecoSAM, and Sustainalytics environmental ratings are included as independent variables in separate models. The dependent variable is the natural logarithm of environmental intensity. The second specification introduces controls for industry and country fixed effects. N is the number of observations in each model. Observations are firm-year pairs for the years 2010-2018.

The results above provide, on average, evidence across many industries. Whether ratings reflect intensity might differ across industries. A few observations are worth highlighting. First, there is a large variation across industries. For example, both MSCI and RobecoSAM ratings exhibit large negative correlations with some industries of the Utilities sector. However, for industries such as household durables and real estate development, the correlation is very low or even positive. Second, the industries with the highest correlation differ across rating providers. While for construction materials there is a sizeable negative correlation for Sustainalytics, the correlation is positive for RobecoSAM.[34]

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[33] The correlation between the environmental ratings are also moderate in the range of 0.31 to 0.46 consistent with the findings of other studies (Christensen, Serafeim and Sikochi 2019; Berg, Kolbel and Rigobon 2019).

[34] Using the 3% discount rate environmental intensity, we find the following meaningful differences across estimates: We define meaningful as the correlation coefficient moving by more than 0.1 in either direction (the correlation coefficient ranges from -1 to +1). For the MSCI rating, the correlation becomes more negative for automobile and

Our overall conclusion is that although ratings may well provide important insights to how different firms attempt to manage 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 impact.

4.4 Financial Materiality of Environmental Intensity

Do market prices reflect environmental intensity? If investors believe that larger environmental intensity might be a risk for the company, because of regulatory, customer or investor future actions, then all else equal, firms with larger negative environmental intensity would trade at lower valuation multiples. Past literature has provided support to this idea by demonstrating empirical linkage to environmental performance and valuation.[35] Furthermore, even if market prices do not reflect environmental intensity, we are interested in understanding whether our measure provides a financially material signal for financial risk and return. We note that we do not attempt to make a causal claim here that the environmental impact of a firm is necessarily the reason why we observe differences in risk and return. Rather, we are asking the question of whether environmental intensity provides a meaningful signal of corporate valuation.

Table 4 shows that the environmental intensity scaled by sales is negatively correlated with both Tobin's Q (a measure of the market value over the replacement value of assets) and the price to book value of equity ratios.[36] This is after controlling for other determinants of valuation ratios, such as return on assets, leverage, firm size, capital expenditures, R&D expenditures, and dividends divided by sales.[37] All models include industry, country, and year fixed effects. Both the dependent variables and the environmental impact variables are log-transformed to mitigate skewness. The estimates suggest that a firm with twice the environmental intensity scaled by sales has 2.4% lower Tobin's Q and 5.2% lower price to book value of equity. In terms of the environmental intensity scaled by operating income, a firm with twice the intensity value has 0.3% (2.0%) lower Tobin's Q (price to book value of equity).

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multi-utilities. For the RobecoSAM rating, the correlation becomes more negative for automobile and less negative for Equity REITS and Specialty Retail. For the Sustainalytics rating, the correlation becomes more negative for Road and Rail and Pharmaceuticals, and less negative for Banks, Independent Power Producers, and Equity REITS.

[35] Matsumura et al. (2014) find that for every additional thousand metric tons of carbon emissions decreases firm value by $212,000 on average pricing of carbon emissions and Konar and Cohen (2001) find that a 10% reduction in toxic chemical releases added $34.1 million to intangible firm value.

[36] Firms with negative book value of equity are excluded from the model where price to book value of equity is the dependent variable.

[37] Leverage is measured as one minus the ration of book value of equity over total assets. Firm size is measured as the log transformed firm sales. Capital expenditures are scaled by total assets since they are recognized as assets. R&D expenditures, as a flow variable, are scaled by sales. Dividends, as a flow variable, are scaled by sales.

Table 4: 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	0.336	0.005	0.188	0.100	0.048	0.839	-0.191	0.427
Env Imp / Sales 0%	-0.024	0.000			-0.052	0.000		
Env Imp / Op Inc 0%			-0.003	0.500			-0.020	0.021
ROA	4.128	0.000	4.717	0.000	6.172	0.000	6.797	0.000
Leverage	0.119	0.000	0.089	0.006	0.953	0.000	0.959	0.000
CapEx / Sales	0.487	0.000	0.411	0.000	0.882	0.000	0.765	0.000
R&D / Sales	1.688	0.000	1.537	0.000	2.415	0.000	2.100	0.000
Dividend / Sales	0.342	0.000	0.322	0.000	0.767	0.000	0.692	0.000
Sales	-0.016	0.000	-0.009	0.032	-0.003	0.732	0.011	0.195

Table 4 describes OLS models that regress independent variable, 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. All models include year, country, and industry effects. Both dependent variables and the environmental intensity variables are log-transformed. N is the number of observations. Observations are firm-year pairs.

Table 5 examines dynamic materiality of environmental intensity in relation to Tobin's Q and price to book value of equity. We note that the materiality of environmental intensity increases over time, as demonstrated by the negative and significant interaction terms (DM) in relation to both Tobin's Q and price to book value of equity. DM is the interaction term between the environmental intensity and a time trend variable that takes the value of zero on 2010 and increases by one for each subsequent year. In other words, the negative association between environmental intensity and market valuation has become more sizable in more recent years. The same conclusion holds true for environmental intensity scaled by operating income as shown by the negative and statistically significant interaction terms.

Table 5: Dynamic Materiality of Environmental Intensity

	Tobin's Q				Price to Book Value of Equity			
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	0.302	0.011	0.188	0.100	-0.013	0.956	-0.192	0.424
Env Imp / Sales 0%	-0.006	0.434			-0.019	0.219		
DM (Env Imp / Sales)	-0.003	0.000			-0.006	0.000		
Env Imp / Op Inc 0%			0.011	0.033			0.003	0.779
DM (Env Imp / Op Inc)			-0.003	0.000			-0.004	0.000
ROA	4.129	0.000	4.726	0.000	6.174	0.000	6.814	0.000
Leverage	0.120	0.000	0.088	0.006	0.955	0.000	0.959	0.000
CapEx / Assets	0.478	0.000	0.402	0.000	0.866	0.000	0.751	0.000
R&D / Sales	1.685	0.000	1.541	0.000	2.410	0.000	2.105	0.000
Dividend / Sales	0.340	0.000	0.311	0.000	0.764	0.000	0.674	0.000
Sales	-0.016	0.000	-0.009	0.026	-0.003	0.708	0.010	0.221

Table 5 describes OLS models that regress independent variables listed in the parameter column on dependent variables, Tobin's Q and Price to Book Value of Equity. ROA is return on assets. All models include year, country, and industry effects.

Table 6 presents estimated coefficients on environmental intensity, examining the intensity value's relation with the Sharpe ratio (i.e. stock return over volatility) and its components. Panel A (B) scales environmental impact by sales (operating income). The key insights are as follows: First, environmental intensity is negatively, yet insignificantly related to the Sharpe ratio. This relation is driven by both the numerator and the denominator. More environmentally intensive firms have lower stock returns and higher volatility. Environmental intensity scaled by operating income is more strongly and significantly associated with these financial characteristics.

Table 6: Returns, Risk and Environmental Intensity

Dependent Variable	Sharpe ratio		Stock return		Volatility	
Panel A						
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	0.230	0.293	20.001	0.003	55.478	0.000
Env Imp / Sales 0%	-0.016	0.234	-0.199	0.636	0.318	0.043
ROA	3.534	0.000	101.533	0.000	-11.536	0.000
Leverage	-0.297	0.000	-6.426	0.007	4.450	0.000
CapEx / Sales	-0.167	0.715	5.273	0.750	6.167	0.017
R&D / Sales	0.333	0.223	12.790	0.430	-4.407	0.188
Dividend / Sales	-0.410	0.029	-33.705	0.000	-22.594	0.000
Sales	0.007	0.383	-0.722	0.004	-1.517	0.000
Panel B						
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	0.267	0.243	22.607	0.001	51.709	0.000
Env Imp / Op Inc 0%	-0.045	0.000	-0.822	0.004	0.613	0.000
ROA	2.807	0.000	84.292	0.000	0.293	0.902
Leverage	-0.247	0.002	-4.362	0.090	3.830	0.000
CapEx / Sales	-0.579	0.031	-12.900	0.182	5.881	0.027
R&D / Sales	0.780	0.043	16.919	0.184	-5.496	0.199
Dividend / Sales	-0.445	0.026	-35.325	0.000	-22.246	0.000
Sales	0.005	0.581	-0.861	0.001	-1.404	0.000

Table 6 describes OLS models that regress independent variable, log-transformed environmental intensity, on dependent variables, Sharpe ratio, stock return, and stock price volatility. Sharpe ratio is defined as stock return over the calendar year divided by stock price volatility over the calendar year. All models also include year, industry, and country fixed effects. Specifications for the environmental intensity calculated using a 0% discount rate are included.

Figure 4a shows the estimated coefficient on environmental intensity from industry specific models.[38] Figure 4b explores the dynamic materiality of environmental intensity across industries. We note

[38] To ensure more robust estimates, we only include estimates for industries that have at least 20 degrees of freedom and are statistically significant.

that both figures are produced using a more comprehensive sample that includes firm-year observations with up to 50% of imputed contribution to environmental impact instead of the usual 25% in order to increase the number of observations and as a result the statistical power of the test given these industry-specific models use a much smaller number of observations. We show only the industries for which the coefficient on environmental intensity is significant. We use Env Impact / Sales 0% variable to represent environmental intensity in this case to avoid reporting overload from using all environmental impact estimates, but the results are qualitatively similar using the other variables. We are interested in understanding for which industries prices reflect environmental impact, as well as how the materiality of environmental intensity has varied over time across industries.

A few interesting observations emerge from this analysis. For most industries, we find that environmental intensity is associated with lower market valuation. 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.[39] 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. However, this has changed over time.

Figure 4b shows that environmental intensity is becoming increasingly material in recent years for several industries with large environmental impact including electric utilities, construction materials, and oil industries. Interestingly, however, the materiality of environmental intensity has also noticeably grown in industries that are not traditionally associated with large environmental impact, such as IT services.

[39] While there are 14 industries that exhibit a negative and significant association between environmental intensity and market valuation there is only one industry that exhibit positive and significant: construction and engineering.

Figure 4a: Market Pricing and Environmental Intensity by Industry

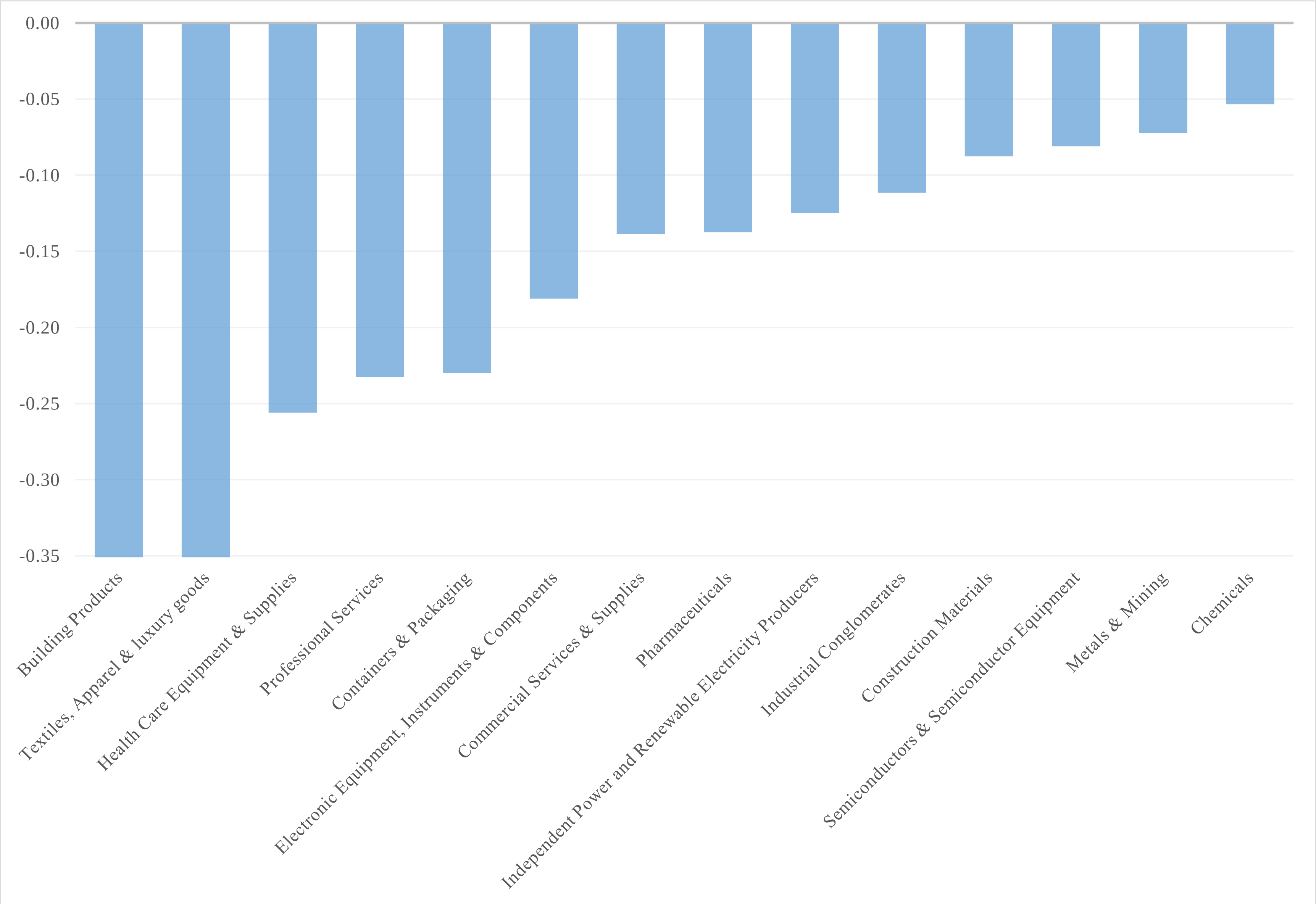
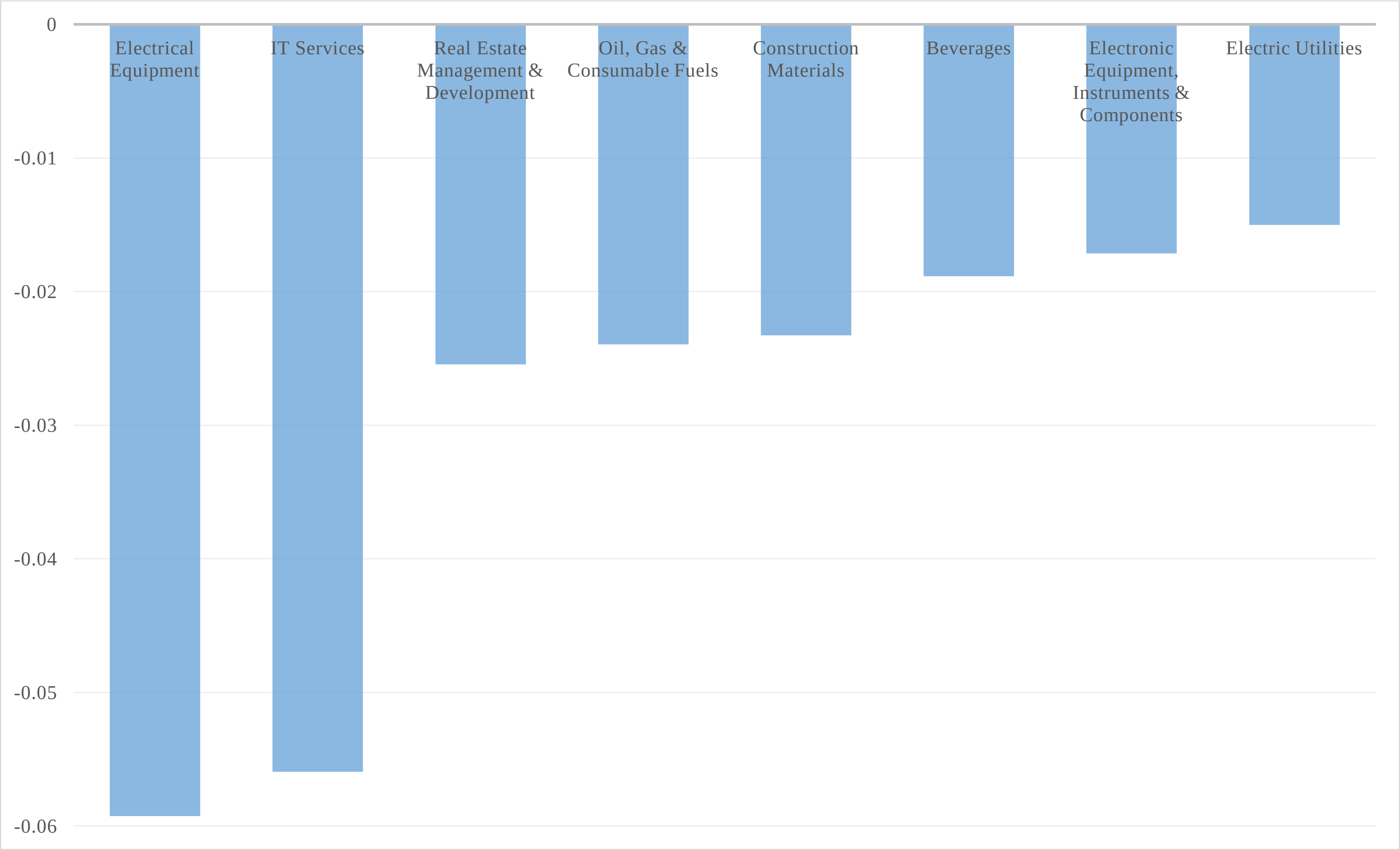


Figure 4b: Dynamic Materiality of Environmental Intensity by Industry[40]



[40] Capital markets industry's dynamic materiality coefficient, though not shown in Figure 4b, is also statistically significant and very negative influencing the scale of the chart and thereby omitted from the chart. While there are nine industries that have seen significant increase in materiality there are only two industries exhibiting significant decrease in materiality: health care equipment and supplies and household durables.

5. Areas for Further Analysis

5.1 Baselines and Thresholds

Our methodology analyzes absolute organizational environmental impact. This effectively assumes that the alternative is that the organization is not in business at all. However, this assumption ignores the fact that organizations fulfill critical needs for society and the economy, and that some level of environmental disruption, if not degradation, is required. Future research will focus on organization performance relative to science-based targets or critical thresholds, beyond which impacts are potentially exponentially worse for humanity and the environment.

5.2 Uncertainty analysis

A next step for future research is to include estimates of uncertainty, as recommended by the ISO 14007 and 14008 protocols. As with all statistical modeling, there is a range of possible environmental impacts. Determining the confidence interval of potential impacts will provide additional insights into the variability of a particular outcome and provide a level of statistical significance to projections. Moreover, measures of uncertainty will allow for more detailed modeling and scenario analysis. For example, the ability to integrate sensitivity analysis into portfolio analysis would be incredibly beneficial to investors attempting to model climate change impact on their portfolios.

5.3 Big-Data

The possibility of using big-data is certainly another avenue for investor information. However, a key tenet of the Impact-Weighted Accounts design methodology is that to be scalable, it needs to be actionable and cost-effective (Serafeim, Zochowski, and Downing 2019) There are substantial costs to the data-science resources needed to parse and use big data, and this methodology does not pre-suppose such resources. The EPS model was chosen for its deep grounding in environmental science, long development track record with five updates since 1994, and open source methodology and metrics (Steen 1999). It provides significant scale to investors and companies without the need for expensive analytics capacity.

6. Caveats

Several objections may arise out of the methodological choices made in the study. One of the biggest is that of granularity. Best practices for Life Cycle Analysis (LCA) indicate that environmental impacts are highly localized and dependent on local environmental and population dynamics (PricewaterhouseCoopers 2015). Further, the use of global monetization coefficients ignores local burdens of environmental degradation and disease. We acknowledge that in an ideal scenario, investors would have complete access to the environmental footprint of an organization and its supply chain, including local resource extraction, emissions and emission height, which could use leading environmental models to determine exact populations and resources at risk. However, the realities of corporate disclosure are far from this ideal state. Corporate activities are aggregated to business unit or corporate reporting level and environmental disclosures cover the entire organization. Further, from data available from Bloomberg, only 110 companies provide all six environmental data points necessary to produce an environmental intensity value. This requires some estimates to be made. The choice to complete missing data points with Exiobase industry production factors presents a meaningful assumption, though not unprecedented as others have used similar methodologies (e.g. S&P Global Trucost). We have sought to be transparent by limiting the amount of valuation derived from Exiobase data and by sensitivity testing.

The second caveat to our results is that we measure only environmental intensity from the operations of the firm. Therefore, we are not measuring any downstream impacts from the use of products and upstream impacts from the organization's supply chain. For example, in the case of GHG those would be included in Scope 3. There are very few organizations that report Scope 3 emissions. Moreover, there is no consensus currently as to what should and should not be included within Scope 3 emissions. In terms of the other emissions and water data, we are not aware of any that disclose those for upstream and downstream impact. Therefore, extending the scope of measurement for environmental impact in a scalable way that applies to thousands of organizations, as in our study, and is fit for purpose for large-scale statistical analysis, is not feasible at this time.

A final objection relates to reporting and selection bias in the sample in which only companies with better metrics are reporting results, or put worse, environmentally performing units into separate holding companies, which do not report the worse results. This objection intuitively makes sense and this is why the methodology proposes to use estimates of industry factors of production rather than simply zeros for those factors to deal with the disclosure problem. The sensitivity analysis suggests that there are meaningful company-specific impacts that are not incorporated when using the industry factors. This is evidenced by the significant dispersions in environmental intensity between the first and third quartiles documented in Section 4.1. These results suggest that we may be over- or under-penalizing companies with less declared data. For the companies that are being over-penalized our methodology creates incentive to declare more data publicly as investor uptake shifts. For companies that are being under-penalized, we posit that as reporting continues to shift toward greater disclosure, lack of disclosure in-itself will increase as a signal of poor environmental performance.

7. Conclusion

Our paper seeks to propose a methodology whereby investors, companies or regulators may use established environmental resources, reasonably accessible in the public domain,[41] to measure an organization's environmental impact from operations. Our results demonstrate the potential for this approach. Within the paper, we conduct several analyses: we first seek to examine whether year, country, industry or subindustry association, or company specific effects provide the greatest explanatory power of overall environmental intensity and to sensitivity test the impact of discounting. Next, we seek to understand the relationship between our calculated environmental intensity and widely used ratings that intend to measure how well a company is managing environmental related risks and opportunities. Lastly, we test whether market prices reflect environmental intensity using our monetized estimates, as well as whether the materiality of environmental intensity changes over time.

We find the median environmental impact as a percentage of an organization's sales (operating income) is close to 2% (22%) and above 10% (100%) in 11 out of 67 industries, suggesting a significant level of 'hidden liabilities' and potential for value erosion if environmental impacts are priced. Our environmental impact monetization methodology differentiates between industry effects and company specific effects under both a 0% and 3% discount rate. We find that roughly 60% (56%) of the variation in environmental impact scaled by sales (operating income) is driven by industry membership, while approximately 28% (44%) can be attributed to firm specific factors, with the remaining variation driven by country and more granular industry classifications.

We further find that our calculated environmental intensity exhibits negative, yet moderate correlation to the ratings of three widely used environmental ratings providers, consistent with firms that have greater adverse environmental impact receiving lower ratings. However, we find that our estimates of environmental intensity contain information different from that in environmental ratings especially when comparing firms within industries. This makes sense given that ratings providers are not necessarily measuring impact. Rather, they intend to integrate multiple signals of how well a company is managing environment-related risks and opportunities. Our reason for comparing our result to theirs is to determine whether our work provides results that are consistent with other methodologies and to determine if it provides additional value to the ESG space. Our results indicate that the answer to both is yes.

Regarding the question of whether the calculated environmental intensity is reflected in market prices, we find a negative correlation of environmental intensity with both Tobin's Q and price to book equity valuation for the full universe of companies examined. The estimates suggest that a firm with double

[41] Not all resources are free; however, we consider them to be in the public domain given either strong current use among investors (as in the case of Bloomberg and Thomson Reuters) or accessible cost (such as the Environmental Priority Strategies).

the environmental intensity scaled by sales (operating income) has 2.4% (0.3%) lower Tobin's Q and 5.2% (2.0%) lower price to book value of equity. Further, we conclude that environmental intensity has become increasingly material over time across industries.

Additionally, regarding the question of whether our environmental intensity measure provides a meaningful signal of financial risk and return, we find that firms with higher environmental intensity have lower stock returns and higher volatility. The results are more prominent and significant when we examine the relationship between environmental intensity scaled by operating income and the financial risk and return measures.

A final interesting finding emerges when we examine the relationship between environmental intensity and market pricing by industry. As expected, environmental intensity is associated with lower market valuation for most industries, including several industries with large environmental impact such as construction materials and chemicals. We note that materiality of environmental intensity has increased in industries with large environmental impact such as oil, electric utilities, and construction materials.

Overall, our work intends to posit a methodology by which to monetize environmental impact in a scalable and cost-effective manner to create greater transparency and comparability. We recognize that more work needs to be done to improve these measurements. Further, there are several areas for immediate future analysis, including incorporation of non-zero baselines and critical thresholds, as well as uncertainty analysis. In our own work, we are now developing data and analytics for total value chain environmental impact.

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Appendix

Exhibit 1. Details of Chosen Models

Environmental Priority Strategies

The Environmental Priority Strategies (EPS) database provides publicly available, scientifically-based methodology to transform the direct results of an organization's operations, referred to as outputs, such as emissions, into their impacts, referred to as characterization pathways. The database also provides a comprehensive set of conversions from impacts denominated in the standard terms of impact, such as quality adjusted life years, into monetary values (usually $/kg emission or input) referred to as monetization factors. The impacts covered are defined as "safeguard subjects."

The database has a high level of transparency and replicability with all the underlying academic studies documented. The comprehensive coverage of this database is a significant advantage over more niche solutions focused on one type of impact or environmental capital. The unification of characterization and monetization factors into a single $/kg of a given emission for each impact type (hereafter the EPS coefficients) provides significant time savings for investors employing a monetization methodology. Further, unlike numerous proprietary methodologies, the EPS database exists in the public domain and is accessible to all investors.

To find the monetary values, the EPS uses the following price discovery methodology.
"Goods like crops, meat, fish, wood, water and labor are traded in the market and their monetary values can be found from various statistics. Even if the environmental goods we value are defined as capability for production, we value changes in capability, which are units of crop, meat, fish, wood, water, and labor. Producer prices in the market are used as proxies for environmental damage costs per unit good. Producer prices are more suited for estimating value losses per unit good from environmental damage than consumer prices. Costs for farming, fishing, etc., are about the same with and without environmental damage, which results in less value created per unit good, while transports, processing and marketing costs do not change per unit good. A decrease of a stock of abiotic resources are valued through the cost for its restoration with a sustainable alternative…Biodiversity is almost impossible to value. Not only is it a complex good, which is difficult to measure, its quantitative relations to other environmental goods is largely unknown. The only monetary measure that can be estimated is the cost of prevention of declining biodiversity" (Steen 2019).

AWARE
The AWARE Model represents the outcome of a 2+ year consensus building process by the Water Use in Life Cycle Assessment (WULCA), a working group of the UNEP-SETAC Life Cycle Initiative. The model is based on water remaining per unit of surface in a given watershed relative to the world average, after human and aquatic ecosystem demands have been met and provides scaling factors to express water use at the river basin or country level in terms of world-eq. Water availability and human water consumption is based on the WaterGap2 Model and ecosystem demands are modeled by environmental water requirements.

EXIOBASE
"EXIOBASE is a global, detailed Multi-Regional Environmentally Extended Supply-Use Table (MR-SUT) and Input-Output Table (MR-IOT). It was developed by harmonizing and detailing supply-use tables for many countries, estimating emissions and resource extractions by industry. Subsequently the country supply-use tables were linked via trade creating an MR-SUT and producing a MR-IOTs from this. The MR-

IOT that can be used for the analysis of the environmental impacts associated with the final consumption of product groups." [42]

EXIOBASE was developed within the European Union projects EXIOPOL, CREEA, and DESIRE, to provide a global environmentally extended multi-regional input-output table as a baseline for supply chain analysis.

Exiobase provides data on 44 counties and 5 rest of the world regions, 164 industries covered by the International Standard Industrial Classification (ISIC) and 417 emission categories and over 1000 emission, material, and resources categories.

Exhibit 2. Estimated Time Horizons for Resources

Emission	Years
CO2	
Human Health (all pathways)	85
Crop Production Capacity (all pathways)	85
Meat Production Capacity (all pathways)	85
Fish Production Capacity (all pathways)	85
Wood Production Capacity (all pathways)	85
Drinking Water (all pathways)	85
Biodiversity (all pathways)	85
CO	
Human Health	
Climate Change Pathways	85
Oxidant Formation Pathways	1
Direct Exposure Pathways	1
Crop Production Capacity	
Climate Change Pathways	85
Oxidant Formation Pathway	1
Meat Production Capacity (all pathways)	85
Fish Production Capacity (all pathways)	85
Wood Production Capacity (all pathways)	85
Drinking Water (all pathways)	85
Biodiversity (all pathways)	85
NOx	
Human Health	
Secondary Particles	1
Climate Change Pathways	85
Oxidant Formation Pathways	1
Crop Production Capacity	
Climate Change Pathways	85
Oxidant Formation Pathway	1
Meat Production Capacity (all pathways)	85
Fish Production Capacity (all pathways)	1

[42] EXIOBASE consortium, "Exiobase - Home," accessed November 13, 2019.

	Wood Production Capacity (all pathways)		
		Oxidant Formation	1
		N-Fertilization	1
		Climate Change	85
	Drinking Water (all pathways)		85
	Biodiversity (all pathways)		1
		Acidification	1
		Eutrophication	1
		Climate Change	85
SO_x			
	Human Health		
		Secondary Particles	1
		Climate Change Pathways	85
		Direct Exposure	1
	Crop Production Capacity		85
	Meat Production Capacity (all pathways)		85
	Fish Production Capacity (all pathways)		1
	Wood Production Capacity (all pathways)		85
	Drinking Water (all pathways)		85
	Biodiversity		
		Climate Change	85
		Acidification	1
	All (corrosion)		1
N_2O			
	Human Health (all pathways)		85
	Crop Production Capacity (all pathways)		85
	Meat Production Capacity (all pathways)		85
	Fish Production Capacity (all pathways)		85
	Wood Production Capacity (all pathways)		85
	Drinking Water (all pathways)		85
	Biodiversity (all pathways)		85
NH_3			
	Human Health		
		Climate Change Pathways	85
		Secondary Aerosols	1
	Crop Production Capacity		85
	Meat Production Capacity (all pathways)		85
	Fish Production Capacity		85
		Acidification	1
		Eutrophication	1
		Fertilizing	1
	Wood Production Capacity (all pathways)		1
	Drinking Water (all pathways)		85
	Biodiversity		
		Acidification	1

Eutrophication	1
Climate Change	85
PM 2.5	
Human Health	
Direct Exposure Pathways	1
Climate Change Pathways	85
Crop Production Capacity (all pathways)	85
Meat Production Capacity (all pathways)	85
Fish Production Capacity (all pathways)	85
Wood Production Capacity (all pathways)	85
Drinking Water (all pathways)	85
Biodiversity (all pathways)	85
VOC	
Human Health	
Oxidant Formation	85
Climate Change Pathways	1
Secondary Particles	1
Cancer	1
Crop Production Capacity	
Oxidant Formation	85
Climate Change Pathways	1
Meat Production Capacity (all pathways)	85
Fish Production Capacity (all pathways)	85
Drinking Water (all pathways)	85
Biodiversity	85
Halogenated Organic Compounds	
All Impacts and Pathways	85
PAH, Land Use, As, Cd, Cr, BOD, N-Tot, P-Tot, Pesticides	1

Exhibit 3. Waterfund Contact Information

The Water Cost Index, produced by Waterfund LLC, is an ever-changing set of rates updated regularly at www.worldswaterfund.com. Please contact Evan Olsen (Phone: +1 (415) 834-5640; Email: evan.olsen@worldswaterfund.com) for current Water Cost Index information.

Exhibit 4. 17 Relevant SDG Targets

SDG 1.5: By 2030, build the resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters.

SDG 2.1: By 2030, end hunger and ensure access by all people, in particular the poor and people in vulnerable situations, including infants, to safe, nutritious and sufficient food all year round.

SDG 2.2: By 2030, end all forms of malnutrition, including achieving, by 2025, the internationally agreed targets on stunting and wasting in children under 5 years of age, and address the nutritional needs of adolescent girls, pregnant and lactating women and older persons.

SDG 2.3: By 2030, double the agricultural productivity and incomes of small-scale food producers, in particular women, indigenous peoples, family farmers, pastoralists and fishers, including through secure and equal access to land, other productive resources and inputs, knowledge, financial services, markets and opportunities for value addition and non-farm employment.

SDG 2.4: By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality.

SDG 3.3: By 2030, end the epidemics of AIDS, tuberculosis, malaria and neglected tropical diseases and combat hepatitis, water-borne diseases and other communicable diseases.

SDG 3.4: By 2030, reduce by one third premature mortality from non-communicable diseases through prevention and treatment and promote mental health and well-being.

SDG 3.9: By 2030, substantially reduce the number of deaths and illnesses from hazardous chemicals and air, water and soil pollution and contamination.

SDG 6: Ensure availability and sustainable management of water and sanitation for all.

SDG 12.2: By 2030, achieve the sustainable management and efficient use of natural resources.

SDG 14.1: By 2025, prevent and significantly reduce marine pollution of all kinds, in particular from land-based activities, including marine debris and nutrient pollution.

SDG 14.2: By 2020, sustainably manage and protect marine and coastal ecosystems to avoid significant adverse impacts, including by strengthening their resilience, and take action for their restoration in order to achieve healthy and productive oceans.

SDG 14.3: Minimize and address the impacts of ocean acidification, including through enhanced scientific cooperation at all levels.

SDG 14.c: Enhance the conservation and sustainable use of oceans and their resources by implementing international law as reflected in UNCLOS, which provides the legal framework for the conservation and sustainable use of oceans and their resources.

SDG 15.1: By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements.

SDG 15.2: By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally.

SDG 15.5: Take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity and, by 2020, protect and prevent the extinction of threatened species.