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Impact-Weighted Accounts Project Research Report

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 monetized environmental impact estimates in a comparable way across companies 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 close to 2% (20%) 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. Close to 60% (53%) of the variation in environmental impact scaled by sales (operating income) is driven by industry membership, while approximately 30% (36%) can be attributed to firm specific factors, with the rest of the variation driven by country and more granular industry classifications. Environmental intensity exhibits significant, yet moderate correlation with various environmental ratings across industries and no correlation within industries, and it is associated with lower corporate market valuation, lower stock returns, and higher risk, consistent with investors viewing environmental impacts as financially material and pricing them in some but not all industries.

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.

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

[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/.

[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.

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 11.6%, but the median is only 1.9%. For several industries, such as utilities, construction materials, marine and airlines, the level of environmental impact is so large that it is equal to more than 25% of revenues. Similarly, we discover that the average environmental intensity scaled by operating income, assuming a zero discount rate, is 91.7% and the median is 19.4%. A handful of industries have such a high level of environmental impact that it is equivalent to over 150% of their operating income. Pricing of those environmental externalities would lead to significant value erosion for these firms.

Next, we seek to explain what drives variation in environmental intensity across organizations. For the intensity scaled by sales, we find that industry membership explains close to 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 significant factors. For example, the environmental intensity scaled by revenue (operating income) for an airline at the 75th percentile of the distribution is 32% (500%) while an airline at the 25th percentile of the distribution has an environmental intensity of 18% (234%). 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. We provide more detailed insights on the industries for which different ratings represent a

[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.

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

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, the relation persists after accounting for environmental ratings, which we find not to be related to valuation multiples. Third, we identify the industries, such as electronic equipment, textiles and apparel, construction materials, and chemicals, in which the relation between valuation multiples and environmental impact is the strongest. We infer that environmental impact is a financially material signal across most industries.

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 2018. 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.

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[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 (CO2); methane (CH4); nitrous oxide (N2O); hydrofluorocarbons (HFCs); perfluorocarbons (PFCs); sulphur hexafluoride (SF6), and nitrogen triflouride (NF3)

[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 (CO2); methane (CH4); nitrous oxide (N2O); hydrofluorocarbons (HFCs); perfluorocarbons (PFCs); sulphur hexafluoride (SF6), and nitrogen triflouride (NF3)

[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.

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 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

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[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.

[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.

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

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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.

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 Worldscope

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 2018, resulting in 87,426 organization-year observations. Of these 87,426 observations, only 15,356 have GHG total data. By adding data from Thomson Reuters's Asset4 ESG database, we attempt to both expand the quantity and verify the quality of the environmental data in our sample.

Research has documented large disagreements between ESG data providers that increase with the quantity of publicly available data (Christensen, Serafeim and Sikochi 2019). Moreover, the underlying ESG data of these ratings are often criticized for inconsistent quality, making analysis challenging. This uncertainty is in part driven by ESG data not being audited similarly to standard financial reports. Additionally, ESG data are not reported consistently, both in reporting formats across organizations and in the types of metrics. Reporting frameworks such as GRI and SASB have attempted to mitigate some of these issues by creating a standard set of metrics for organizations to report on, but additional progress is still necessary.

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 conduct an analysis of comparing values reported by Thomson Reuters and Bloomberg. First, we observe there are a substantial number of organizations with data covered by one provider and not the other. We collect data from 2010 to 2018, resulting in 19,972 organization-year observations that have data for total greenhouse gas emissions. Of these 19,972 observations, 11,576 have data from both Bloomberg and Thomson Reuters. 6,384 have data only from Thomson Reuters. 3,369 only have data from Bloomberg. Of the observations with data from both providers, the correlation between the data value reported by Bloomberg and Thomson Reuters is 0.9094. For values of water discharged, the correlation is 0.6786 and for values of water withdrawal, the correlation is 0.1360. Moreover, this correlation varies notably across years. For example,

[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.

the water discharge correlation is 0.3045 in 2016 but 0.9375 in 2015, suggesting that a few errors of large magnitude between the Bloomberg data and Thomson Reuters in certain years may be affecting the overall correlation values. Table 1 describes the overlap in emissions data as reported by Bloomberg and Thomson Reuters. Table 1 also includes correlation coefficients, reported yearly, for observations with both Bloomberg and Thomson Reuters data.

Table 1: Reporting Difference between Bloomberg and Thomson Reuters and Correlation Coefficients of Matched Data Points

	Year	Bloomberg Observations	Thomson Reuters Observations	Matched Observations	Correlation
GHG total	2010	983	1,502	799	0.9089
	2011	1,114	1,640	907	0.8935
	2012	1,306	1,783	1,023	0.8981
	2013	1,588	1,843	1,201	0.9101
	2014	1,819	1,941	1,339	0.9109
	2015	1,973	2,157	1,484	0.9093
	2016	2,131	2,338	1,624	0.9035
	2017	2,136	2,509	1,657	0.8948
	2018	2,306	2,247	1,546	0.9698
	Total	15,356	17,960	11,580	0.9094
Water withdrawal	2010	443	1,080	334	0.8482
	2011	537	1,205	399	0.2429
	2012	687	1,345	497	0.9043
	2013	817	1,449	586	0.9653
	2014	970	1,561	706	0.7576
	2015	1,490	1,690	1,107	0.7919
	2016	1,642	1,838	1,224	0.0801
	2017	1,958	1,997	1,426	0.0646
	2018	1,844	1,783	1,208	0.5394
	Total	10,388	13,948	7,487	0.1360
Water discharged	2010	533	398	274	0.9258
	2011	607	442	316	0.9308
	2012	655	492	352	0.9386
	2013	738	545	402	0.9122
	2014	818	595	447	0.9050

	2015	857	625	464	0.9375
	2016	886	678	500	0.3045
	2017	913	765	544	0.4993
	2018	957	685	509	0.6998
	Total	6,964	5,225	3,808	0.6786
NOx	2010	561	509	368	0.9677
	2011	607	543	396	0.9069
	2012	673	579	440	0.9145
	2013	723	603	462	0.9516
	2014	763	639	491	0.9883
	2015	799	658	510	0.1211
	2016	841	693	539	0.1444
	2017	897	803	588	0.1580
	2018	982	723	570	0.1768
	Total	6,846	5,750	4,364	0.2175
SOx	2010	556	498	373	0.1215
	2011	608	523	403	0.1201
	2012	667	551	434	0.7120
	2013	716	583	457	0.6497
	2014	759	609	482	0.9963
	2015	789	629	498	0.3449
	2016	824	665	525	0.4063
	2017	877	773	578	0.4235
	2018	954	698	559	0.3208
	Total	6,750	5,529	4,309	0.2346
VOC	2010	236	269	171	0.9292
	2011	271	287	192	0.7485
	2012	302	301	213	0.9958
	2013	334	320	231	0.9980
	2014	363	345	252	0.9974
	2015	360	347	253	0.9987
	2016	375	363	265	0.9995
	2017	375	379	267	0.9884
	2018	386	346	253	0.5806

Total	3,002	2,957	2,097	0.8834

Table 1 describes the emissions and water data collected from Bloomberg and Thompson Reuters for each year in our sample. Other than correcting for units, data are exactly as reported by Bloomberg and Thompson Reuters. The column Bloomberg (or Thomson Reuters) observations is the total number of observations that have non-missing data for that emissions/water variable from Bloomberg (Thomson Reuters). Matched Observations counts the number of observations that have both non-missing data from Bloomberg and Thomson Reuters for that emissions/water variable. Correlations are pairwise correlations such that N is the number of Matched Observations.

To minimize concerns about the quality of the environmental data, we create a methodology to attempt to confirm their accuracy. We create two separate methodologies, one for observations that have data from both providers and one for observations that have data from only one provider.

Test 1 – Matched Observations

If an observation has data from both Bloomberg and Thomson Reuters, we compare both values against each other and require a certain level of agreement. Specifically, if the absolute difference between the Bloomberg and the Thomson Reuters values divided by the average of the two values is greater than 10%, we remove those values from our analysis. However, this 10% cut-off is more easily breached by smaller values. If both values are small, a smaller absolute difference will result in a larger percent difference than if both values are large. If both values are small, even if the percent difference is greater than 10%, the difference in the final environmental impact will be small and economically insignificant. Therefore, if both values from Bloomberg and Thomson Reuters are in the bottom quintile of the distribution of that variable (in a given year), the values are kept in our analysis even if the percent difference of the two variables is greater than 10%. If an observation has data from both Bloomberg and Thompson Reuters, we use the Bloomberg data as default values in our analysis. Using Thomson Reuters data instead keeps all our inferences intact.

Test 2 – Unmatched Observations

If values are only available from one of the two data providers, 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. Table 2 defines the number of observations lost for each step of Test 1 and Test 2 for GHG total, water withdrawal, and water discharged.

To assess the efficacy of Test 2, we administer Test 2 to observations that have passed Test 1, as those values have been confirmed accurate with a high degree of certainty. Conditioning on observations that pass Test 1, we find an organization's GHG total intensity to be fairly consistent year-over-year. This analysis produces a median value of -2%, with the 10th percentile of the distribution being -24% and the 90th percentile being 27%. Replicating this test for other emissions/water types produces similar results. We, therefore, conclude that Test 2 is a reasonable test to assess the accuracy of an organization's data, as organizational intensity is, on average, fairly consistent year-over-year.

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 19,914 organization-year observations. Figure 3 describes summary statistics for this sample.

Table 2: Observations Gained and Lost through Bloomberg-Thomson Reuters Agreement Tests

		GHG Total			Water Withdrawal			Water Discharged		
		Gain/Loss	Initial Total Observations	New Total	Gain/Loss	Initial Total Observations	New Total	Gain/Loss	Initial Total Observations	New Total
Test 1: Matched Observations	Match Test 1	-1827	11,580	9,753	-1142	7,487	6,345	-525	3,808	3,283
	Match Test 2	+268	11,580	10,021	+80	7,487	6,425	+32	3,808	3,315
Test 2: Only Thompson Reuters Data	No Match Test 1	-438	6,380	5,942	-491	6,461	5,970	-103	1,417	1,314
	No Match Test 2	+292	6,380	6,234	+335	6,461	6,305	+59	1,417	1,373
Test 2: Only Bloomberg Data	No Match Test 1	-245	3,776	3,531	-164	2,901	2,737	-208	3,156	2,948
	No Match Test 2	+128	3,776	3,659	+82	2,901	2,819	+103	3,156	3,051
		Final Observation Count		19,914	Final Observation Count		15,549	Final Observation Count		7,739
		Observations Lost		-3,198	Observations Lost		-2,294	Observations Lost		-1,030
		Retention Rate		91.6%	Retention Rate		92.3%	Retention Rate		92.3%

Test 1 addresses observations that have data both from Bloomberg and Thomson Reuters. Match Test 1 sets an observation to missing if the absolute difference of the Bloomberg and Thomson Reuters value, divided by the average of the two values, is greater than 10%. If an observation fails Match Test 1 (is set missing), it continues to Match Test 2. For an observation that fails Match Test 1, yet both Bloomberg and Thomson Reuters values are in the bottom quintile of that emission's distribution (distributions calculated on a yearly basis), Match Test 2 supersedes Match Test 1 and does not set that observation to missing. Test 2 addresses only observations that have data from either Bloomberg or Thomson Reuters but not both. No Match Test 1 sets an observation to missing if the intensity value (emission value divided by revenue) in year t is 50% greater or lesser than the intensity value in year $t-1$. If an observation fails No Match Test 1, it proceeds to No Match Test 2. If an observation fails No Match Test 1 (year t), but the intensity value in year $t+1$ does not fail No Match Test 1 (intensity value in year $t+1$ does not increase or decrease by a magnitude of at least 50% relative to year t), that observation (year t) is not set to missing.

Table 3: Summary Statistics of Sample

	Obs.	Mean	Median	S.D.	Min	Max
GHG total	19,914	3,888,781	189,444	18,900,000	0	676,000,000
Water withdrawal	12,176	226,000,000	2,191,757	2,240,000,000	0	72,600,000,000
Water discharged	5,534	183,000,000	3,384,081	1,310,000,000	0	36,100,000,000
Water discharged (imputed)	12,556	163,000,000	1,440,624	1,500,000,000	0	49,400,000,000
SOx	5,343	23,128	204	160,991	0	4,008,760
NOx	5,629	33,818	721	390,642	0	10,100,000
VOC	2,896	525,306	298	15,300,000	0	638,000,000
Carbon offsets	1,881	1,276,189	9,545	10,000,000	0	243,000,000

Table 3 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 a value 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 19,914 observations in our sample, 14,285 are missing NOx data, 17,018 are missing VOC data, 14,571 are missing SOx data, 7,738 are missing water withdrawal data, and 14,380 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

[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.

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 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 4,727 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 0.6796 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

[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.

[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).

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. 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 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

[28] GHG emissions are reduced by carbon offsets.

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 20% imputed contribution to environmental impact. We find the average imputed contribution is less than 10%. This restriction produces a final sample of 13,228 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 Figure 4). 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.

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. Table 4 shows summary statistics for the sample's environmental intensity. The average intensity value scaled by sales, when the discount rate is zero, stands at 11.6%. The median is much lower than the mean at 1.9% and the third quartile of the distribution at 8.8%. This means that a minority of firms have very large values bringing the average up. As expected, environmental intensity is lower when discount rate is 3%. The average stands at 6.6% with the median of 0.8% and the third quartile at 3.8%.

The environmental intensity values scaled by operating income demonstrate even greater variability, as shown by large interquartile ranges. The average value, when the discount rate is zero, is 91.7%, with the median of 19.4% and the third quartile of the distribution at 86.8%. Therefore, similar to

[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.

the environmental intensity scaled by sales, a small number of firms with large values pull the average up. The average, when the discount rate is 3%, stands at 56.2%. The median is significantly lower at 8.1% and the third quartile stands at 37.4%. The environmental intensity scaled by operating income is also lower when the discount rate is 3%. The average stands at 56.2% with the median of 8.1% and the third quartile at 37.4%.

Table 4: Summary Statistics for Environmental Intensity

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

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

Table 5 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 58%, 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 64%, 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 close to 60%. The last model replaces industry with subindustry effects. The explanatory power increases from 64% to 69%, 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 5: Sources of Variation in Environmental Intensity

Environmental Intensity	Year effects	+ Industry effects	+ Industry, Country effects	+ Country effects	+ Subindustry, Country effects
Env Imp / Sales 0%	0.03%	58.48%	63.80%	11.36%	69.03%
Env Imp / Op Inc 0%	-0.03%	52.92%	58.11%	10.14%	63.31%

Table 5 describes the 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. Table 6 shows the average, first and third quartiles for environmental intensity, along with the number of observations for each industry. Not surprisingly, industries in the utility sector score very high. The same is true for industries in the transportation sector (marine and airlines), but also in resources (metals and mining, as well as oil and gas). Construction materials, 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 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 four 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 18% in the third and first quartiles respectively.[30]

The side-by-side comparison of industry-specific distributions of environmental intensity values scaled by sales and operating income points to another interesting note: Table 6 demonstrates 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 one of the lowest median environmental intensity values of 0.3% when scaled by sales, the median intensity value of air freight and logistics industry spikes up to 18.3% when scaled by profit. Likewise, other industries with low profit margins such as construction and engineering, machinery, and automobiles display an analogous trend.

As expected, in most of the cases, the distribution of environmental intensity shifts to the left 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. For example, the decline in environmental intensity is more pronounced for electric utilities and construction materials industries than for independent power and renewable electricity providers and the marine industry. 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.

[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.

Table 6: Summary Statistics of Environmental Intensity by Industry

	Env Imp / Sales						Env Imp / Op Inc						
	Discount Rate 0%			Discount Rate 3%			Discount Rate 0%			Discount Rate 3%			
GICS Industry	Median	Q3	Q1	Median	Q3	Q1	Median	Q3	Q1	Median	Q3	Q1	N
Electric Utilities	100.0%	100.0%	53.4%	41.3%	71.8%	22.3%	500.0%	500.0%	330.9%	311.8%	500.0%	144.6%	328
Independent Power and Renewable Electricity Producers	100.0%	100.0%	19.8%	69.3%	100.0%	9.9%	500.0%	500.0%	98.2%	500.0%	500.0%	40.2%	148
Construction Materials	87.5%	100.0%	26.9%	34.2%	68.4%	11.4%	500.0%	500.0%	441.9%	309.7%	500.0%	168.8%	195
Multi-Utilities	73.8%	100.0%	28.8%	29.8%	48.3%	11.8%	460.3%	500.0%	214.4%	186.2%	318.2%	82.4%	139
Marine	60.9%	61.0%	39.4%	66.4%	73.9%	47.8%	494.1%	500.0%	488.2%	500.0%	500.0%	500.0%	3
Airlines	26.7%	31.7%	18.0%	10.1%	11.8%	7.2%	384.2%	500.0%	233.9%	147.3%	261.9%	93.6%	103
Paper & Forest Products	21.3%	24.9%	17.7%	10.5%	13.3%	8.1%	388.5%	500.0%	205.9%	202.9%	351.5%	104.1%	77
Metals & Mining	19.1%	41.3%	9.6%	9.1%	21.2%	4.5%	129.4%	444.1%	49.5%	62.8%	210.3%	25.1%	540
Oil, Gas & Consumable Fuels	17.0%	29.5%	8.4%	7.1%	12.9%	3.4%	119.9%	263.6%	60.9%	49.2%	114.5%	24.6%	449
Gas Utilities	14.8%	16.8%	12.8%	5.8%	6.4%	5.0%	30.6%	46.5%	27.0%	11.7%	18.5%	10.4%	11
Chemicals	13.1%	31.0%	7.7%	5.5%	12.9%	3.2%	153.9%	314.4%	72.9%	65.9%	136.2%	31.8%	749
Water Utilities	9.3%	19.8%	5.6%	3.4%	7.1%	2.1%	43.5%	114.9%	16.0%	15.8%	41.6%	5.8%	49
Containers & Packaging	7.8%	16.3%	5.7%	3.5%	7.8%	2.6%	138.6%	210.8%	79.7%	57.4%	92.4%	42.5%	85
Industrial Conglomerates	5.5%	12.9%	1.8%	2.2%	5.5%	0.7%	67.2%	177.4%	26.5%	26.8%	70.7%	10.7%	181
Semiconductors & Semiconductor Equipment	5.4%	9.3%	1.1%	2.1%	3.5%	0.5%	38.9%	91.6%	8.5%	14.5%	34.9%	3.6%	408
Textiles, Apparel & luxury goods	4.4%	10.1%	0.8%	1.9%	4.1%	0.4%	41.5%	175.8%	5.5%	17.9%	76.8%	3.3%	120
Road & Rail	3.5%	7.3%	2.3%	1.4%	2.9%	0.9%	46.3%	72.5%	19.6%	18.6%	28.9%	7.8%	120
Equity Real Estate Investment Trusts (REITs)	3.5%	7.2%	1.7%	1.5%	3.8%	0.7%	12.5%	30.0%	4.4%	5.3%	17.0%	1.7%	558
Transportation Infrastructure	3.4%	7.4%	0.9%	1.3%	5.6%	0.3%	13.0%	24.4%	2.7%	4.9%	26.3%	1.0%	48
Energy Equipment & Services	2.9%	19.3%	0.0%	1.8%	7.2%	0.0%	34.1%	160.0%	0.0%	17.3%	67.4%	0.0%	66
Food Products	2.9%	6.3%	1.7%	1.2%	3.1%	0.7%	46.4%	85.6%	19.3%	19.1%	38.7%	8.1%	480
Hotels, Restaurants & Leisure	2.6%	5.6%	1.1%	1.1%	2.3%	0.4%	17.2%	46.0%	5.6%	6.9%	19.4%	2.3%	461

Building Products	2.4%	9.8%	1.3%	0.9%	3.8%	0.5%	27.9%	133.6%	12.0%	10.2%	50.4%	4.4%	183
Household Products	2.2%	10.7%	1.7%	1.3%	5.6%	1.0%	12.4%	69.7%	9.9%	7.0%	35.8%	5.4%	57
Auto Components	2.2%	4.3%	1.5%	0.9%	1.7%	0.5%	31.9%	53.1%	18.9%	12.0%	20.7%	7.3%	329
Beverages	2.1%	3.7%	1.3%	1.0%	1.9%	0.6%	17.8%	35.2%	9.7%	8.2%	18.9%	5.4%	198
Wireless Telecommunication Services	1.9%	3.3%	1.0%	0.7%	1.2%	0.4%	10.6%	19.4%	5.9%	4.0%	7.5%	2.3%	211
Electronic Equipment, Instruments & Components	1.9%	6.8%	0.8%	0.7%	2.7%	0.3%	25.8%	95.2%	9.0%	10.3%	39.0%	3.5%	456
Electrical Equipment	1.6%	2.7%	0.9%	0.6%	1.2%	0.4%	19.4%	55.1%	11.8%	8.4%	21.7%	4.6%	237
Personal Products	1.6%	2.8%	0.9%	1.1%	1.2%	0.7%	15.3%	27.0%	8.7%	9.4%	12.0%	5.1%	37
Food & Staples Retailing	1.5%	2.5%	0.9%	0.6%	1.0%	0.3%	38.4%	84.9%	25.3%	15.0%	32.6%	9.5%	225
Biotechnology	1.5%	2.3%	0.7%	0.8%	1.2%	0.3%	6.0%	9.4%	2.4%	3.1%	5.1%	1.1%	68
Aerospace & Defense	1.4%	2.0%	1.0%	1.1%	1.3%	0.9%	16.5%	61.8%	11.3%	13.0%	40.7%	8.9%	49
Diversified Telecommunication Services	1.4%	2.4%	0.8%	0.5%	0.9%	0.3%	8.8%	17.4%	4.5%	3.4%	6.5%	1.8%	308
Diversified Consumer Services	1.3%	1.8%	1.1%	0.5%	0.7%	0.4%	5.7%	6.6%	3.7%	2.1%	2.4%	1.4%	19
Real Estate Management & Development	1.2%	3.8%	0.6%	0.5%	1.7%	0.2%	5.4%	12.9%	2.7%	2.2%	5.7%	1.1%	478
Entertainment	1.2%	2.4%	0.3%	0.5%	0.9%	0.1%	6.7%	25.7%	2.1%	3.4%	9.3%	0.9%	47
Machinery	1.1%	2.0%	0.6%	0.5%	0.8%	0.3%	15.2%	33.9%	7.8%	6.0%	13.1%	3.3%	543
Multiline Retail	1.1%	2.1%	0.8%	0.4%	0.8%	0.3%	16.4%	40.3%	12.8%	6.2%	15.8%	4.8%	113
Commercial Services & Supplies	1.1%	5.6%	0.4%	0.4%	2.3%	0.2%	15.0%	114.1%	6.3%	5.9%	41.4%	2.3%	289
Health Care Providers & Services	1.1%	1.9%	0.5%	0.4%	0.7%	0.2%	8.1%	18.4%	4.7%	3.3%	6.9%	2.0%	69
Diversified Financial Services	1.1%	7.3%	0.3%	0.4%	1.0%	0.1%	4.4%	16.8%	1.0%	1.7%	4.0%	0.4%	54
Construction & Engineering	1.0%	2.7%	0.5%	0.4%	1.2%	0.2%	27.0%	69.1%	13.0%	10.7%	27.0%	5.1%	324
Automobiles	1.0%	1.4%	0.8%	0.4%	0.6%	0.3%	18.8%	30.5%	11.4%	7.9%	15.4%	4.5%	187
Distributors	1.0%	1.0%	0.7%	0.3%	0.4%	0.3%	23.0%	38.9%	14.6%	8.4%	14.7%	5.3%	10
Pharmaceuticals	0.9%	2.3%	0.6%	0.4%	1.0%	0.3%	6.5%	16.2%	3.3%	2.6%	6.3%	1.3%	274
Specialty Retail	0.8%	1.3%	0.5%	0.3%	0.5%	0.2%	9.0%	16.8%	5.1%	3.4%	6.6%	2.0%	265

Life Sciences Tools & Services	0.8%	5.7%	0.7%	0.4%	2.1%	0.3%	5.7%	49.0%	3.7%	2.4%	17.9%	1.5%	67
Tobacco	0.8%	9.0%	0.7%	0.3%	7.1%	0.3%	2.8%	26.6%	2.4%	1.2%	21.1%	1.0%	22
Media	0.8%	1.5%	0.3%	0.4%	0.6%	0.2%	8.2%	16.9%	2.5%	3.8%	7.8%	2.0%	74
Technology Hardware, Storage & Peripherals	0.8%	1.7%	0.5%	0.3%	0.6%	0.2%	22.2%	38.2%	11.2%	8.5%	14.6%	4.2%	255
Health Care Equipment & Supplies	0.7%	2.1%	0.5%	0.3%	0.9%	0.2%	4.6%	12.8%	2.4%	1.8%	5.5%	1.0%	128
Trading Companies & Distributors	0.6%	1.4%	0.3%	0.2%	0.5%	0.1%	7.4%	17.2%	4.3%	2.8%	6.3%	1.6%	147
Communications Equipment	0.6%	1.5%	0.5%	0.3%	0.6%	0.2%	3.9%	9.9%	2.2%	1.8%	3.7%	1.0%	45
Air Freight & Logistics	0.5%	2.6%	0.0%	0.2%	1.3%	0.0%	18.3%	40.0%	0.0%	6.6%	19.4%	0.0%	13
IT Services	0.5%	0.9%	0.2%	0.2%	0.4%	0.1%	4.4%	7.3%	1.9%	1.9%	3.0%	0.7%	243
Household Durables	0.5%	1.2%	0.2%	0.2%	0.5%	0.1%	7.4%	22.4%	1.3%	2.8%	8.9%	0.5%	273
Leisure Products	0.5%	1.0%	0.4%	0.2%	0.4%	0.2%	6.5%	13.5%	4.4%	3.2%	5.6%	1.8%	45
Internet & Direct Marketing Retail	0.4%	1.1%	0.3%	0.2%	0.4%	0.1%	3.3%	10.2%	2.4%	1.8%	5.1%	0.9%	59
Professional Services	0.3%	0.8%	0.1%	0.1%	0.3%	0.1%	3.0%	8.0%	1.4%	1.1%	3.3%	0.5%	143
Interactive Media & Services	0.3%	1.1%	0.1%	0.1%	0.4%	0.0%	1.4%	3.1%	0.1%	0.5%	1.3%	0.1%	41
Software	0.3%	0.4%	0.2%	0.1%	0.2%	0.1%	1.4%	2.6%	0.9%	0.5%	1.0%	0.4%	133
Banks	0.3%	0.5%	0.1%	0.1%	0.2%	0.1%	1.3%	2.4%	0.6%	0.5%	1.0%	0.3%	588
Capital Markets	0.2%	0.4%	0.1%	0.1%	0.2%	0.0%	0.7%	1.6%	0.3%	0.3%	0.6%	0.1%	301
Consumer Finance	0.2%	0.5%	0.1%	0.1%	0.2%	0.0%	0.8%	1.7%	0.5%	0.4%	0.7%	0.2%	45
Thrifts & Mortgage Finance	0.1%	0.2%	0.1%	0.1%	0.1%	0.0%	0.5%	0.7%	0.3%	0.2%	0.3%	0.1%	20
Insurance	0.1%	0.2%	0.0%	0.0%	0.1%	0.0%	1.0%	2.1%	0.5%	0.4%	0.9%	0.2%	187

Table 6 describes summary statistics for environmental intensity by GICS industry. Discount rates are calculated by discounting EPS monetary factors. Median, Q3 and Q1 refer to the median, third and first quartile of the distribution of environmental intensity across firm-year observations in each industry. N is the number of observations and observations are firm-year pairs. Industries are sorted by descending order of Env Imp / Sales 0%.

4.2 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. Table 7 presents univariate correlation estimates. 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.[31] 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 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.[32]

Table 7: Correlation Matrix of Environmental Intensity and Ratings

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

Table 7 is the univariate correlation matrix for the environmental intensity scaled by sales and operating income (0% discount rate), environmental intensity scaled by sales and operating income (3% discount rate), MSCI environment rating, RobecoSAM environment rating, and Sustainalytics environment rating. Across all tables hereafter, MSCI, RobecoSAM and Sustainalytics will be simplified using the first letter of their names – M, RS, and S, respectively.

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 8 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

[31] We log transform the environmental intensity to decrease the skewness of the distribution that we documented in Table 4.

[32] 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).

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 8: 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 8 describes the OLS results of regressing environmental ratings on environmental intensity scaled by sales for 0% discount rate. MSCI, RobescoSAM, 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.

The results above provide, on average, evidence across many industries. Whether ratings reflect intensity might differ across industries. Table 9 shows estimated univariate correlation coefficients for each industry, along with p-values and number of observations. 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.

In an untabulated analysis, 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 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.

Table 9: Correlation between Environmental Intensity and Ratings by Industry

GICS Industry	E Rating M	E Rating RS	E Rating S	p-value M	p-value RS	p-value S	N M	N RS	N S
Independent Power & Renewable El. Pr.	-0.714	0.115	0.218	0.000	0.620	0.188	98	21	38
Commercial Services & Supplies	-0.624	-0.147	-0.193	0.000	0.283	0.226	198	55	41
Multi-Utilities	-0.531	-0.604	-0.153	0.000	0.000	0.186	123	37	76
Chemicals	-0.510	-0.228	-0.130	0.000	0.006	0.209	485	145	95
Building Products	-0.374	0.186	0.486	0.000	0.264	0.019	120	38	23
Oil, Gas & Consumable Fuels	-0.358	-0.047	-0.129	0.000	0.627	0.141	374	109	132
Construction Materials	-0.343	0.504	-0.472	0.000	0.002	0.528	139	36	4
Industrial Conglomerates	-0.326	-0.481	-0.014	0.000	0.001	0.947	126	44	25
Food & Staples Retailing	-0.312	-0.268	0.200	0.000	0.038	0.243	190	60	36
Machinery	-0.260	-0.188	-0.320	0.000	0.046	0.030	378	113	46
Pharmaceuticals	-0.258	-0.486	0.247	0.000	0.000	0.124	232	76	40
Electric Utilities	-0.215	0.161	-0.039	0.000	0.163	0.673	281	76	118
Airlines	-0.202	-0.053	0.278	0.081	0.810	0.189	76	23	24
Electronic Equipment, Instr. & Comp.	-0.183	0.051	-0.363	0.002	0.658	0.032	293	77	35
Electrical Equipment	-0.160	-0.175	-0.268	0.049	0.224	0.315	152	50	16
Textiles, Apparel & luxury goods	-0.156	-0.319	-0.093	0.197	0.246	0.751	70	15	14
Specialty Retail	-0.144	-0.229	-0.049	0.036	0.140	0.688	211	43	70
Insurance	-0.132	0.215	0.281	0.129	0.228	0.244	133	33	19
Beverages	-0.121	-0.149	0.302	0.136	0.277	0.093	152	55	32
Construction & Engineering	-0.116		0.143	0.087		0.572	217	1	18
Automobiles	-0.111	-0.191	-0.592	0.157	0.203	0.026	165	46	14
Food Products	-0.106	-0.239	-0.379	0.064	0.016	0.000	306	102	90
Banks	-0.102	-0.370	-0.597	0.030	0.000	0.000	449	164	79
Technology Hardware, Storage & Per.	-0.082	-0.061	-0.636	0.293	0.686	0.005	167	46	18
Equity Real Estate Investment Trusts	-0.080	-0.118	0.080	0.121	0.164	0.364	373	141	132
Diversified Telecommunication Services	-0.073	-0.078	-0.793	0.256	0.502	0.000	242	76	40
Road & Rail	-0.072	-0.304	0.096	0.505	0.140	0.779	88	25	11

Auto Components	-0.052	-0.169	0.215	0.440	0.175	0.313	222	66	24
Software	-0.051	0.200	0.223	0.608	0.290	0.064	103	30	70
Metals & Mining	-0.051	0.094	-0.017	0.318	0.340	0.857	391	106	110
Semiconductors & Sem. Equipment	-0.039	0.081	-0.198	0.562	0.503	0.076	229	71	81
Hotels, Restaurants & Leisure	-0.037	-0.011	0.068	0.495	0.916	0.502	336	93	101
Capital Markets	-0.033	-0.373	-0.618	0.631	0.003	0.000	218	62	58
IT Services	0.003	-0.102	0.180	0.973	0.473	0.220	179	52	48
Health Care Equipment & Supplies	0.014	-0.592	0.342	0.883	0.001	0.026	116	28	42
Professional Services	0.027	-0.047	0.601	0.778	0.796	0.039	113	32	12
Household Durables	0.052	-0.039	-0.339	0.475	0.797	0.097	191	47	25
Multiline Retail	0.114	0.505	-0.560	0.275	0.012	0.002	93	24	27
Wireless Telecommunication Services	0.117	-0.199	0.843	0.141	0.154	0.001	161	53	12
Trading Companies & Distributors	0.124	-0.228	-0.329	0.175	0.181	0.145	122	36	21
Real Estate Management & Development	0.147	0.049	0.443	0.007	0.651	0.023	328	89	26

Table 9 describes the univariate correlations between the environmental ratings of MSCI, RobecoSAM, and Sustainalytics and environmental intensity scaled by sales. N is the number of observations for each ratings by GICS industry and observations are firm-year pairs. Results are sorted by magnitude of correlation estimate between MSCI environmental rating and environmental intensity (the most negative estimates on top).

4.3 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.[33] 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 risk and return.

Table 10 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.[34] This is after controlling for other determinants of valuation ratios, such as return on assets in the first model, as well as return on equity and leverage in the second model. 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 2.5% lower Tobin's Q and 5.0% 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 1.4% (7.8%) lower Tobin's Q (price to book value of equity).

Table 10: Market Pricing of Environmental Intensity

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

Table 10 describes OLS models that regress independent variables (environmental intensity) on dependent variables, Tobin's Q and Price to Book Value of Equity. Tobin's Q is a measure of market value over the replacement value of assets. ROA is return on assets. ROE is return on equity. All models include year, country, and industry effects. Both dependent variables and the independent variables are log-transformed. N is the number of observations. Observations are firm-year pairs.

Table 11 presents the estimates for Tobin's Q after including the environmental ratings as independent variables, as the results for the other valuation multiple are broadly similar. We note that the sample decreases sharply especially when including the RobecoSAM or Sustainalytics ratings, and

[33] 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.

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

therefore those results need to be interpreted with caution. The coefficient on environmental intensity remains statistically significant except for when including the Sustainalytics rating, whose sample is much smaller at 2,170 observations. The MSCI and Sustainalytics ratings exhibit no correlation with Tobin's Q, while the RobecoSAM rating exhibits a negative correlation, suggesting that firms with better environmental rating according to that data provider trade at a discount.

Table 11: Market Pricing of Environmental Intensity Controlling for Environmental Ratings

Dependent Variable	Tobin's Q					
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	0.050	0.432	0.086	0.216	0.149	0.398
Env Imp / Sales 0%	-0.020	0.016	-0.028	0.014	-0.012	0.527
E Rating M	0.003	0.294				
E Rating RS			-0.010	0.001		
E Rating S					-0.001	0.402
ROA	3.910	0.000	4.235	0.000	3.032	0.000
N	9,506		2,721		2,170	

Table 11 describes OLS models that regress independent variables on dependent variable Tobin's Q. 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. The dependent variable and the independent variable (environmental intensity) are log-transformed. N is the number of observations in each model. Observations are firm-year pairs.

Table 12 presents estimated coefficients on environmental intensity, examining the intensity value's relation with the Sharpe ratio (i.e. stock return over volatility), its components and market beta. Panels A and C (B and D) scale environmental impact by sales (operating income). Panels C and D further include the environmental ratings as a control variable in addition to year, industry, and country fixed effects. For the sake of conciseness, we calculate the average across ratings for each firm-year.

The key insights are as follows: First, environmental intensity is significantly and negatively 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. Moreover, they exhibit higher systematic risk as reflected by higher beta. Environmental intensity scaled by operating income is even more strongly associated with these financial characteristics. Finally, environmental ratings do not exhibit a significant relationship with any of the financial characteristics other than volatility.

Table 12: Financial Materiality of Environmental Intensity

Dependent Variable	Sharpe ratio		Stock return		Volatility		Beta	
Panel A								
Variable	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	-0.216	0.055	-7.644	0.027	20.294	0.000	0.859	0.000
Env Imp / Sales 0%	-0.045	0.001	-0.850	0.034	0.661	0.000	0.039	0.014
N	12,375		12,880		12,379		11,311	
Panel B								
Variable	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	-0.319	0.000	-11.353	0.000	19.630	0.000	0.838	0.000

Env Imp / Op Inc 0%	-0.070	0.000	-1.520	0.000	0.791	0.000	0.048	0.000
N	11,681		12,150		11,684		10,656	
Panel C								
Variable	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	-0.173	0.204	-4.708	0.270	24.277	0.000	0.852	0.000
Env Imp / Sales 0%	-0.039	0.009	-0.724	0.099	0.375	0.043	0.035	0.059
Env Rating	0.002	0.742	0.016	0.931	-0.515	0.000	0.000	0.944
N	9,375		9,746		9,375		8,528	
Panel D								
Variable	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	-0.223	0.038	-6.569	0.010	23.933	0.000	0.829	0.000
Env Imp / Op Inc 0%	-0.061	0.000	-1.266	0.000	0.695	0.000	0.050	0.000
Env Rating	-0.004	0.556	-0.196	0.292	-0.457	0.000	0.001	0.872
N	8,950		9,299		8,950		8,144	

Table 12 describes OLS models that regress independent variable, log-transformed environmental intensity, on dependent variables, Sharpe ratio, stock return, stock price volatility, and market beta. Sharpe ratio is defined as stock return over the calendar year divided by stock price volatility over the calendar year. Market beta is calculated as the relationship between firm stock returns and country market returns using monthly data over the past 3 years. All models also include year, industry, and country fixed effects. Specifications for the environmental intensity calculated using a 0% discount rate are included. Panels C and D also include control for the average rating across MSCI, RobecoSAM and Sustainalytics (denoted as Env Rating).

Table 13 estimates the relation between environmental intensity and each of the financial characteristics separately for each industry.[35] We use Env Impact / Op Inc 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, and whether environmental impact is associated with risk and return characteristics across different industries.

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

[35] To ensure more robust estimates, we only include estimates for industries that we have at least 20 degrees of freedom.

Table 13: Market Pricing, Returns, Risk and Environmental Intensity by Industry

	Tobin's Q		Sharpe ratio		Stock return		Volatility		Beta	
GICS Industry	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Construction Materials	-0.373	0.001	-0.662	0.001	-11.763	0.001	1.437	0.340	0.056	0.520
Specialty Retail	-0.322	0.001	0.013	0.870	0.262	0.906	0.953	0.269	0.042	0.636
Textiles, Apparel & luxury goods	-0.316	0.000	-0.131	0.368	-1.084	0.843	0.815	0.469		
Multiline Retail	-0.264	0.018			-9.237	0.009				
Health Care Equipment & Supplies	-0.246	0.001	-0.129	0.170	-4.848	0.096	-0.756	0.431		
Trading Companies & Distributors	-0.197	0.003	-0.102	0.248	-1.826	0.553	2.419	0.017	0.176	0.100
Pharmaceuticals	-0.184	0.000	-0.101	0.212	-1.387	0.436	0.537	0.465	0.085	0.345
IT Services	-0.177	0.000	-0.216	0.014	-3.541	0.250	3.189	0.001	-0.096	0.156
Capital Markets	-0.176	0.064	0.001	0.993	0.087	0.977	0.262	0.816	-0.299	0.026
Machinery	-0.153	0.000	-0.081	0.008	-1.223	0.205	1.343	0.006	0.094	0.010
Electronic Equipment, Instruments & Comp.	-0.151	0.000	-0.130	0.005	-4.023	0.019	1.420	0.001	0.089	0.035
Wireless Telecommunication Services	-0.150	0.325	0.154	0.198	2.976	0.282	0.210	0.779	0.446	0.005
Building Products	-0.148	0.001	-0.179	0.002	-4.048	0.003	1.726	0.008	0.083	0.036
Chemicals	-0.144	0.000	-0.145	0.000	-2.391	0.060	1.036	0.067	0.146	0.023
Technology Hardware, Storage & Peripherals	-0.139	0.022	-0.173	0.025	-5.564	0.012	0.498	0.337	0.047	0.264
Semiconductors & Semiconductor Equipment	-0.126	0.000	-0.148	0.000	-2.978	0.039	1.432	0.022	0.074	0.006
Food Products	-0.124	0.000	-0.142	0.008	-2.753	0.018	0.344	0.538	-0.036	0.363
Beverages	-0.122	0.002	-0.128	0.187	-3.470	0.143	1.762	0.265	-0.012	0.839
Professional Services	-0.091	0.363	0.058	0.685	2.239	0.430	0.735	0.578	0.147	0.346
Commercial Services & Supplies	-0.090	0.001	-0.006	0.894	-0.635	0.562	0.680	0.122	-0.063	0.151
Diversified Telecommunication Services	-0.088	0.060	-0.059	0.635	1.378	0.576	1.661	0.018	0.075	0.135
Electrical Equipment	-0.085	0.072	0.042	0.638	2.211	0.460	0.904	0.173	0.010	0.792
Automobiles	-0.084	0.036	-0.140	0.137	-4.300	0.145	-0.353	0.763	0.122	0.002
Household Durables	-0.083	0.038	-0.087	0.239	-1.941	0.367	-0.009	0.992	0.106	0.036
Auto Components	-0.082	0.022	-0.125	0.011	-3.790	0.024	0.451	0.374	0.000	0.996
Metals & Mining	-0.080	0.000	-0.059	0.177	-1.812	0.321	0.691	0.169	0.051	0.236
Food & Staples Retailing	-0.077	0.080	-0.091	0.268	-1.168	0.502	0.263	0.692	-0.094	0.225

Insurance	-0.061	0.215	-0.184	0.265	-6.559	0.011	0.495	0.556	0.299	0.049
Oil, Gas & Consumable Fuels	-0.059	0.035	-0.044	0.526	-1.783	0.321	0.224	0.663	-0.064	0.176
Construction & Engineering	-0.047	0.002	-0.033	0.517	0.550	0.786	0.580	0.087	0.005	0.898
Real Estate Management & Development	-0.027	0.034	-0.064	0.059	-2.474	0.007	-0.997	0.003	-0.017	0.480
Industrial Conglomerates	-0.026	0.595	-0.017	0.819	-1.269	0.503	0.623	0.307	0.148	0.064
Equity Real Estate Investment Trusts (REITs)	-0.012	0.361	-0.039	0.263	0.247	0.771	1.141	0.001	0.094	0.003
Banks	-0.011	0.139	0.023	0.753	-1.063	0.610	1.278	0.036	0.000	0.995
Independent Power and Renewable El. Prod.	-0.005	0.752	0.009	0.913	-0.997	0.319	0.069	0.833	0.014	0.567
Multi-Utilities	-0.004	0.807	0.074	0.459	0.007	0.997	0.661	0.234	-0.036	0.523
Hotels, Restaurants & Leisure	0.022	0.603	0.022	0.560	0.164	0.889	-0.291	0.645	-0.045	0.440
Electric Utilities	0.030	0.000	0.003	0.980	0.522	0.738	0.071	0.864	0.050	0.019

Table 13 describes OLS models that regress independent variable, log-transformed environmental intensity scaled by operating income using a 0% discount rate, on financial characteristics as dependent variables. All models also include year and country fixed effects. Each specification is run separately by GICS industry. Results are sorted by the magnitude of 0% discount rate coefficient (the most negative values on top) when dependent variable is Tobin’s Q.

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 shown in Table 6. 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,[36] 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.

We find the median environmental impact as a percentage of an organization's sales (operating income) is close to 2% (20%) 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 close to 60% (53%) of the variation in environmental impact scaled by sales (operating income) is driven by industry membership, while approximately 30% (36%) 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

[36] 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).

ratings providers, MSCI, RobecoSAM, and Sustainalytics, 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.

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 the environmental intensity scaled by sales (operating income) has 2.5% (1.4%) lower Tobin's Q and 5.0% (7.8%) lower price to book value of equity. Moreover, when environmental ratings are included in the model, the monetized environmental estimates have a more meaningful economic and statistical association than any of the ratings, suggesting greater explanatory value and greater statistical significance. In fairness to the ratings providers, they are not necessarily measuring impact. Rather, they intend to integrate multiple signals of how well a company is managing environment-related risks and opportunities. 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 space. Our results indicate that the answer to both is yes.

Additionally, regarding the question of whether our environmental intensity measure provides a meaningful signal of financial risk and return, we find a statistically significant, negative correlation of environmental intensity with the Sharpe ratio and its components. Results from our analysis show that firms with higher environmental intensity have lower stock returns, higher volatility, and higher systematic risk. The results are even more prominent when we examine the relationship between environmental intensity scaled by operating income and the financial risk and return measures. Furthermore, we find that environmental ratings do not demonstrate a significant relationship with these financial characteristics besides volatility.

A final interesting finding emerges when we examine the relationship between environmental intensity and each of the financial characteristics by industry. As expected, environmental intensity is associated with lower market valuation, lower returns, and higher risk for most industries, including several industries with large environmental impact such as construction materials and chemicals. However, more surprisingly, we find that environmental intensity is not reflected in some industries with visibly large environmental impacts such as those in the Utilities sector.

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.

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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." [37]

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
CO_2	
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
NO_x	
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

[37] 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
SOx			
	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
N2O			
	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
NH3			
	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.