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LIFE CYCLE ASSESSMENT OF INVESTMENT FUNDS

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Climate change presents a unique challenge for economics: it is the greatest and widest-ranging market failure ever seen.

Nicholas Stern

The Stern Review on The Economics of Climate Change, 2006

Extended summary

While sustainable finance is a subject of current regulatory developments worldwide, there is yet no commonly agreed upon standard for measuring the sustainability performance of investment products. The aim of this thesis is to adapt best practice scientific methods for sustainability assessment stemming from the industrial ecology field, namely input-output life cycle assessment (IOLCA) for the quantification of the environmental and social impacts associated with equity investment funds, contributing thus to mitigating greenwashing risk and supporting policy makers and financial market participants.

A model based on IOLCA is developed to estimate impacts for companies and investment funds in a robust way. In essence, country-sector life-cycle-based monetary impact factors are derived using IOLCA and then attributed to companies and investment funds, using revenue, and holding information to proportionally attribute impacts. To prove the usability of the model and resulted estimates, it is applied in a suite of case studies.

IOLCA has been chosen as methodology due to its proven applicability for meso- and macro-level assessments of impacts. Moreover, the monetary-based approach on which economic input-output tables are based is best suitable for the assessment of impacts associated with financial flows, unlike process-based sustainability assessments that rely on physical data. The developed model contributes to extending the state of the art of IOLCA models for sustainable assessment of investments by improving country and sector resolution in company-level information and extending the sustainability indicators analysed from GHG emissions to other environmental categories and social indicators.

After introducing main concepts that are at the basis of this research, Chapter 2 presents a critical review of existing methods and frameworks for sustainability assessment in the investment funds space. A first prototype of the IOLCA-based model to compute greenhouse gas (GHG) emissions associated with companies and investment funds is described in Chapter 3. In an associated case study, the carbon footprints of a sample of 670 Europe-domiciled self-labelled socially responsible investment (SRI) funds are estimated and compared to the carbon footprints of an equivalent sample of funds without an SRI-themed investment mandate. The underlying database of GHG emissions at company and fund level is available for the sample of 10,000 companies and 1,340 funds, as online Supplementary Information to the published article. Surprisingly, SRI funds are not consistently less carbon intensive than conventional funds and many SRI funds still hold investments in carbon intensive companies. Inside the universe of SRI funds, Article 9 funds – funds having a social or environmental objective as self-classified under the European Union (EU) Sustainable Finance Disclosure Regulation (SFDR) were found to be consistently less exposed to highly-polluting companies. Thus, the development of stricter criteria for the classification of funds is welcomed and is expected to lead to a better stratification of the SRI funds universe and ease the process of choosing a reliable SRI fund for investors.

Chapter 4 and Chapter 5 are dedicated to the study of non-GHG environmental metrics and social metrics, given that GHG emissions are overrepresented as impact categories in the sustainable finance space. The extension of impact categories is a novelty compared to existing IOLCA models which focuses on one or few impact categories. This part of the research became even more relevant with the emergence of the SFDR, which addresses a wide range of environmental and social issues. As a methodological contribution, we linked mandatory and voluntary indicators from SFDR with life-cycle-based indicators that are ready to use and can be adapted to estimate impact at investment fund level. We estimated 13 environmental and 13 social indicators for a sample of 230 SFDR self-labelled funds, listed on the Luxembourg Green Exchange (LGX). These sampled funds are exposed to significant direct and indirect impacts that have not been previously assessed at investment fund level, such as water stress and human toxicity, or social impacts, such as exposure to child labor in the supply chains of invested companies. The impact of the 230 funds can be compared to the impact of EU's consumption footprint. For example, for impact category water stress the impacts of the holdings of the 230 funds are equivalent to the impact of 4 million EU citizens' consumption over one year. The majority of the impact attributable to the funds are traced to a very small number of large publicly listed companies. This finding implies that investors could efficiently use their voting rights to drive change. In a more in-depth case study in Chapter 5, important trade-offs between GHG emissions and vulnerable employment indicators were identified. For example, while companies in the Utilities sector ranked high on GHG emissions, they ranked low for exposure to vulnerable employment. The contrary was found for companies in the Retail sector.

In the last chapter of this thesis, Chapter 6, the novel dataset of IOLCA-estimated company-level impacts are used to construct independent variables representing sustainability characteristics of stocks, in order to study a debated research question in the asset pricing literature: *Are sustainability characteristics of companies positively correlated with their stock market returns?* A cross-sectional regression is run for the time period from 2012 to 2021, for over 25,000 unique companies. The sustainability characteristics studied were GHG emissions, human toxicity, acidification, particulate matter pollution, water use and vulnerable employment. GHG emissions are positively priced in the cross-section of returns. In addition, water stress and vulnerable employment also appear to be positively correlated with stock returns, albeit only for indirect impacts. These results call for wider action on informing financial markets about the full-scope impacts on the natural environment and the society that are associated with companies and their economic activities globally.

This research has implications for financial institutions and policy makers alike. First, estimating impact by means of IOLCA uncovers the large indirect exposure that funds have via their holdings and their respective supply chains. These impacts could not be measured using company proprietary data, given the lack of capability to retrieve, assess and verify supplier data.

As implication for portfolio allocation strategies, investors should be cautious in choosing funds that reduce their carbon footprint by tilting their portfolios towards companies from industries that are by-default low carbon, without having a direct contribution to decarbonization. Moreover, the indirect carbon footprint may reveal large exposures to high-intensive industries that are overlooked when only assessing direct exposure. This indirect carbon exposure poses additional risks for investors, as in the future supply chain responsibility may be mandated. Additional caution should be taken when assessing funds that finance the low-carbon transition. Some funds may hold investments in companies that are highly carbon intensive, but that are nonetheless key for the low-carbon transition, such as manufacturing of parts for installation of low-carbon electricity. These funds may have a higher carbon footprint than funds that invest proportionally in the Tech and Finance industry. Thus, absolute measures of impact should be only an element of the assessment of a fund and should be complemented by assessment of contribution to the sustainability transition.

As a methodological contribution, this thesis helps towards the systematization of sustainability assessment of equity investment funds by providing a science-based method to estimate impacts on a wide array of life-cycle-based indicators. Through case studies we show that the identification of best investment alternative from a sustainability point of view is not straightforward. Depending on the scope considered (direct or life cycle), the metric (weighted average intensity or relative footprint) and impact categories (environmental, such as GHG emissions, water stress, and/or social, such as vulnerable employment), the ranking of funds varies.

Given that the model is based on impact factors derived from input-output databases, the impact values represent country-industry level revenue-weighted values. The case study results are thus a rough estimate of the real-world impact that could be attributed to companies and funds, respectively. On a case by case basis, more detailed assessments would be needed in order to arrive at more accurate impact values. Finally, estimation of absolute impact associated with equity investment funds' holdings is only a first step in the process of assessing an investment product on its contribution to the sustainability transition.

Contents

List of publications

Primary publications

1. **Popescu, I.S.**, Hitaj, C., Benetto, E., 2021. *Measuring the sustainability of investment funds: A critical review of methods and frameworks in sustainable finance* J. Clean. Prod. 314, 128016. https://doi.org/10.1016/j.jclepro.2021.128016

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2. **Popescu, I.S.**, Gibon, T., Hitaj, C., Rubin, M., Benetto, E., 2023. *Are SRI funds financing carbon emissions? An input-output life cycle assessment of investment funds*. Ecol. Econ. 212, 107918. https://doi.org/10.1016/J.ECOLECON.2023.107918

Author contribution: co-design of research, method co-development, literature review, data collection, data analysis and writing

3. **Popescu, I.S.**, Schaubroeck, T., Gibon, T., Petucco, C., Benetto, E., 2023. *Investment funds have substantial estimated environmental and social impacts with trade-offs*. Under review at Nature Communications Earth & Environment https://dx.doi.org/10.21203/rs.3.rs-3345219/v1

Author contribution: co-design of research, method development, literature review, data collection, data analysis and writing

4. **Popescu, I.S.**, Rubin, M., Hitaj, C., 2023. *Stock returns and sustainability beyond carbon – A quantitative approach to environmental and social indicators* (submitted to and rejected from the Journal of Accounting Research, special issue on ESG, preparing for re-submission)

Author contribution: co-design of research, literature review, data collection, empirical analysis, and writing

Secondary publications and research outputs

5. Gibon, T., **Popescu, I.S.**, Hitaj, C., Petucco, C., Benetto, E., 2020. *Shades of green: life cycle assessment of renewable energy projects financed through green bonds*. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/abaa0c

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6. **Popescu, I.S** Section 6.1. *REFUND – Assessing the environmental impact of investment funds* of report edited by LSFI and PwC, 2022. Sustainable Finance in Luxembourg: A quantitative and qualitative overview. https://www.pwc.lu/en/sustainable-finance/sustainable-finance-in-luxembourg.html

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7. Hitaj, C., **Popescu, I.S.**, Schaubroeck, T., Gibon, T., 2023. *Social dimension of green finance*, in: Falcone, P.M., Sica, E. (Eds.), Sustainable Finance and the Global Health Crisis. Routledge, pp. 241–277. https://doi.org/10.4324/9781003284703-14

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List of abbreviations

AM	Asset managers
AO	Asset owners
AuM	Assets under management
CDP	Carbon Disclosure Project
CF	Carbon Footprint
CPRS	Climate Policy Relevant Sectors
CSRD	Corporate Sustainability Reporting Directive
EC	European Commission
EEMRIO	envrionmentally extended multi-regional input-output
ESG	Environmental, social, and governance
ESRS	European Sustainability Reporting Standards
EU	European Union
EXIOBASE	environmentally extended input-output database
FactSet RBICS	FactSet Revere Business Industry Classification System
FI	Financial institution
GHGs	Greenhouse gases
GSIA	Global Sustainable Investment Alliance
HLEG	EU High-Level Expert Group on Sustainable Finance
IEA	International Energy Agency
IICGG	Institutional Investors Group on Climate Change
ILO	International Labor Organisation
IO	Input-Output analysis
IOLCA	input-output life cycle assessment
IPCC	Intergovernmental Panel on Climate Change
ISO	International Organization for Standardization
LCA	Life Cycle Assessment
MRIO	multi-regional input-output
NFRD	The non-financial reporting directive of the European Union
NGFS	Network for Greening the Financial System

NZA	United Nations-convened Net-Zero Asset Owner Alliance
OECD	Organisation for Economic Co-operation and Development
PACTA	Paris Agreement Capital Transition Assessment
PAIs	Principal Adverse Impacts
PEF	Product Environmental Footprint
PRI	United Nations Principles for Responsible Investment
PSILCA	socially extended input-output database
RCF	Relative Carbon Footprint
RTS	Regulatory Technical Standards
SBTi	Science Based Targets Initiative
SDGs	Sustainable Development Goals
SFDR	Sustainable Finance Disclosure Regulation
SLCA	Social life cycle assessment
SMEs	Small and medium-sized enterprises
SRI	Socially responsible investing
TCFD	Task Force on Climate-Related Financial Disclosures
TEG	European Commission's EU Technical Expert Group on Sustainable Finance
TPI	Transition Pathway Initiative
UN	United Nations
UNCTAD	The United Nations Conference on Trade and Development
UNEP	United Nations Environment Programme
UNEP FI	UNEP Finance Initiative
WACI	Weighted Average Carbon Intensity

1 Introduction

1.1 Background

The quest of this present research is rooted in the concept of *negative externalities* coined by English economist Arthur Pigou in the 1920s and the associated *Pigouvian tax* that argues for setting a tax on the negative externalities caused by the activities of companies. However, *who should bear the responsibility for causing the externality?* When talking about allocation of responsibility for climate change impacts, the most common approaches are the *production-based approach* and the *consumption-based approach* (Huysman et al., 2016; Liu, 2015). The production-based approach, the basis for national climate policies, allocates the responsibility to the producer, i.e., on the territory it was produced. However, the ones who benefit from the production of goods are very often not located in the producing countries. As we live in an interconnected, globalized world, where inequality is soaring, another approach developed, attributing the impact responsibility to the consumer, *consumption-based approach*. But are the consumers the only ones to blame? As we live in a market economy, the profit holders often benefit from the consumption, without being allocated any responsibility for it, despite the pressure that they put on companies to grow. Thus, in a more recent approach, the responsibility would be allocated based on financial ownership of the impact – *investment-based accounting of impact* (Zhang et al., 2020). Indeed, it has been documented that ownership of investment is linked to a much higher carbon footprint then when not accounting for the value of investment intangibles (Starr et al., 2023). It is under this last paradigm that we position our research. Investment performance should not only be measured in terms of monetary gains, but equally in terms of sustainability impacts. Investors, as holders of capital, have the possibility and perhaps the responsibility to question the actions of the companies that they invest in and to demand better practices, for the planet and for the people.

Central banks themselves are acknowledging the environmental and climate risks to the financial system and the need to re-direct financial flows towards financing the sustainability transition of our economy (NGFS, 2022). After all, the role of financial markets is to ensure that money is channelled efficiently between those who have access to it to those who need it. Studies put the financing gap towards achieving the SDGs to trillions of USD (UNEP, 2019). However, there is a large knowledge gap in terms of impacts associated with financial products which slows down the efforts to close the financing gap. Without correct measurement of impact, the efficiency of sustainable investing risks to be watered down by greenwashing. Investors will have the belief that they are doing good with their money, whereas so-called sustainable finance products may be conventional ones *in disguise* (Nitsche and Schröder, 2015).

Investors are increasingly interested in sustainable investment products, lured by the promise of *"doing well while doing good"* (Talan and Sharma, 2019): making a higher return on investment compared to a conventional choice, while at the same time having a positive impact on the environment or the society –still debated in finance (Friede et al., 2015). The question of positive environmental or social contribution of a sustainable investment product is much harder to answer and less researched, given the lack of robust tools to measure their environmental or social performance (Popescu et al., 2021; Rekker et al., 2019; Thomä et al., 2019a). In the absence of a scientifically backed international standardized measure to judge the environmental performance of sustainable products, *greenwashing risk*[1] is increasingly higher (Nitsche and Schröder, 2015). As regulations in this direction are developing globally, with the EU SFDR – *Sustainable Finance Disclosure Regulation* (EC, 2019a) being the most notorious, tools to measure the real sustainability of investment funds are needed.

This thesis is a working package of the REFUND project, financed by the Fonds National de la Recherche (FNR) Luxembourg, grant number REFUND O19/13947579. REFUND aimed to develop life-cycle-based metrics for funds and bonds. In this thesis, the REFUND methodology for funds has been developed. The methodology has been applied on different samples of investment funds. This research thus contributes to filling the gap in terms of measurement of sustainability at investment product level.

The goal that pervades though all the chapters of this thesis is to prove the suitability of input-output life cycle assessment as methodology for providing science-based estimates of environmental and social impact at investment fund level, in order to lower greenwashing risk and trigger real impact sustainable investments. Its results aspire to inform policy makers and financial professionals about the estimated environmental and social impacts associated with investments.

In section 1.1, an introduction into sustainable finance and sustainable investment funds is provided. Section 1.2 discusses about the imperative of sustainability assessment in sustainable finance. Section 1.3 discusses the role of sustainability measurement for investment funds and Section 1.4. introduces input-output life cycle assessment as a methodology. In Section 1.5 we present the overarching research question and the design and structure of the research undertaken in this thesis.

1.2 Sustainable finance

When I started my PhD, I was under the impression that sustainable finance is a novel field, that it has just begun, and it was going to revolutionize everything. Afterall, I only learned about sustainable finance when I was in my first year of Master's, during my Corporate Governance course. With great wonder I discovered that the same questions that I was asking myself, have already been asked many times before and numerous attempts at answering them have been made starting the 1970s – proof is a paper by Milton R. Moskowitz which argues that companies that are socially responsible will be better off in the long term (Figure 1.1). His arguments at that time were in contrast to the famous *Friedman doctrine*, named after the Nobel prize winner Milton Friedman, that *"a company has no social responsibility to the public or society; its only responsibility is to its shareholders"* (Friedman, 1970). While the debate is still ongoing, the difference nowadays

[1] *Greenwashing refers to making claims about sustainability that are not backed by real actions*

compared to then is that sustainable finance is not a niche field anymore and it is becoming part of the norm.

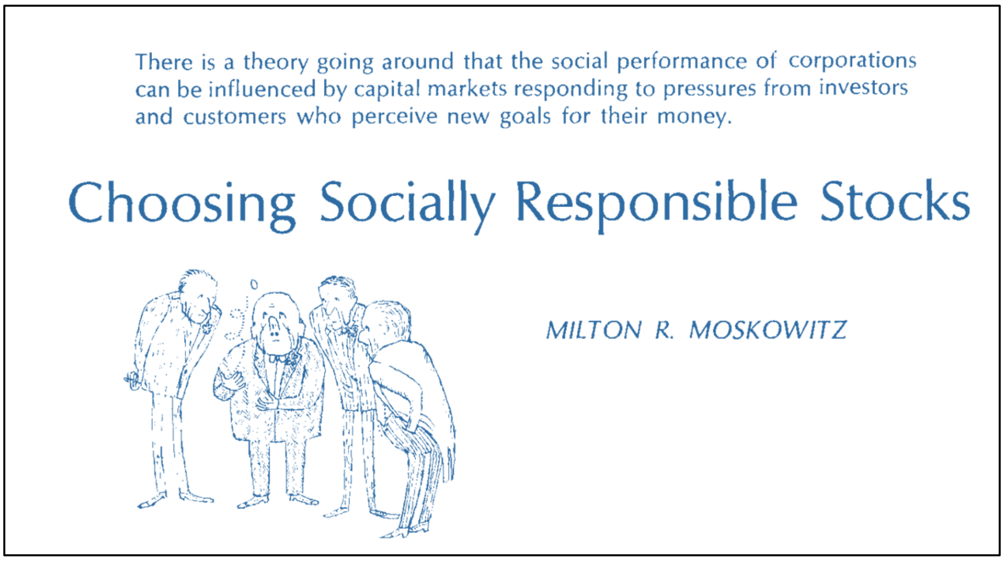


Figure 1.1: Extract from original paper "Choosing Socially Responsible Stocks" (Moskowitz, 1972)

The divestment movement, whereby for example institutional investors pledge to stop financing fossil fuel companies, is rapidly expanding. Central banks are mandating climate stress tests to understand the loss that banks may undergo in the future because of climate change-triggered physical and transition risks. Finance and climate change are no longer two unrelated subjects, they have now become intertwined. For the first time, the Intergovernmental Panel for Climate Change (IPCC) discusses the role of finance in its fifth assessment report (Gupta and Harnisch, 2014): Article 2.1(c) of the Paris Agreement is an imperative call on countries to *"make financial flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development*" (UNFCCC, 2015).

Sustainable finance refers to the integration of environmental, social and governance (ESG) considerations into the investment decision making process, according to the definitions from the European Commission (EC, 2023). The United Nations Environmental Programme (UNEP) makes clear the distinction between "green finance", climate finance" and "sustainable finance", terms that are sometimes used interchangeably. *Sustainable finance* is the most inclusive term, whereby the investment decision can include social, environmental, governance and economic factors, and comprises both public and private investors. *Climate finance* includes a sub-set of environmental issues and is generally used to refer to public funds dedicated to decarbonisation of the economy. *Green finance* includes a more extended palette of environmental risks and opportunities besides climate, and usually refers to both private and public investment (UNEP, 2016).

In 2004, for the first time, a handful of financial institutions have joined forces and have advised on the inclusion of ESG criteria in the financial decision making process and on adopting a long-term view on investing, according to the conclusions reached in the UN report "*Who cares wins*" (UN Global Compact, 2004). In the report, it is argued that companies that are aware and act on environmental and social issues are better able to manage risks, anticipate regulatory changes and accessing new markets.

Financial markets' players are now aware of the long-term risks that climate change and the sustainability crisis pose on the stability of returns. Afterall, the financial system can only function if supported by a stable and functioning real economy, alongside thriving societies and ecosystems (Schoenmaker and Schramade, 2019). In less than 20 years, sustainable finance went from one very niche branch of finance to reaching the whole financial system. In this present thesis, the focus is on sustainable equity investment funds, a sub-group of the universe of sustainable finance products.

Equity investment funds are funds that primary hold shares of publicly traded companies. Asset managers (e.g., Robeco Asset Management) invest money on behalf of the asset owners (e.g., pension funds) in a portfolio of financial products. These funds can be available to retail investors (i.e., citizens) or to institutional investors (e.g., pension funds). Sustainable equity investment funds refer to the funds that take social, environmental, and governance criteria into account when investing (e.g., Robeco Sustainable European Stars Equities). In this thesis, the case studies are conducted on investment funds registered in Europe. By only looking at EU-domiciled funds, our results are not affected by regional differences in investing behaviour between regions of the world. Nonetheless, these funds hold investments in companies all over the world.

According to a global study (GSIA, 2021), sustainable investment stood at 35.3 trillion USD in 2020, about 35.9% of the total invested assets under management (AuM). In the cited report, sustainable investments are considered all those investments that factor environmental, social and governance (ESG) criteria in the portfolio allocation decision, with impact funds being the most restrictive category, these funds are specifically seeking to make a positive environmental or social contribution (Figure 1.2).

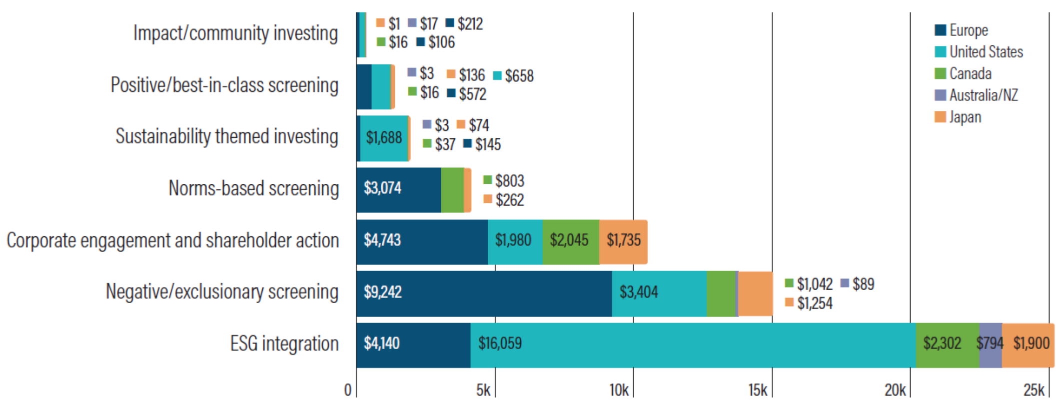


Figure 1.2: Sustainable investment funds by asset strategy and by region. Graph is sourced from GSIA report 2020, Figure 6 (GSIA, 2021)

So far there is no global verification scheme to validate the ESG approach of the investment funds. In Europe, another study reports that up to 2 trillion EUR are invested in so-called sustainable funds (ALFI, 2022). Out of 33 thousand funds, around 4,400 are considered sustainable. The top jurisdictions for sustainable fund registration are

Luxembourg, Ireland, the UK, and Germany. With the sustainable finance industry evolving at a rapid pace, it is worrying that measurement and validation of sustainability claims is not standardized, leading to a high risk of greenwashing. Since this research work has started, the regulations in the sustainable finance space have been evolving and will hopefully lead to improving the effectiveness of sustainable investing.

In the European Union, the landmark EU Taxonomy Regulation entered into force in June 2020 and presents a classification of environmentally sustainable activities, backed by scientific criteria and ensuring a life cycle thinking approach to impact assessment (EC, 2020). Specifically, to be environmentally sustainable, the impact of an economic activity should be assessed over its life cycle, including downstream and upstream production stages. Clear criteria are set for each economic activity, thereby standardizing the measurement of sustainability impact. In addition, an economic activity will only be considered sustainable if it does not harm other environmental objectives and if it complies with social safeguards, therefore ensuring that all relevant information is considered before deeming an economic activity sustainable. In the Delegated Acts complementing the EU Taxonomy, these criteria are set and a life-cycle approach to impact assessment is mandated, based on latest scientific developments specific to each economic activity (EC, 2021a). This regulation helps prevent greenwashing and supports investors with defining truly sustainable activities.

Alongside the EU Taxonomy, the Sustainable Finance Reporting Directive (SFDR) has been implemented to require sustainable financial products' providers to report on relevant sustainability impact indicators (EC, 2019a). However, there are still elements to be improved, as reporting under the SFDR does not fully integrate the life cycle principles under the EU Taxonomy. For example, the SFDR regulation is not covering all important impact categories in its mandatory disclosures and indicators recommended lack detail in terms of methodologies and main emissions/impacts that funds would need to trace. These regulatory developments are also driving our research and we specifically link our proposed indicators to the indicators mandated under the SFDR in Chapter 4. The need to measure impact in sustainable finance is discussed in detail in the next sub-section.

1.3 The imperative of sustainability assessment in sustainable finance

Measuring the impact associated with a financial product is not a trivial task, and investors are easily deterred by the lack of accuracy and high uncertainty in environmental and social data. The main argument for more precise, standarzided and reliable sustainability assessment in finance is often summarized by the quote "*What gets measured, gets managed*". If investors and stakeholders do not know which projects or companies have the worst/best sustainability performance, it is impossible for them to choose the better option. Measurement of the sustainability footprint of a financial product would mean computing the sustainability of the underlying projects/companies that the specific financial product is tied to and allocating, on a financial share basis, the footprint back to the financial product. This can be done via absolute metrics or intensity metrics (expressed per unit of revenue or per amount invested). Moreover, if one is interested in the additional impact that the investment creates – i.e., not just the associated footprint but the change in impact compared to a counterfactual – then one would need to measure the relative impact, or the financial product's "*additionality"* (Brest and Born, 2013). In this thesis we focus on the calculation of associated sustainability footprint.

The development of a single global standard for the purpose of sustainability assessment of financial products is delayed by a lack of consensus regarding the extent to which companies and, in turn, investors should be considered responsible and thus asked to report on sustainability issues. Should all environmental and social issues be assessed, or just the ones that prove to be material for the respective company? In the second case, a company should undergo a materiality assessment to determine whether the specific impact could pose a material risk for the company or not, which would be considered as "*single materiality*". In the first case, summarized as "*double materiality*" a company would need to report on a complete list of environmental and social indicators, at the recommendation of the regulator (Figure 1.3).

The "*double materiality"* concept was introduced by EU regulators in the context of the sustainability disclosure standards for corporates (EC, 2022) and it aims to make companies liable to report on impacts of the company on all aspects of sustainability, not only climate. This approach is more in line with the stakeholder approach, where a company should consider its effects on all parties that it interacts with, not only shareholders. Full value chain impact is needed in order to understand the full risk exposure of an investment. For example, if the suppliers of a company are located in a country hit by extreme weather events or with major human rights issues, this may impact the capability of the main company to generate revenue. To better account for these risks, regulations are increasingly mandating reporting of impact on a life cycle basis (considering the whole value chain).

From the capital markets perspective, there is also a growing interest to integrate sustainability information in the financial decision making process. Of course, the capital markets perspective is rather concerned with the financial materiality of sustainability information. On the one hand, a good sustainability performance means that a company is fit to operate in a low-carbon future and/or contributes to this future. Moreover, sustainable companies and their products will tend to be preferred by consumers, as their preferences also shift towards sustainability (Giglio et al., 2020; Pastor et al., 2021). On the other hand, a negative sustainability performance of companies can lead to lower prices for their stocks, due to reduced demand, empirically tested using as sustainability characteristics GHG emissions (Hong and Kacperczyk, 2009) and toxic pollution (Hsu et al., 2022). In another perspective, non-sustainable stocks can experience higher returns, as investors demand compensation for holding assets that are exposed to higher long-term risks (Bolton and Kacperczyk, 2023). To what degree capital markets integrate sustainability information in the pricing of stocks remains a debated issue in academia. A recent popular paper, using for the first time information on both direct and indirect GHG emissions, finds that investors positively price this information in a global sample of stocks, for a period from 2005 to 2018 (Bolton and Kacperczyk, 2023). These results are consistent with the risk-return framework presented above.

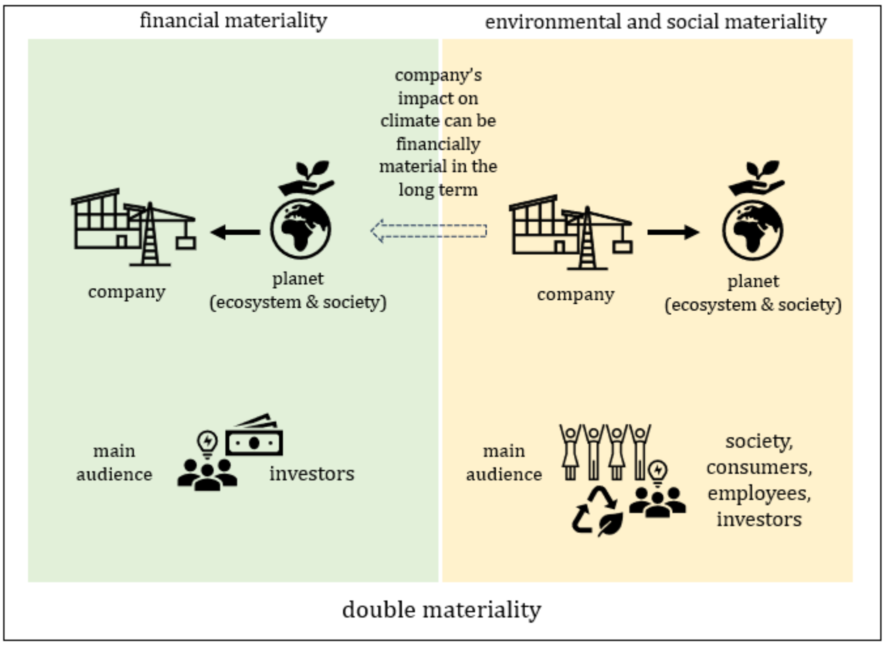


Figure 1.3: Double materiality concept. Own illustration, based on original from the European Commission's document on Guidelines on reporting climate-related information (EC, 2019b)

For finance professionals to integrate information about the sustainability of their investments, they need reliable and standardized data (Vörösmarty et al., 2018). However, the quality of sustainability data reported by public companies worldwide is still very low (Busch et al., 2020). Even for the same company, there can be divergence between numbers reported for different purposes (Stanny, 2018). Moreover, where available, company self-reported data is often incomplete, and does not cover the full impact responsibility, such as emissions caused down the supply chain (CDP, 2020). The reason is that companies often lack visibility and control over their suppliers, and, in certain industries, one company may even depend on more than 5,000 suppliers. In an ideal scenario, companies and financial product providers would have access to primary data to help reporting on all sustainability issues. This is however not the case and probably will never be, given the effort needed to precisely measure and assign the impacts at the source of production. Data coverage at firm level is thus often unreliable, even for widely used indicators like greenhouse gas emissions. Nonetheless, global levels of emissions are generally known with good precision, especially when looking at different GHGs. For example, for methane emissions, satellite data can help with tracing emissions at point of production (Climate Trace, 2023). The issue is thus about the allocation of those impacts to the ownership company. Without standardised information that allows for precise allocation, estimation methods prove useful for the allocation of impact between all companies in a specific sector and from a specific geography. Life cycle assessment and input-output analysis have been widely used for estimating impact at product, system and country level and are promising tools to adapt to financial products as well.

1.4 Input-Output Life Cycle Assessment (IOLCA)

In the last 30 years, the study of carbon footprint has evolved in terms of the dimension assessed, expanding from the level of products and individuals to organizations, countries, regions, and the whole economy (Shi and Yin, 2021). This shift is also characterized by the switch in terms of associated field of research – from ecology to economy, leading thus the closer integration of the two subject areas. While for micro level, such as product carbon footprints, process-based life cycle assessment is used, in the business economics literature on carbon footprint (of sectors, or whole economies), input-output models are employed, due to their fit in covering meso- and macro-assessments (Yu and Chen, 2022). The differences between the two are summarized in Table 1.1.

Life cycle assessment (LCA) is a science-based methodology for measuring the environmental effects associated with products and systems, over their entire life, from raw material extraction and processing to main production phase, up to use phase and waste management, known as *cradle-to-grave* analysis. LCA is a standardized methodology via the International Standards Organisation's ISO 14040 series (ISO, 2006). *Climate change impact* is one of the most known impact categories assessed via LCA, but there are other impact categories that correspond to damages to ecosystems or to humans, such as *water use*, *acidification*, or *toxicity*. The EU, in its Product Environmental Footprint (PEF) guidelines recommends 16 main indicators for environmental impact assessment. These are based on so-called impact assessment methods, that differ between them by having different weights allocated to the composing environmental flows under an impact category (PEF, 2021). These indicators are explored in Chapter 4 of this thesis.

Social life cycle assessment (SLCA) builds on the elements of an environmental LCA but aims to measure social impacts. The integration of SLCA along a traditional LCA allows for a more comprehensive assessment of impacts, with identification of trade-offs (Sala et al., 2015). Since social issues are as much of a focus in terms of Sustainable Development Goals (SDGs) as environmental issues, it is useful to have a methodology that can assess both. Social assessments are more complex and more care must be taken when making decisions based on SLCA results, given that cultural and value-based differences affect how social impacts may be perceived by different countries or groups of people (Sala et al., 2015). Given this complexity, but also the fairly recent take-off of SLCA, methodological and harmonization issues still remain in SLCA. UN-led initiatives to standardize social indicators and discuss interpretation of results are ongoing (UNEP, 2020). The advantage of a SLCA is that all categories of stakeholders are considered in the assessment: *employees*, *local community*, *value chain actors* (such as workers in the supply chain), *society*, and *consumers*. Some specific indicators would be for example *presence of child labor*, *poverty rate*, *respect of human rights*, r*ight to strike*, etc.

Table 1.1: Differences between life cycle assessment and input-output LCA, adaptation based on information from (Beylot et al., 2020) *and* (Rebitzer et al., 2004)

Feature	**Process-based LCA**	**Input-Output LCA**
Data source	Process or product-level data	Sector level data, based on economic national accounts
Level of assessment	Micro	Macro
Approach	Bottom-up (from the smallest functional unit to the total impact at company-level)	Top-down (using sector-level value for impact to estimate company-level impact)
Flows	Physical units	Monetary units
Life cycle stages	Complete life cycle can be covered	Upstream value chain and direct operational phase
Processes involved	Some processes may be missing	Complete coverage of processes and inter-industry links involved
Environmental assessment	process-based life cycle inventory	monetary-based life cycle inventory
Method for impact assessment (example)	Environmental Footprint methods 2017 (EF 2017)	

Linking back to sustainable finance, LCA is a recommended assessment method under the GHG protocol (widely used corporate-level GHG accounting standards) for estimating the impact of a specific company, where information about the products is known, by using *activity-based impact factors* (GHG Protocol, 2013). Moreover, the importance of a life-cycle-based approach is emphasized in the recent EU Taxonomy, part of the EU-wide sustainable finance action plan. Namely, when an investor needs to decide whether an economic activity is Taxonomy-aligned or not, the impacts over the life cycle of the activity have to be assessed, on more environmental issues and while respecting social standards (EC, 2019c). However, the application of LCA to company and financial product level is restricted by the availability of physical activity data from the respective company or companies underlying the financial product. LCA would be viable only when having a project finance instrument, like for example a green bond (Gibon et al., 2020) – explored in another stream of work for the bigger project under which this thesis is written.

Input-output analysis originally stems from the economic field and allows to trace global transactions between sectors and countries (Miller and Blair, 2009). IO tables are compiled by national statistical offices based on data reported by companies from the country. Thus, IO tables represent in essence an aggregation and averaging of all transactions observed in the real economy. The economic input-output tables allow to define, for any specific country-sector combination, the economic transactions needed to produce 1 unit (i.e., one million EUR) of that sector. This can be viewed as the *"production recipe"* of the sector and is basically a list of all country-sector combinations that are in the composition of the respective sector and their associated proportional share in producing a 1 unit of the sector and allows to calculate the full chain of inter-connections between sectors (Figure 1.4). The environmental extensions are based on scientific data that provide the total environmental impact for the specific country-sector combination.

By dividing the total environmental burden of a sector by its total economic output, the impact factors are obtained (measured in unit of impact per million EUR).

There are key advantages of using EEMRIO data. First of all, it allows for a homogenous illustration of impact intensity, per unit of monetary revenue, which in turn allows for comparisons between sectors and product groups that would otherwise have very different physical impact factors between them, making comparison cumbersome. Second, it is a method that can be streamlined across countries and hence across companies, given the wide availability of the needed input data, i.e., revenue split by region and industry. This means that a large number of companies can be assessed in a limited time frame and for a low cost. Finally, IOLCA covers all the processes that would be involved in the supply chain and direct production phase for a specific industry and thus common issues related to the system boundary that are characteristic to process based LCA are not applicable here.

There are however a few main drawbacks to using monetary-based impact factors. First, they are generic and do not account for differences between different products, suppliers, or companies. Second, the resulted impact footprint at company level is highly influenced by the spending or revenue profile of a company, which does not always reflect the real physical flows of products. Thus, impacts are also influenced by product prices: two companies may have same physical number of units purchased or sold, but if the price is different the impact will be different as well when calculated with the spend-based method (GHG Protocol, 2013). Additionally, IOLCA is not able to capture fine improvements in terms of efficiency and reduction of impacts, given that information about company-level specific characteristics is not available, making it thus unsuitable for calculating progress in terms of reduction of impacts compared to a baseline – an assessment usually possible using process-based LCA.

For fund investments that usually have portfolios of hundreds or even thousands of holdings, *top-down life-cycle-based methodology (IOLCA)*, using *environmentally extended multi-regional input-output data,* can prove much more useful and faster than conducting a traditional LCA as they require much less data from the fund provider and can be automatized to perform the estimation of impact in a relatively short time frame. Using IOLCA one can extract country-sector impact factors that are time dependent. These are then used for estimation of impact at the level of economic activities. IOLCA represents the backbone for deriving monetary-based impact factors, sometimes referred to as *spend-based factors* (GHG Protocol, 2013). EEMRIO is recommended as a reliable source of proxy GHG emissions data, when data of higher accuracy is not available (GHG Protocol, 2013; Goldhammer et al., 2017). Many studies have used IOLCA to reveal the direct and indirect impacts associated with different industries (Cabernard et al., 2021) and different regions or countries (Beylot et al., 2019; Liu et al., 2022) and companies (Huang et al., 2009; Zhang et al., 2020). It is also widely used by companies when reporting on their scope 3 upstream GHG emissions (CDP, 2020).

Despite its potential usability, there is scarce academic research on the topic of linking IOLCA and sustainable financial products. Specifically, the *shadow impacts* (Ritchie and Dowlatabadi, 2014) of the non-tangible financial markets have been overlooked in literature, apart from a few key studies and industry reports. Several academic papers have discussed the association of financial holdings, corporate revenues and environmental impacts (Koellner et al., 2007; López et al., 2019; Ritchie and Dowlatabadi, 2014; Starr et al., 2023; Zhang et al., 2020). Moreover, the financial industry became more and more aware of the need to estimate their impacts (Kepler Cheuvreux et al., 2015a), which has also driven developments on the regulatory side (EC, 2019a). At the same time, proprietary tools for assessment of sustainability of companies and financial products and that take a life-cycle-based approach have been developing in the industry (Sycomore AM, 2018; Trucost, 2019a). Trucost data provider has been used by recent research in sustainable finance to verify the hypothesis that markets are positively pricing the direct and indirect carbon emissions associated with stocks.

However, their methodologies are often not openly available, and the data is behind a paywall. Existing case studies only cover small samples of funds and a wide comparison between sustainability-themed and conventional funds and a discussion of implications is missing from current research.

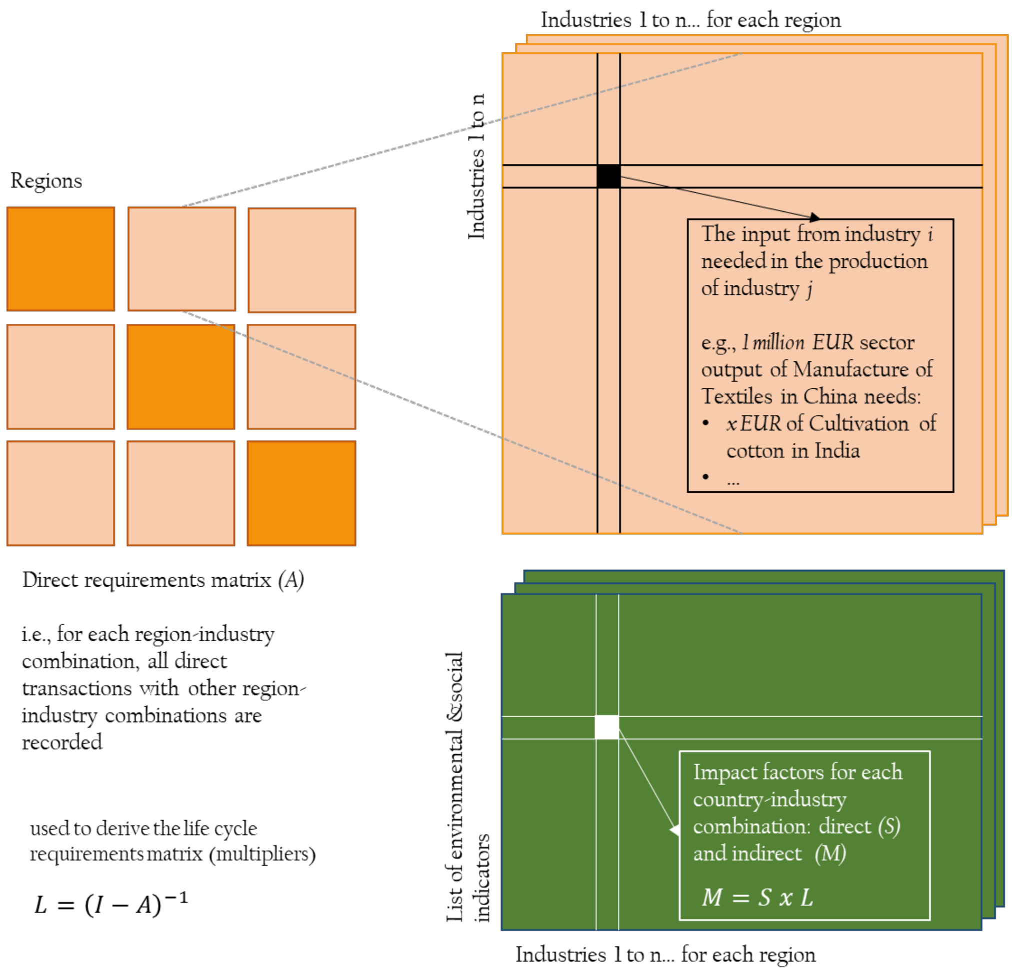


Figure 1.4: Representation of an EEMRIO database, own illustration

1.5 PhD thesis goal, research question and structure

Academic research has an important role to play in advancing the subject of impact measurement in sustainable finance, given the novelty of the field and the lack of mature tools to measure and to propagate sustainable investing. The interdisciplinarity of the domain requires adapting sustainability assessment methods from the industrial ecology field to investment products. The present PhD thesis further advances this topic by addressing the following overarching research question:

> **How can input-output life cycle assessment be employed to better assess the sustainability performance of investment funds ?**

The main research question is broken down in five sub-research questions, with each chapter of this thesis corresponding to one of the sub-research questions:

> *RQ1. Are state-of-the-art tools for sustainability assessment of investment funds fit for purpose ?*
>
> *RQ2. Are SRI funds more carbon intensive than conventional funds when using IOLCA-based holding-level GHG emissions estimates ?*
>
> *RQ3. Can we consistently estimate IOLCA-based environmental and social impacts for a meaningful link to EU policy-driven sustainable finance disclosure requirements ?*
>
> *RQ4. Are there trade-offs between IOLCA-estimated vulnerable employment and GHG emissions at industry level ?*
>
> *RQ5. Are investors pricing sustainability characteristics of companies in the cross-section of stock returns ?*

with each sub-RQ having a corresponding hypothesis:

> *H1. Current frameworks and tools for sustainability assessment of investment funds are not yet reliable and sufficiently science-based*
>
> *H2. SRI funds have a lower carbon footprint than conventional funds, when we measure the carbon footprint using IOLCA-based models*
>
> *H3. Investment funds have significant social and environmental impacts beyond climate change, and these can be estimated using IOLCA-based models*
>
> *H4. Specific trade-offs between vulnerable employment and GHG emissions can be identified between companies in different industries*
>
> *H5. Sustainability characteristics beyond GHG emissions are positively priced in the cross-section of stock returns*

The thesis starts in **Chapter 2** with a systematic critical review of state-of-the-art methods and frameworks in sustainable finance based on academic articles and grey literature. This chapter aims to answer the research sub-question: *"Are state-of-the-art tools for sustainability assessment of investment funds fit for purpose ?"*. A review was deemed necessary as there was no previous overview in literature of tools specifically focused on sustainability assessment of investment funds. A seven-criteria matrix is proposed to assess the suitability of the tools and define the criteria of an ideal tool.

Chapter 3 introduces the first prototype of the IOLCA-based model, that proposes an enhanced method compared to previous research to estimate the carbon footprint of an equity investment fund. The chapter answers the following research question: *"Are SRI funds more carbon intensive than conventional funds when using IOLCA-based holding-level GHG emissions estimates ?"*. For the model prototype, first the input-output database EXIOBASE is chosen, and the impact factors for GHG emissions are derived and adjusted. The proprietary financial database FactSet is used to extract revenue and holding information for the company and fund sample. A concordance file is manually created to make a clear link between the different classifications of EXIOBASE versus FactSet. Based on the IOLCA impact factors, company-level revenue split, and fund-level holding information, carbon footprints for companies and funds are estimated. A validation of the model is conducted at this point, using reported company data on GHG emissions. Finally, a case study comparing the carbon footprint of two equal samples of sustainable and conventional equity investment funds is conducted to illustrate the application of the model.

The next sub-question to answer in **Chapter 4** is *"Can we consistently estimate IOLCA-based environmental and social impacts for a meaningful link to EU policy-driven sustainable finance disclosure requirements ?"*. Given the increased focus on environmental issues beyond climate change and the need to consider social aspects in the sustainable investment decision making process, explicitly stated for example in the EU Taxonomy Regulation, a natural subsequent development was the extension of the IOLCA-based model previously developed, to cover 25 additional environmental and social indicators. The IO database EXIOBASE is used for extraction and adaptation of non-GHG environmental impact categories, based on EU Product Environmental Footprint methods and the database PSILCA is used for social impact categories, in line with latest UNEP guidelines for social LCA. In this chapter, we seek to match indicators from arising sustainable finance reporting regulations with life-cycle-based indicators that are ready-to-use and applicable to investment funds and their equity holdings. A subsequent case study was conducted in the paper, aimed at understanding the magnitude of impact, both on environmental and social dimensions, of all sustainable investment funds listed on the Luxembourg Stock Exchange.

The inclusion of more environmental and social impacts brings about the question of co-benefits and trade-offs between impact categories. Specifically in **Chapter 5** the following sub-question is answered: *"Are there trade-offs between IOLCA-estimated vulnerable employment and GHG emissions at industry level ?"*. IO database EXIOBASE is used for GHG emissions and vulnerable employment indicators, and a detailed case study is conducted on Mining and Apparel industries and an additional case study to identify impact trade-offs for one climate transition investment fund.

In **Chapter 6**, we test the suitability of our IOLCA-based company-level sustainability estimates for answering an empirical asset pricing question, namely *"Are investors pricing sustainability characteristics of companies in the cross-section of stock returns ?"*. We hypothesize that investors are positively pricing the environmental and social performance of companies measured using an IOLCA-based model in the cross section of stock returns. IO database EXIOBASE is used to derive estimates at company level on five impact categories, on a time series, from 2012 to 2021 and covering over 25,000 unique companies. Finally, in Chapter 7 the main contributions but also limitations of this research will be presented and serve as conclusion of this PhD thesis.

2 A critical review of methods and frameworks for measuring the sustainability of investment funds[2]

Abstract

Investors increasingly demand that asset managers measure the non-financial performance of their investment portfolios. Amidst concerns of greenwashing, reliable sustainability assessment methods are needed to ensure that funds are channeled towards priority sectors for the transition to a low-carbon and more inclusive economy. This critical review provides a classification, analysis, and evaluation of current sustainability measurement methods for investment funds from both industry and academia. The evaluation is based on a seven-criteria matrix, developed based on gaps identified in seminal academic works and in reports from international organizations. Following the evaluation, we find that carbon footprints and exposure metrics and environmental, social and governance (ESG) ratings, while widely used, have several shortcomings, failing to capture the real-world sustainability impact of investments. We suggest that open-source, science-based and sustainability-driven assessment methods are prioritized going forward. Methods can be upgraded by incorporating measurement of positive impact creation and by adopting a life-cycle perspective. Given the need to anchor sustainability assessments in the reality, the compatibility of investment products with science-based targets for sustainable development should become a central element of reporting requirements. Finally, methods incorporating a forward-looking perspective, as well as an assessment of investor's additionality are scarce and should be given priority in future research.

[2] Adapted from article published as *Popescu, I.S., Hitaj, C., Benetto, E., 2021. Measuring the sustainability of investment funds: A critical review of methods and frameworks in sustainable finance J. Clean. Prod. 314, 128016.* https://doi.org/10.1016/j.jclepro.2021.128016

2.1 Introduction

Capital markets need to join the race of reaching the ambitious Paris Agreement and the United Nations (UN) 2030 Agenda for Sustainable Development (UNCTAD, 2014; UNFCCC, 2015). Up to 7 trillion USD are required every year to reach the 17 Sustainable Development Goals (SDGs) by 2030 (UNEP, 2019). The reality is that these needs are not yet close to being covered. A report of the UN Framework Convention on Climate Change (UNFCCC) estimated that only 681 billion USD flowed into climate finance in 2016 (Yeo, 2019). The asset management industry, in contrast, estimates that investments in so-called "sustainable assets" are 17 times larger than the UNFCC estimate – up to 12 trillion USD in US assets, and 11 trillion EUR in Europe (Eurosif, 2018; US SIF, 2018). This discrepancy raises the question of how many funds are in fact targeted towards sustainability. In Europe, only 108 billion EUR of the 11 trillion EUR in sustainable assets are impact investments – investments actively seeking to generate a positive environmental or social return (EFAMA, 2020; Eurosif, 2018). However, as more and more investment products labelled "sustainable" enter the market, concerns about *green-* and *impact-washing* are growing (OECD, 2020a; Revelli, 2017).

The European Union (EU) Taxonomy Framework (henceforth, the Taxonomy) and the regulation on the "Sustainability-related disclosures in the financial services sector" (Regulation (EU) 2019/2088) will usher in a new era of sustainability measurement and reporting. At the same time, numerous regional initiatives to support sustainable finance are developing, such as China's Green Industry Guiding Catalogue (UN PRI, 2021). In the context of heterogenous regulations, and given the need to develop clear standards, the Organization for Economic Cooperation and Development (OECD) urged the financial world to develop a common understanding of impact measurement, calling it an "impact imperative" (OECD, 2019a). It is this imperative that also drives our research.

While there is no universal definition of sustainability, we follow the construct of the three sustainability pillars: social, economic and environmental (Elkington, 1998; Purvis et al., 2019; Sala et al., 2013). In the investment world, sustainability is generally represented by the environmental, social and governance pillars (ESG) (UN Global Compact, 2004). Despite the two terms being used interchangeably, sustainability is rather focused on the impact humanity has on the planet and society while ESG frames the notion in terms of material risks posed by the environmental and social factors to businesses. In the management domain, the discussion is concentrated around the topics of corporate sustainability performance (CSP) and the triple bottom line theory (Dragomir, 2018; Elkington, 1998; Linnenluecke and Griffiths, 2013; Rahdari and Anvary Rostamy, 2015). In our paper, we use the general term of sustainability to encompass the social and environmental dimensions.

We consider socially/sustainable responsible investment (SRI) funds as funds using ESG portfolio screenings, as well as engagement, with the final aim of having a long-term, positive sustainability impact. This definition combines literature- and practice-based definitions (Eurosif, 2018; Renneboog et al., 2008; UN PRI, 2018). Impact measurement in the context of sustainable investing can be defined as *"the process of measuring and monitoring the amount of change created by an organization's or an investor's activities"*

(OECD, 2020a). Existing measurement and reporting tools do not reflect in totality the direct contribution of financial investments to sustainability goals. Moreover, measurement tools are not consistent in methodology. For example, ESG scores from different providers diverge significantly (Berg et al., 2019), which muddles the signal such scores send to investors.

Recent review papers note that while the general research on responsible investing is expanding, not enough attention is given to measuring the sustainability performance of investments (Fabregat-Aibar et al., 2019; Losse and Geissdoerfer, 2021). To the best of our knowledge, there are no published academic reviews analyzing and comparing sustainability measurement tools geared towards the investment funds industry, despite several studies highlighting this as a significant gap (Capelle-Blancard and Monjon, 2012; Diaz-Rainey et al., 2017; Hoepner and McMillan, 2009; Revelli, 2017; van Dijk-de Groot and Nijhof, 2015).The existing research in sustainable investing is largely concerned with the relation between ESG and financial performance (Friede et al., 2015; Geczy et al., 2005; Statman and Glushkov, 2016), the development of low-carbon investment strategies (Andersson et al., 2016; Bender et al., 2019), or the challenges posed by data and accounting choices (Busch et al., 2020; Thomä et al., 2018; Vörösmarty et al., 2018). Previous review papers have studied how sustainability measurement is performed at the company level (Angelakoglou and Gaidajis, 2015; Morioka and de Carvalho, 2016) or have addressed a single category of methods, like ESG ratings (Escrig-Olmedo et al., 2019), climate assessments and carbon footprint metrics (Thomä et al., 2018).

With our critical review, we highlight the advantages and shortcomings of existing sustainability assessment tools used by the financial sector. Our analysis is particularly timely, since the developed criteria and identified drawbacks of current tools can guide the creation and implementation of a more robust assessment of sustainability called for by the Taxonomy.

In the Methods section, we firstly explain the procedure followed for selecting the documents for review. We then present a framework to categorize identified methods. We develop an evaluation matrix comprising seven criteria representing the consensus of international bodies (OECD, 2020a; UN PRI, 2019; UNEP FI, 2017) and leading sustainable finance initiatives (Net-Zero Alliance, 2020; TCFD, 2017a). In the Results section, we describe, compare, and evaluate identified methods. In the Discussion, which is arguably the most important part of our article, we identify which methods come closest to measuring the real-economy sustainability impacts of investments. Finally, we conclude with our key findings and recommendations for future research.

2.2 Methods

2.2.1 Critical review framework

2.2.1.1 Systematic review

The review process was conducted in the systematic approach proposed by the PRISMA framework (Moher et al., 2009). The combined searches for specific keywords in the Web of Science database led to a first pool of 1269 articles (Table 2.1). We focused only on articles that combine the three fields addressed by our review: investment industry (e.g., "fund"), sustainability (e.g., "sustainable", "ESG") and performance measurement (e.g., "assessment", "impact"). We conducted the exclusion based on the analysis of article title and abstract, which led to a selection of 135 relevant articles.

We used citation chaining to identify additional relevant articles. Key articles were screened based on backward (list of references cited by the article) and forward (papers that have cited the article) citation searches, leading to the identification of 32 additional articles. Subsequently, we performed searches in the Scopus database, to identify relevant articles not captured in the Web of Science database search. After removing duplicates, 154 relevant articles remained, which we sorted according to the main research questions addressed. Restricting the results to the topic of "Evaluation and Measurement", we obtained 12 papers that either propose a novel framework for measurement or use existing methods specifically for the measurement of investment fund sustainability.

2.2.1.2 Non-systematic review

In parallel, we carried out a review of methods used by the sustainable investment industry. We consulted 25 frameworks, tools and guidelines developed by national and international initiatives (e.g., Task Force on Climate-Related Financial Disclosures - TCFD), as well as private data providers (e.g., Morningstar), or NGOs (e.g., 2 degrees investing initiative).

2.2.2 Framework for analysis and evaluation of methods

This section presents the process we followed to categorize, analyze, and evaluate *sustainability measurement methods, tools and frameworks* applied in the sustainable investment industry. We use the general term of "methods" to refer to the plethora of frameworks, metrics, indicators, and assessment tools for measuring sustainability impact. As noted previously in a review of sustainability assessment metrics, there is no consistent terminology for classification (Sala et al., 2013). This article builds on the approach developed by Angelakoglou & Gaidajis (2015) used to review methods for assessing the environmental sustainability of industrial systems.

Table 2.1: Systematic literature search, based on the PRISMA protocol

PRISMA Step	Description
Eligibility	Period of publication: no limit Language: English Type: all types
Information sources	Primary database: Web of Science Additional sources: Scopus, backward and forward citation searches Date of consultation: August 2020
Search process	Fields: article titles, abstracts, and keywords Search keywords: “sustain* invest*” “sustainab* performance" AND "mutual fund" "social* responsible invest*" "responsible invest*" NOT "socially responsible invest*" "ESG fund" "climate" AND "mutual fund" "climate" AND "investment portfolio" "carbon footprint" AND "invest*"
Study Selection	First exclusion criterion: not matching the sustainable finance domain Second exclusion criteria: related only to the financial performance of sustainable finance not related to investment funds

2.2.2.1 Characterization and grouping of methods

Our paper further contributes to the existing classification frameworks for impact assessments in sustainable finance. For example, Thomä et al. (2018) group methods into three categories: “(1) carbon footprinting, (2) green/brown metrics and (3) climate scores”. A recent working paper from the OECD suggests four categories for impact measurement in sustainable investment at large: “(1) principles and guidance, (2) frameworks and methodologies, (3) standards, certifications and ratings and (4) metrics and indicators” (OECD, 2020a).

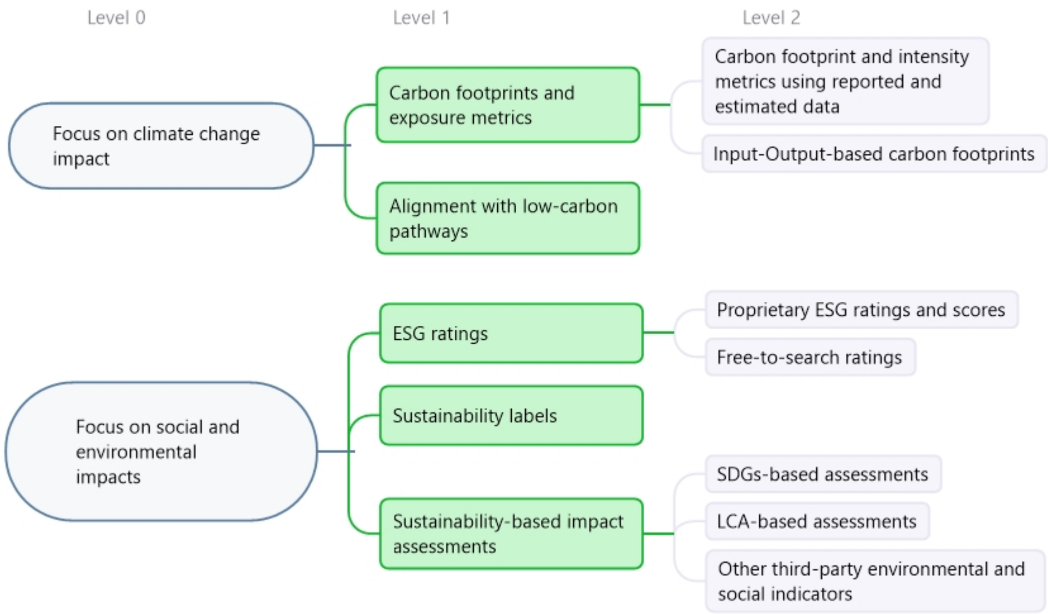


Figure 2.1: Categorization of methods by focus and methodology. Note: Level 0 splits the tools based on their focus – either climate or environmental and social focus. Level 1 defines five categories, based on methodological differences. Level 2 further distinguishes methods based on more in-depth methodological differences

We use a four-level tree map for the classification of assessment methods (Figure 2.1). At level 0, we define two main categories of methods, by the main impact(s) tools focus on and at level 1, we define five larger *families of methods,* grouped according to their similarities in terms of methodology: (A) Methods focused on climate change impacts: 1) Carbon footprint and exposure metrics and (2) Alignment with low-carbon scenarios assessments and (B) Methods focused on environmental and social impacts: (1) ESG ratings, (2) Sustainability labels, and (3) Sustainability-based impact assessments. Finally, at level 3, each method groups different *tools*. The tools are *specific implementations of methods* and have unique methodologies.

In the Results section, Table 2.3 presents the tools identified in academia and practice, together with a short description. While not an exhaustive compilation of all available example methodologies, it is a representation of the array of tools available to regulators and institutional and retail investors. In addition, some tools, though developed for use at company-level, have been included in this list, as they have been used to measure impact at fund level by aggregating impact based on fund holding information (e.g., the Net Environmental Contribution tool). We note that tools that fit in more than one category (e.g., tools measuring alignment with low-carbon pathways using carbon footprinting) have been assigned to only one representative category based on primary features. Links to source documents for all methods from the non-systematic review are provided in Table S1 of the Supplementary Material available in the online version of this article.

2.2.2.2 Defining criteria for evaluation

We reviewed the literature to identify the characteristics of ideal methods, as there is no pre-established set of criteria fit for this purpose. Principally, we drew from internationally accepted guidelines published by the UN, UN Environmental Programme (UNEP), UN Principles for Responsible Investment (UN PRI), and OECD – organizations that set the strategic direction on sustainability for financial markets (OECD, 2019a, 2020a; UN PRI, 2018; UNEP FI, 2017). We further consulted documents that specifically target the domain of sustainable finance and are internationally-accepted guidelines or regulations, namely the regulations under the European Commission (EC) Action Plan on Sustainable Finance (EC, 2018a) and the TCFD (Task Force on Climate-related Financial Disclosures (TCFD), 2017). We then complemented our findings with insights from financial market players leading the sustainable finance transition, namely the Institutional Investors Group on Climate Change (IICGG) and the UN-convened Net-Zero Asset Owners Alliance (IIGCC, 2020; Net-Zero Alliance, 2020). Finally, we consulted recent reviews and influential papers from the sustainable finance field and sustainability assessment in general (e.g. Capelle-Blancard and Monjon, 2012; O'Rourke, 2003; Olsthoorn et al., 2001). In defining the criteria for evaluation, our contribution consisted in collating the needs and gaps identified in the literature and reorganizing them in a way that is most relevant for the investment fund industry.

Based on our findings, we develop a novel set of seven criteria, representing the consensus from stakeholders in the sustainable investment market: (1) double materiality, (2) reliability, (3) life-cycle consideration, (4) comprehensiveness of impact categories, (5) compatibility with science-based targets (SBTs) for sustainable development, (6) prospectiveness and (7) investor's additionality. We consider these criteria mutually exclusive and complementary. "Double materiality" and "Investor's additionality" are specific to the investment industry only. The criteria on "Reliability" and "Prospectiveness" address the practical side of the method and its applicability. The other three criteria address sustainability impact measurement from a scientific point of view. In Table 2.2 we illustrate the questions specific to each criterion used to evaluate selected tools. More detailed references and extracts from the cited documents can be found in Table A.1 of the Appendix.

2.2.2.2.1 Double materiality

Two central questions posed by the PRI to responsible asset managers are "Does your fiduciary duty extend beyond strictly financial benefits for stakeholders?" and "Is positive real-world impact an explicit part of your primary objective for investment results?" (UN PRI, 2018; UNEP FI, 2017). This perspective challenges investors to extend the risk-return investment criterion with a third factor – real-world impact, redefining the fiduciary duty of managers. Previous review papers have identified this aspect as a gap in current research (Capelle-Blancard and Monjon, 2012; Talan and Sharma, 2019). The financial industry should build on the developments in the sustainability assessment domain, in order to correctly apply sustainability considerations and further lead to cleaner production (O'Rourke, 2003; Sala et al., 2013). The EU, in its guidelines for non-financial reporting by corporations, addresses the concept of double materiality, referring to the impact companies have on climate change and not only the inverse relation, which will also be incorporated in the upcoming EU Ecolabel for financial products (EC, 2019d).

Table 2.2: The seven criteria for the evaluation of sustainability measurement tools in sustainable investing

Criteria	Questions for the evaluation of a method	References
Double Materiality	*Q1. Does it assess real sustainability, by moving from risk assessment to positive impact generation?* *Q2. Is it focusing rather on actions than on policy and strategy?*	(EC, 2019d) (OECD, 2020a) (UN PRI, 2018) (UNEP FI, 2017)
Reliability	*Q1. Is data complete and reliable?* *Q2. Is the methodology transparent and reproducible?* *Q3. Does it allow for an easy comparison between different investment products?* *Q4. Is there a verification / audit of data and methodology?* *Q5. Is the methodology quantitative rather than qualitative?*	(EC, 2019d) (EU, 2019) (OECD, 2020b) (OECD, 2020a) (TCFD, 2017a)
Life-cycle consideration	*Q1. Does the tool adopt a life-cycle perspective, considering impact along the full value chain?* *Q2. Does the metric account for impacts in the downstream value chain (consumption and end-of-life)?* *Q3. Does the metric account for impacts in the upstream value chain (raw materials extraction and acquisition/supply chain)?*	(EC, 2019d) (OECD, 2019b) (TCFD, 2017a)
Comprehensiveness of impact categories	*Q1. Are other environmental impacts beyond greenhouse gas emissions represented?* *Q2. Does the metric consider social impacts?* *Q3. Are trade-offs between different impact categories presented?*	(EC, 2019d) (OECD, 2019a) (TCFD, 2017a) (UNEP FI, 2017)
Compatibility with science-based targets for sustainable development	*Q1. Is the method acknowledging the carbon budget and the defined trajectories for limiting global warming (i.e., Paris Agreement 1.5 / 2 °C warming)?* *Q2. Is the method linking impact to the SDGs?* *Q3. Does it address other scientific goals (e.g., planetary boundaries)?*	(EC, 2019d) (IIGCC, 2020; Net-Zero Alliance, 2020) (OECD, 2020a) (TCFD, 2017a)
Prospectiveness	*Q1. Are the metrics presenting impact in terms of progress towards a goal?* *Q2. Is the method accounting for targets set by the company and planned investments?* *Q3. Is it incorporating a long-term approach to impact?*	(IIGCC, 2020) (TCFD, 2017a) (UN PRI, 2019)
Investor's additionality	*Q1. Does the metric quantify the engagement and activism of the fund manager towards achieving impact?* *Q2. Is the real contribution of the investment quantified?*	(IIGCC, 2020; Net-Zero Alliance, 2020) (TCFD, 2017a) (UN PRI, 2018) (UNEP FI, 2017)

2.2.2.2.2 Reliability

Reliability of assessment tools refers to the qualities of being easy to understand, accessible and adaptable to different financial products (Task Force on Climate-related Financial Disclosures (TCFD), 2017). Comparable, standardized and transparent data are needed in the development of such assessment tools (OECD, 2020a, 2019a; Schumacher et al., 2020; Task Force on Climate-related Financial Disclosures (TCFD), 2017; UN, 2019). To increase reliability and be viable, methods must have stringent requirements on impact measurement (Chatterji and Levine, 2006; Net-Zero Alliance, 2020). Lack of trust in ESG data is most often cited as the principal obstacle to having more robust and comparable measurement tools (Busch et al., 2016). Measurement methods must strike the right balance between relying on self-reported company data, that are not always verified or verifiable, and independent data, that are usually available only aggregated at industry level and lack information specific to companies. At the same time, relying on data providers comes with a high cost and a lack in transparency of methodology design. In addition, transparency and comprehensiveness are needed in order to ensure that impact measurement tools are trustworthy (Olsthoorn et al., 2001; TCFD, 2017a).

2.2.2.2.3 Life cycle consideration

A key criterion that stems from the sustainability science is the consideration of impact over the complete life cycle of all activities/products underpinning held companies – from raw material extraction to production, use, and end-of-life. The importance of a life-cycle perspective on impact assessment is identified in previous research (Cinelli et al., 2014; Escrig-Olmedo et al., 2019; Hertwich and Wood, 2018; Lauesen, 2019; Visentin et al., 2020), in the EU Action Plan on Sustainable Finance (EC, 2019e), and in reports aimed at standardizing carbon footprinting (PCAF, 2018). Assessing the impact over the life cycle of an economic activity is clearly called upon by the EU Taxonomy, and science-based criteria are set under each economic activity (EC, 2021a). For carbon emissions, Hertwich & Wood (2018) show that between 1995 and 2005 emissions embedded in the supply chain of industries grew by 84%, while direct emissions increased by 47%. Measuring and reporting on value chain impacts would force asset managers and companies alike to better monitor and incentivize change of unsustainable practices in the supply chain and use phase (OECD, 2019b). Incorporating a life-cycle approach has to be done in a consistent way, establishing which categories of impacts are to be included and respecting a standardized way of reporting (GHG Protocol, 2013; ISO/TS 14072, 2014; ISO 14040, 2006; Lauesen, 2019).

2.2.2.2.4 Comprehensiveness of impact categories

Current guidelines in the financial industry, such as the TCFD, focus on measuring climate change impact and usually reduce this issue to the disclosure of carbon emissions. Too great a focus on greenhouse gas (GHG) emissions can mean other impacts are overlooked, which in the long term may negatively impact society, the economy and the environment (Morioka and de Carvalho, 2016; UN, 2015; UNEP FI, 2017). In the Taxonomy, this is addressed by the criteria of "do no significant harm" and "meeting minimum social and governance standards" (EC, 2020). Specifically, the EU Taxonomy defines six key environmental objectives, extending impact assessment from climate change impacts to other relevant categories, namely: water, pollution, circular economy and biodiversity and ecosystems (EC, 2021a). Investment managers should avoid greenwashing, or SDG-washing, defined by the OECD as reporting positive impact on one SDG, while ignoring negative impacts on others (OECD, 2020a). As such, an extended set of sustainability indicators is needed, in order to identify synergies, trade-offs and unintended consequences (Vörösmarty et al., 2018). The life-cycle assessment (LCA) methodology provides a good framework for defining a comprehensive set of impact categories (Huijbregts et al., 2017). Multi-criteria decision analysis (MCDA) is used in the field of sustainability analysis to assess the impact of multiple indicators within the same framework (Cinelli et al., 2014; Santoyo-Castelazo and Azapagic, 2014; Wang et al., 2009).

2.2.2.2.5 Compatibility with science-based targets (SBTs) for sustainable development

Another criterion is the ability of an assessment tool to frame impact in terms of investment contribution to defined sustainability goals. Absolute values or comparisons to conventional benchmarks cannot unveil the contribution investment portfolios make on reaching global sustainability targets (Rekker et al., 2019). The international community refers most often to targets set in the Paris Agreement (Battiston et al., 2017), the SDGs (UNCTAD, 2014) or the nine planetary boundaries (Rockström et al., 2009). By focusing on specific climate targets that limit the amount of emissions in a future period, funds can push businesses to reconsider their operations in order to be prepared for the low-carbon transition (IPCC, 2018; Schoenmaker and Schramade, 2019; UNFCCC, 2015). In the investment management industry, the concept of net-zero investment portfolios is becoming popular, as investor-led initiatives demand robust frameworks that align portfolios with a 2050 zero-emissions target (IIGCC, 2020; Net-Zero Alliance, 2020). While it may be more complex than reporting absolute values, linking impact to a scientific framework not only gives more credibility to investments, but also helps identify the companies and activities that can bring the most significant impacts.

2.2.2.2.6 Prospectiveness

Impact should not only be linked to a sustainability goal (as defined in the preceding criterion) but should also show, in a dynamic way, how the investments contribute to achieving progress, on longer time frame. Just like a financial valuation is forward-looking (e.g., predicting the value of the company for a five-year time frame), so the sustainability impact estimations should be. A prospective approach to impact, as opposed to retrospective assessments, would allow investors to capture planned developments in terms of sustainability solutions and to better identify risks and opportunities (Angelakoglou and Gaidajis, 2015; Fraser, 2017; Ness et al., 2007). The TCFD recommends reporting of emissions across more periods, to allow for a trend analysis (TCFD, 2017a). In addition, more and more frameworks look at decarbonization targets and commitments made by companies (CDP, 2019). For example, metrics for sustainable investment should evaluate investment plans and climate targets set by companies that investment managers hold in their portfolios, ensuring a reasonable time frame for environmental and social impacts to materialize (IIGCC, 2020; Net-Zero Alliance, 2020; Schoenmaker and Schramade, 2019).

2.2.2.2.7 Investor's additionality

Direct investor impact, also expressed through the concept of "additionality", can be defined as the contribution of the investor, that would have not been achieved without his/her involvement (Brest and Born, 2013; Net-Zero Alliance, 2020; So and Staskevicius, 2015). SRI funds, through capital allocation choices and shareholder engagement, can send signals to corporations and influence the cost of capital of companies (Haigh and Hazelton, 2004; Kölbel et al., 2019; O'Rourke, 2003; Statman, 2000). Previous research stressed that more concentrated, actively managed portfolios and support for sustainability-related shareholder resolutions would allow investors to stimulate change (Boermans and Galema, 2019; Dimson et al., 2015; Dyck et al., 2019a; Schoenmaker and Schramade, 2019; UN PRI, 2018). Accounting for investor's additionality could incentivize capital markets to play an active role in the sustainability transition. An investment fund that is actively managed in this way should be rewarded, compared to an investment fund that remains passive (IIGCC, 2020).

2.3 Results

2.3.1 Presentation of methods for assessing the sustainability of investment funds

In Table 2.3, we summarize the tools identified through the systematic and non-systematic literature reviews. In the "Source" column, we specify the different types of references: DP – third-party data provider (including labeling agencies), I – independent organization, A – academic literature. Below, we provide a description of methods, and present their advantages as well as their challenges.

2.3.1.1 Carbon footprints and exposure metrics

Carbon footprints are a measure of the emissions embodied in the operations of investee companies. The TCFD – the overarching guideline for climate-related reporting – recommends the use of *Weighted Average Carbon Intensity* (measured in tCO_2eq per MEUR of revenue), as it considers the proportion of ownership of all assets in the portfolio (TCFD, 2017a). In this context, carbon can refer to the wider array of GHGs that are generally measured, while keeping the name of carbon for ease of use and using carbon dioxide equivalents (CO_2eq) for quantification. In practice, 34% of PRI signatories report on *portfolio carbon footprint* (carbon footprint per 1 million of currency invested), while 14% report on *weighted average carbon intensity* (PRI, 2019).

Despite their widespread use and increased initiatives for standardization (PCAF, 2018), carbon footprinting exercises see large variations in terms of accounting and normalization choices (2DII, 2013; Busch et al., 2020). In terms of scope, most carbon footprinting exercises only include direct emissions scope 1 and scope 2), not including emissions from the supply chain or the use phase (scope 3). In terms of data, methodologies rely on company-reported values (First State Investments, 2016), estimates (Koellner et al., 2007; Ritchie and Dowlatabadi, 2014), or a combination of both (Carbon4finance, 2020). Estimates are derived using industry averages from external databases, such as Environmentally Extended Multi-Regional Input-Output databases (EEMRIO) (Inrate, 2020; Trucost, 2019b).

2.3.1.2 Alignment with low-carbon pathways

New methodologies have developed to measure the alignment of portfolios with the goals of the Paris Agreement, generally by measuring the temperature alignment (Institut Louis Bachelier, 2021). One such tool is the Carbon Impact Analytics (CIA) tool from Carbone4finance. It measures the compatibility of electricity-related assets with the warning scenarios, based on the sustainable development scenario (SDS) from the International Energy Agency (IEA) (Carbon4finance, 2020). A more advanced tool is the Paris Agreement Capital Transition Assessment (PACTA). It measures the alignment of investment portfolios to the 2°C warming scenarios, based on the five-year investment plans of underlying companies (2DII, 2013), covering companies from the sectors most affected by global warming. It has been applied to various portfolio samples and sectorial analyses (Schumacher et al., 2020; Thomä et al., 2019b).

2.3.1.3 ESG ratings

Established rating agencies, e.g., Morningstar, MSCI and Refinitiv, have developed proprietary models to independently score funds. ESG ratings are one of the most popular tools to assess the sustainability of corporates and investment funds. These are available upon subscription to investment professionals and are characterized by large coverage. The methodology is based on different scales of scoring (numerical value) or rating (using letters), based on the ESG profiles of underlying equity holdings. ESG company ratings are derived from the weighting of hundreds of quantitative and qualitative E, S and G factors (Chatterji et al., 2009; Refinitiv, 2020). Some academic studies have developed novel methods to improve weighting models of ESG ratings for funds (Cabello et al., 2014; Petrillo et al., 2016).

Aside from established ESG data providers, free-to-search fund ratings have emerged that do not require a paid subscription. For example, Climetrics rates funds on a scale of 1 to 5 green leaves, based on the climate risks and opportunities that the underlying fund holdings entail (Climetrics, 2020). Their methodologies are transparent and combine quantitative indicators (e.g., investments in fossil fuels) with qualitative aspects (e.g., management action on sustainability).

Table 2.3: Methods for assessing the sustainability of investment funds, identified by systematic and non-systematic review

Level 1 **Family of methods**	*Level 2* **Method**	*Level 3* **Specific tool for implementation**	**Source**	**Notes on methodology and coverage**
Carbon footprints and exposure metrics	Carbon footprint and intensity metrics using reported and estimated data	yourSRI Carbon Report	DP	Measures Total Carbon Emissions scope 1+2; Total Carbon Emissions scope 1+2+3; uses data from SouthPole
		Carbon Footprint as defined under the Partnership for Carbon Accounting Financials (PCAF)	I	Gives recommendations on best practice in reporting on carbon footprints; aims to develop target-setting methodologies to measure alignment with climate scenarios
		ISS Climate Impact Report Carbon Footprint	DP	Absolute Carbon Emissions scope 1+2+3 and intensities; in addition, it provides assessment of transition and physical risks, as well as scenario analysis
		yourSRI Carbon Report	DP	Weighted Average Carbon Intensity (relative to Revenue or Investment); uses SouthPole Carbon data
		Carbon Inefficiency Ratio	A	Company-level CO2 emissions from third-party ESG database (ASSET4) to compute Carbon Inefficiency Ratio to Sales for funds comparison (Boermans and Galema, 2019)
	Input-Output-based carbon footprints	Trucost Carbon Scorecard	DP	Comprises carbon footprints, exposure to fossil fuels, use of renewable energy, as well as alignment with transition scenarios for electricity companies
		Inrate Climate Impact	DP	Uses IO and LCA to compute portfolio carbon footprint and carbon intensity, covering whole value chain (supply chain, use phase, disposal)
		Environmental Impacts and Damages / Shadow Impact Calculator	A	Novel IO-LCA databases used to derive industry average emissions factors, adapted at holding level (Koellner et al., 2007; Ritchie and Dowlatabadi, 2014)
Alignment with low-carbon pathways		Paris Agreement Capital Transition Assessment (PACTA)	I	Open-source methodology, forward-looking industry data, and using scenarios to estimate the alignment with climate scenarios
		Carbon4finance Carbon Impact Analytics	DP	Uses a bottom-up approach to measure value chain emissions; reports on avoided emissions; is based on life-cycle-based carbon footprint

Level 1 Family of methods	*Level 2* Method	*Level 3* Specific tool for implementation	Source	Notes on methodology and coverage
ESG ratings	Proprietary ESG ratings and scores	MSCI ESG Fund Ratings	DP	ESG risks and opportunities perspective; uses weighted ESG scores of holdings (over 200 ESG data points); covers 36,000 funds and exchange-traded funds (ETFs)
		Morningstar Sustainability Rating	DP	Uses Sustainalytics ESG data and ESG Risk Ratings; looks at ESG risks and opportunities
		Refinitiv Fund ESG Scoring	DP	Based on Refinitiv company ratings
		yourSRI ESG Screening	DP	Rates over 32,000 funds; it is based on MSCI ESG data; fee-based customized reports
		Analytic Hierarchy Process for ESG factor weighting	A	Analytic Hierarchy Process (AHP) to weight ESG factors and ESG database for factors (Equitics – Vigeo Eiris) (García-Melón et al., 2016; Petrillo et al., 2016)
		Reference Point Method for SRI	A	Reference Point Method as a multi-criteria decision technique, based on quality of SRI management and ESG performance of companies (Cabello et al., 2014)
		Third-party ESG data	A	ESG data from third-party provider (ASSET4, KLD Ratings) to compare sustainability of holdings/ funds (Gangi and Varrone, 2018; Kempf and Osthoff, 2008)
	Free-to-search ratings	Fossil Free Funds (As you Sow)	I	Covers U.S.-domiciled funds; databases available on Tobacco, Deforestation, Weapons and Gender Equality
		Climetrics	I	Database covers ~15,000 funds; score based 85% on quantitative (carbon emissions, water security, deforestation) and 15% qualitative (management of sustainability issues) metrics
Sustainability labels		FNG-Label for Sustainable Funds (DE)	DP	Addressed to funds incorporating ESG strategies; 90% of the portfolio should be assessed using ESG criteria
		LuxFlag ESG (LU)	DP	Wide range of labels (ESG, Microfinance, Green Bond, Environment, Climate Finance); 303 labelled funds in 2020
		Nordic Swan Ecolabel	DP	Part of the Nordic Ecolabel for products
		Greenfin Label (FR)	DP	Has explicit criteria related to impact measurement (proof of positive impact)
		Label ISR (FR)	DP	It is supported by the French Ministry of Finance; considers engagement with investees and the proof of positive impact
		Febelfin QS (BE)	DP	Created based on the recommendations from the EU Taxonomy; stringent criteria for coal (max 10% company revenue)

Level 1 Family of methods	*Level 2* Method	*Level 3* Specific tool for implementation	Source	Notes on methodology and coverage
Sustainability-based impact assessments	SDGs-based assessments	CISL Investment Impact Framework	I	Transparent methodology, discussing ideal and possible metrics for measuring impact across six different themes (such as basic needs, wellbeing, and healthy ecosystems), which are derived from the SDGs (Cambridge Institute for Sustainability Leadership (CISL))
		Portfolio Impact Footprint (Impact-Cubed)	DP	Evaluates a portfolio´s holdings based on 16 indicators, covering environment, governance, business model and society); indicators are mapped to the SDGs
	LCA-based assessments	Net Environmental Contribution (NEC) (Quantis)	I	Uses life-cycle-based metrics to determine the contribution of industries to the climate transition
		Biodiversity Footprinting (PRéSustainability)	I	Developed as a case study for ASN Bank, collaboration between PRéSustainability and CREM; detailed biodiversity impact of a bank's portfolio of different assets; based on life-cycle data
	Other third-party environmental and social indicators	Environmental and Social Performance Indicators; TOPSIS	A	Environmental and social indicators sourced from third parties (e.g., UNDP), to measure sustainability of sovereign bonds (Bilbao-Terol et al., 2014; Scholtens, 2010)
		Social impact measurement	A	Qualitative and quantitative methods applied in impact investment (So and Staskevicius, 2015)
		Alternative environmental indicator (DEA Approach)	A	Combining financial with non-financial performance measurement, using different environmental dimensions, based on third-party data from Bloomberg (Allevi et al., 2019)

2.3.1.4 Sustainability labels

In the race to tag financial products with sustainability labels, investment managers are pursuing various certifications to attest their commitment and performance. As of 2019, over 400 European funds with approximately 95 billion EUR assets under management (AuM) obtained such a certification (Novethic, 2019). Unlike ESG scores, which are determined independently, labels are issued at the request of a fund manager in exchange for a fee. The labeling agency conducts an audit of the fund, usually based on data provided by the fund parent entity, to determine if the fund is accomplishing the criteria. Depending on the label, there are different traits that a fund must demonstrate. A main point is the degree to which funds integrate ESG criteria in their investment strategy. In addition, many labels have exclusion criteria (inter alia, tobacco, nuclear energy, coal mining). Other minimum requirements relate to annual reporting on ESG issues (LuxFLAG, 2016; Nordic Ecolabelling, 2017). Some fund labels have stronger requirements, making it mandatory for funds holding the label to report on sustainability performance, such as compatibility with the 2 °C warming scenario or impact on biodiversity (FNG, 2020; Greenfin, 2019).

2.3.1.5 Sustainability-based impact assessments

The last family groups together methods and frameworks that aim either to measure sustainability as defined through the SDGs or focus on industry-specific indicators. Such tools overcome the centricity on GHG emissions. One framework, developed by the Cambridge Institute for Sustainability Leadership, measures impact across the SDGs by proposing a set of ideal and possible metrics to measure impact (CISL, 2019). Other methods, building on the extensive literature on industry sustainability indicators (Roca and Searcy, 2012), propose the use of industry-specific indicators to signal the exposure of portfolios (e.g., "fossil fuel reserve emissions" from the Trucost Carbon Scorecard model). Scholtens (2010) proposes a model to compute the environmental performance of governmental bond funds using diverse environmental indicators, like the Environmental Sustainability Index (ESI) developed by the Yale Center for Environmental Law. A later study extends this methodology by incorporating social indicators, namely the Human Development Index (Bilbao-Terol et al., 2014).

More advanced tools use LCA-based methodologies to measure impact and address a larger set of environmental and social indicators (Gibon et al., 2020; Lauesen, 2019; Sycomore AM, 2018). The sustainability issues addressed are climate, waste, water and air quality. Another novel framework computes biodiversity impact of different financial products of a bank's portfolio (PRéSustainability, 2019).

2.3.2 Evaluation of methods against criteria

Table 2.4 presents the summary evaluation matrix across the seven criteria of 13 selected methods and tools for sustainability measurement. The methods are rated on a color scale from orange to dark green (0 to 3) to assess the degree to which of each of the seven specific criteria are satisfied: Orange – Criterion not addressed; Yellow – Slightly addressing criterion; Light Green – Good level of addressing the criterion, with room for improvement; Dark Green – Best practice in addressing criterion. A detailed examination of all methods on the proposed criteria is contained in Table A.2. Each method is evaluated based on the degree of answering the criterion questions (Table 2.2). The accomplishment (or not) of one criterion can influence the scoring of another one: for example, if a method does not have a transparent methodology, then the criteria related to impact will not be graded with maximum points, as the measurement is not verifiable. The Grey color indicates that a criterion is not applicable to the tool. Indeed, depending on the scope of sustainability measurement, certain criteria are not relevant for assessment. For example, *carbon footprints and weighting metrics* only serve as a tool for measuring the GHG emissions of a fund's holdings, therefore they will not be judged on criteria like *investor's additionality* or *comprehensiveness of impact categories* as these criteria were excluded directly from the design on the tool. Moreover, we notice that some tools could integrate a criterion, but choose not to do so and state this fact in in their methodology. These are marked with 0/Orange in the summary evaluation. An example would be the exclusion of *life-cycle consideration* from a methodology, which is generally explained by lack of data or complexity. The evaluations presented in Table 4 thus pertain to how the methods are currently used in practice rather than what the method could be capable of accomplishing in theory.

When designing and assessing current measurement frameworks, all criteria should be taken into consideration, as together they manage to capture the complete dimensions of sustainability. We propose, initially, an equal weighting of criteria, as the main goal of the evaluation framework is to assess comprehensiveness. Nonetheless, the criteria are not necessarily equal in terms of their importance to all stakeholders. Defining weighting schemes and priority criteria is not in the scope of this paper. These can be further explored based on consultations with stakeholders (Gan et al., 2017) and it could be an important follow-up to our findings. The proposed evaluation matrix can be further used to prioritize criteria and identify tools best tailored for specific sustainability impact assessment goals.

ESG Scores and Ratings for funds have the advantage of being ready-to-use and easy to comprehend by the larger public, due to their simplistic presentation. Moreover, they encompass the whole spectrum of social and environmental factors, though largely from a qualitative point of view. In addition, ESG ratings are the only type of method that reaches a very large coverage, with some providers covering tens of thousands of funds. Finally, free-to-search ratings help end investors identify funds based on their needs, for example, by flagging funds that are investing in fossils (Fossil Free Funds, 2020). On the negative side, ESG ratings usually do not measure the actual impact of funds on sustainability issues. As noted in one methodology, their main aim is to assess the materiality of ESG risks to investors (MSCI, 2020) rather than also accounting for the fund's impact on social and environmental factors. Moreover, rating agencies do not adopt a life-cycle perspective (Escrig-Olmedo et al., 2019), nor report impact linked to science-based targets (Rekker et al., 2019). Given the lack of standardization in the industry, the usability of ratings is reduced (Amir and Serafeim, 2018). Each rating agency uses a different set of metrics and weights to come up with a final ESG score. As this information is not public knowledge, it is difficult to understand what exactly an ESG score is measuring and what weight is given to the different components. There is increased scrutiny of rating methodologies, as scores from different providers diverge (Berg et al., 2019; Delmas and Blass, 2010).

Sustainability labels allow for rapid verification of sustainability claims. However, our assessment of the requirements set out by labeling agencies indicates that the certifications are awarded mostly according to qualitative aspects and consider the commitment of funds rather than their real impacts, increasing the risk of impact washing. In addition, most of the labels are centered on climate change issues and address social issues, such as human rights, only through company exclusions. On the positive side, a few labels are more stringent, by also requiring reporting on alignment with science-based targets and an assessment of the funds' engagement. For example, the Nordic Swan gives extra points to funds that report on environmental indicators and on the level of engagement with companies (Nordic Ecolabelling, 2017). The Belgian label Febelfin recommends funds to disclose the alignment of portfolios with the warming scenarios and has electricity thresholds based on carbon intensity for companies in portfolios (Febelfin, 2019).

Table 2.4: Summary Evaluation Matrix of current methods for sustainable performance measurements in the investment funds industry, based on seven criteria

Sustainability Performance Measurement		Criteria							Total score
Level 2 **Family of methods**	Level 3/4 **Specific Measurement Tool**	Double Materiality	Reliability	Life-cycle consideration	Comprehensiveness of impact categories	Compatibility with SBTs	Prospectiveness	Investor's additionality	**(equally weighted criteria)**
Carbon footprints and exposure metrics	Carbon Footprint	*1*	*1*	*0*		*0*	*0*		**2**
	Trucost Carbon Scorecard	*2*	*2*	*2*	*1*	*2*	*2*		**11**
	IO-based Carbon Footprint	*2*	*1*	*3*		*0*	*0*		**6**
	Weighted Average Carbon Intensity	*1*	*2*	*0*		*0*	*0*		**3**
Alignment with low-carbon pathways	Carbon Impact Analytics (CIA)	*2*	*1*	*2*		*1*	*1*		**7**
	PACTA	*2*	*2*	*1*		*3*	*3*	*1*	**12**
ESG ratings	Proprietary ESG Scores and Ratings	*0*	*1*	*0*	*2*	*0*	*1*		**4**
	Free-to-search Ratings	*2*	*2*	*1*	*2*	*0*	*1*	*1*	**9**
Sustainability labels		*1*	*2*	*0*	*2*	*1*	*1*	*1*	**8**
Sustainability-based impact assessments	CISL Impact Framework	*2*	*2*	*0*	*3*	*3*	*2*		**12**
	Portfolio Impact Footprint	*1*	*1*	*0*	*2*	*2*	*0*		**6**
	Biodiversity Footprinting	*3*	*2*	*3*	*2*	*1*	*0*		**11**
	Net Environmental Contribution	*3*	*2*	*3*	*2*	*2*	*0*		**12**

Legend

0	*Criterion not addressed*
1	*Slightly addressing criterion*
2	*Good level of addressing the criterion*
3	*Best practice in addressing criterion*
	Criterion not applicable for method

While **carbon footprints and exposure metrics** are the conventional, industry-wide accepted tool to report on carbon emissions of funds, they have several shortcomings (Busch et al., 2020; Swedish Investment Fund Association, 2016): despite being a measure of emissions to the real-world economy, carbon footprinting methodologies do not link emissions to decarbonization scenarios and only represent a historical snapshot of a funds' financed emissions, while the TCFD does indeed recommend to report on the historical trend in emissions. In addition, comparability between funds is reduced, given the different accounting and normalization choices (Thomä et al., 2018). Intensity metrics may prove more useful for comparing funds, as they focus on "penalizing" carbon-intensive companies held by the fund and are not biased against holding amount and company size (Task Force on Climate-related Financial Disclosures (TCFD), 2017). Another drawback of the metric is lack of comparability in underlying emissions data and missing life-cycle emissions in computations (Busch et al., 2020; PCAF, 2018). An analysis of the Montréal Pledge signatories shows that less than 10% report scope 3 emissions (Novethic, 2016). This point is being addressed by using input-output databases to include full value-chain emissions and to estimate missing data, while also offering a homogenous data source for emissions (Inrate, 2020; Trucost, 2019b).

Tools measuring the **alignment with low-carbon pathways** are a best practice example for measuring impact against climate targets. As an example, PACTA offers a comprehensive framework, as it addresses climate impact both from the perspective of risk and of contribution to reducing global warming, while also evaluating the asset manager's action on climate change. By analyzing investment plans for a five-year period, it becomes a forward-looking tool, even though investment plans remain subject to change over the analyzed period. Nonetheless, the tool does not address the more in-depth questions related to boundaries for emissions consideration, as it does not specify adopting a life-cycle view when assessing company investment plans. In addition, due to data limitations, not all sectors are mapped on their global warming trajectories. Other alignment tools, like the CIA from Carbone4, only link electricity sectors to the decarbonization scenarios.

Sustainability-based impact assessments focus on specific environmental and social objectives, measured through either single-indicator or multi-indicator frameworks. These tools are more time- and data-intensive than others, due their in-depth consideration of sustainability issues. For instance, the Biodiversity Footprinting Methodology is based on scientific data and captures the positive impact created by different asset classes on biodiversity. Multi-indicator frameworks take a more holistic approach. For example, the Cambridge Institute for Sustainability Leadership provides a framework for reporting on real-world impact across the SDGs, by proposing simple indicators matching the goals and ranking investment portfolios on their alignment. However, it does not incorporate life-cycle assessment, nor does it account for investor's additionality. The Net Environmental Contribution is an example of best practice for such a holistic approach, considering multiple environmental impacts as well as the life-cycle perspective. It is based on a scalable and open-access methodology, and uses data from objective, scientific sources.

2.4 Discussion and Recommendations

We find mixed results in how existing impact assessment methods perform across the different criteria. Overall, PACTA, CISL Impact Framework, and NEC perform the best across all criteria, while carbon footprint, weighted average carbon intensity, and ESG ratings underperform. Below we discuss how existing assessment methods could be improved and how a new assessment method could be constructed to fulfill the criteria identified. We present the characteristics of such an ideal method in Table 2.5.

To incorporate **double materiality** in their frameworks, methods will need to be designed with the main goal of measuring positive impact generated. Two methods**,** Net Environmental Contribution and Biodiversity Footprinting, exemplify best practices. In order to achieve precision and have an in-depth analysis of impact, each sustainability category should be treated separately. More general tools, like measuring impact against the SDGs, should then bring together under the same overarching framework reliable indicator-level methodologies.

In terms of **reliability**, the best practice is having open-source methodologies, that are ideally verified and tested, such as PACTA. Free-to-search ratings stand out through their value proposition – helping end investors choose sustainable options for their investments. We see this developing more and more, with MSCI offering open access to fund ratings (MSCI, 2020). In addition, sustainability certifications in the form of labels are an ideal way to prove sustainability. As current labels rarely demand mandatory enforcement of criteria, new labels, such as the EU Ecolabel for financial products will need to be more stringent in order to avoid greenwashing and promote funds with real impact. In order to be fully trustworthy, methods must incorporate reliable and complete data. Company-disclosed data can be complemented with estimated data points from scientific sources – which have the advantage of being "transparent, reproducible and peer-reviewed" (Vörösmarty et al., 2018).

Worryingly, we only find two types of methods that incorporate a **life-cycle consideration**, by measuring the impact generated at all stages of the holdings' value chain. The life-cycle perspective is needed to prevent impact shifting to other stages. By overlooking this consideration, methods risk to give a false assurance of the completeness of the impact assessment, since impacts from the supply chain or use phase are often larger than impacts caused by direct operations. For example, the scope 3 average carbon intensity of the MSCI ACWI Investable Market Index was 3 times larger than its combined scope 1 and 2 carbon intensity in July 2020 (Baker, 2020).

For the criteria of **consideration of multiple sustainability impact categories**, the SDGs Impact Framework stands out, which addresses a wider array of critical issues, including social justice, health and the environment. Ideal tools in the investment industry should borrow from the methodology of life-cycle assessment, which implies both a holistic assessment of impact, considering all relevant life-cycle stages, and an inclusive consideration of impact categories, by allowing the identification of co-benefits and trade-offs between multiple environmental and social issues. While LCA is not necessarily suited for corporate and fund-level assessments, input-output-based models can serve this purpose. IO models are incorporating LCA principles and are the basis for tools measuring fund impact beyond direct company operations, generated in the supply chain (Busch et al., 2020), and can address both environmental and social concerns (Simas et al., 2014).

As the question of contribution becomes more relevant, **showing compatibility with science-based targets for sustainable development** will be key in reporting. However, only five out of 13 methods incorporate targets in their assessment methodologies. PACTA is one of the tools that stands out, by assessing the alignment of a portfolio of investments with transition scenarios (2DII, 2020).

Table 2.5: Best practices on criteria accomplishment and tool examples

Criterion	Best Practice Tool	Best Practice
Double Materiality	*Biodiversity Footprinting; NEC*	focused, by design, on measuring the positive biodiversity impact achieved
Reliability	*ESG scores and ratings*	coverage of an extensive set of E & S issues
	Free-to-search ratings	centricity on communication to retail investors and open methodology
	Sustainability Labels	external assurance that offers additional reliability through robust certification system
	Biodiversity Footprinting; NEC	open-source, detailed methodology
	CISL Impact Framework	transparent methodology, with presentation of example impact indicators
Life-cycle consideration	*IO-based Carbon Footprints*	incorporation of life-cycle emissions (supply chain or supply chain and use phase)
	Biodiversity Footprinting; NEC	consideration of all life-cycle stages in impact measurement
Comprehensiveness of impact categories	*CISL Impact Framework*	coverage of an extensive set of environmental and social indicators
Compatibility with SBTs for sustainable development	*PACTA*	sectorial alignment with low-carbon scenarios under the Paris Agreement
	CISL Impact Framework	clear link between SDGs, impact categories and individual impact indicators
Prospectiveness	*PACTA*	five-year outlook on portfolio's holdings investment plans
Investor's additionality	*N/A*	N/A

The two final criteria – **prospectiveness** and **investor's additionality** – are the least addressed by existing methods, despite their importance. This is in part due to their complexity and difficulty in measurement. To ensure a **prospective** impact assessment, tools should look beyond historical performance of a portfolio's holdings. We find that the PACTA tool is an effective methodology for measuring alignment of portfolios on a future time frame (Thomä et al., 2019b). We observe that no measure specifically and completely addresses the issue of **investor's additionality**. Some of the methods do evaluate the engagement policies of investment funds and their voting behavior, but do not go further. Arguably, this is one of the most complex criteria to satisfy, given the fine line between what investors can change and what would have happened anyway.

We suggest a five-step process to advance sustainability measurement tools for investment funds. First, a life-cycle perspective is needed (Lauesen, 2019), in order to measure impact across the value chain, as exemplified by tools like NEC or the Biodiversity Footprint. Second, to better serve policy makers and to account for climate and social pledges, impact assessments of funds should be reported in terms of progress made on existing frameworks and targets, such as the 2° C warming scenario of the Paris Agreement or the 17 SDGs. This practice, while employed currently by a few tools, needs to be improved, standardized and extended to address sustainability priorities, using, for example, the nine planetary boundaries or a regrouping of the SDGs (Naidoo and Fisher, 2020; Rockström et al., 2009). Third, the additionality of investors should be quantified and reported. New tools could start by systematically measuring shareholder engagement and its ability to drive positive change, therefore incentivizing the responsible investment industry to play an active role in the sustainability transition. Fourth, robust impact metrics need to expand beyond carbon and even environmental issues to account for social issues, so environmental goals are not pursued at the cost of rising inequality and social injustice. Fifth, the starting point of any robust assessment of sustainability impact lies in publicly available metrics that are standardized across industries for investors to be able to make informed decisions.

Once the underlying data across all sustainability metrics for a corporation become publicly available, different sets of weights can be chosen to reflect different sets of investor preferences – all while remaining transparent and upfront about these choices. In practice, the selection of indicators and the choice of weights can have an outsize influence on the final score, as demonstrated in Berg et al. (2020).[3] Since sustainability scores can dictate where fund flows are directed, it is particularly important that sustainability assessment methods are accurate and reliable and that weights used to generate scores are published.

While our study purports to analyze and evaluate the universe of fund sustainability assessment methods, there are a few limitations. Firstly, our review looks only at how sustainability is measured at investment fund level and does not consider the methods for sustainability assessment at the other stages, such as the asset allocation stage. Secondly, our classification of methods is not mutually exclusive, as some categories cover tools that could be part of other, more complex assessments, defined under different

[3] *In fact, the guidelines for Life Cycle Assessment published by the International Standards Organization (ISO 14044:2006) specifically forbid the use of weighting in LCA for the purpose of making comparative statements about products to the public, as "weighting steps are based on value-choices and not scientifically based". In addition, the ISO 14044:2006 requires that when weights are used in LCA to aggregate results (when not making comparative statements about products to the public), the "data and indicator results reached prior to any normalization, grouping or weighting shall be made available".*

categories. Thirdly, the criteria we propose are not exhaustive and arguments could be made to alter or expand the list. Finally, by choosing to value them equally, we do not account for the different preferences of stakeholders. Depending on the goal of the assessment, the priority rank of methods may change.

2.5 Conclusion

Our article classifies and evaluates existing metrics and frameworks for sustainability assessment of investment funds. We conducted a review of the academic and industry literature on sustainability assessment tools and grouped our findings into distinct categories of methods. In parallel, we identified, based on gaps and needs in sustainable investing, what makes an ideal metric. Here we relied mainly on internationally accepted guidelines published by the OECD, UN, UNEP FI, and PRI, as well as industry initiatives and the academic literature.

The key contribution of this article is the evaluation of diverse methods for sustainability assessment against priority criteria, which can serve as guidance in future research. Similar to other studies on sustainability performance measurement (Sala et al., 2013; Vörösmarty et al., 2018), we find that no existing method meets all criteria. Overall, we find that the Paris Agreement Capital Transition Assessment tool (PACTA), the Cambridge Institute for Sustainability Leadership Investment Impact Framework, and the Net Environmental Contribution (NEC) come the closest to meeting all criteria, while carbon footprint and ESG ratings underdeliver. While the three best-practice tools could be used for a robust assessment, we argue that, in order to address the complexity of sustainability, tools need to develop to satisfy the complete set of criteria. As such, the responsible investment industry must upgrade current tools by adopting a life-cycle approach to impact (Lauesen, 2019) and by looking beyond material risks posed by climate change, towards opportunities to support positive impact creation. The link to science-based targets and a prospective approach would ideally be a central element of reporting requirements, similar to the methodology adopted in the PACTA tool. Standardization at the measurement level (Olsthoorn et al., 2001) and open-source availability of specific methodologies would allow for better comparability, increase trustworthiness of impact reporting and synchronize capital markets with the environmental and social priorities of our economies and societies.

Data availability remains a major hurdle for the advancement of sustainability assessment of investment funds. Reporting by investee companies is still scarce, existing data are often unreliable and hard to access, given that many methodologies are proprietary. Without satisfying the criterion of reliability, a measurement tool may suffer in credibility. Future research should investigate the way in which missing data can be estimated and reported data verified, in order to reduce the greenwashing risk.

Sustainable finance would benefit from more robust metrics, which strike a good balance between simplicity – to communicate to all stakeholders and to be easy to replicate – and comprehensiveness – to correctly assess environmental and social implications of financial flows. With our review, we hope to guide industry and policymakers towards developing suitable methods going forward.

3 An input-output life cycle assessment of investment funds with a case study on carbon emissions of SRI funds[4]

Abstract

Indirect greenhouse gas (GHG) emissions (scope 3) generally represent more than half of the total life cycle impact attributable to a company or an investment. However, widely used sustainability assessment tools for investment funds fail to take these into account. Building on best practices from the industrial ecology field, we develop an Input-Output Life Cycle Assessment (IOLCA) methodology to estimate life cycle GHG emissions of companies and investment funds. We apply our method to a sample of 1,340 sustainable (SRI) and conventional equity funds domiciled in Europe and their 11,275 unique holdings. We extend our application to a case study of funds self-classified as Article 8 and Article 9 funds under the recent European Sustainable Finance Disclosure Regulation (SFDR, 2019). Our model estimates life cycle emissions for 94% of the companies held – compared to 17% coverage in the Carbon Disclosure Project (CDP). When including scope 3, the exposure to GHG emissions of both SRI and conventional funds is two to three times larger than when considering only direct impacts from holdings' operations. Finally, 24% of the sampled Europe-domiciled SRI funds are more exposed to life cycle carbon emissions than the ETF tracking the conventional market index MSCI Europe.

[4] Adapted from article published as *Popescu, I. S., Gibon, T., Hitaj, C., Rubin, M., Benetto, E., 2023. Are SRI funds financing carbon emissions? An input-output life cycle assessment of investment funds. Ecol. Econ. 212, 107918.* *https://doi.org/10.1016/J.ECOLECON.2023.107918*

3.1 Introduction

Many tools aimed at measuring the sustainability of investment funds fail to account for indirect impacts of their holdings (Popescu et al., 2021; Vörösmarty et al., 2018), despite the sustainability science consensus that assessment of carbon emissions should be made on a life cycle perspective, thus including both direct and indirect impacts (Huang et al., 2009; Lauesen, 2019; Zhang et al., 2020). Indirect climate change emissions are largely overlooked due to a lack of self-reported company data (Berg et al., 2019; Freiberg et al., 2020; Hoepner and Rogelj, 2021). However, there is a growing need for reliable, transparent, and science-based measurements of life cycle emissions (Battiston et al., 2017; GSIA, 2019; O'Rourke, 2003). For instance, the EU Sustainable Finance Disclosure Regulation (EC, 2019a) mandates that funds report on scope 3 emissions starting in 2023. Even if these emissions are not under the direct control of the company, they represent the biggest share of impact and are thus a potentially important risk factor (Hertwich and Wood, 2018; Huang et al., 2009; Landier and Lovo, 2020; Lauesen, 2019; Villena and Gioia, 2020; Zhang et al., 2020).

Information on direct scope 1 emissions (from a company's direct operations) and indirect scope 2 emissions (electricity purchased from third parties for use in direct company operations) is largely available and shows a good degree of correlation between different data providers. Data on indirect (upstream and downstream scope 3) emissions is seldom provided and, when available, largely unreliable (Busch et al., 2020). It is unlikely that reported upstream scope 3 emissions data, covering a company's supply chain, will catch up in the coming few years, as noted by a Carbon Disclosure Project report (CDP, 2020), because companies often depend on thousands of direct and indirect suppliers.

With our paper, we aim to contribute to the current literature on sustainability assessments for investment funds' industry by developing an estimation method for life cycle GHG emissions, based on Input-Output (IO) Life Cycle Assessment (LCA), or IOLCA. The benefit of our estimation tool is the ability to cover almost the whole universe of companies (95% sample coverage in emissions estimates, compared to 17% coverage in CDP company self-reported data, as showed in section 3.2.), while using a homogenous method across all emission scopes and companies. Our main novelty comes from using a detailed country and sectorial breakdown of companies' revenue, sourced from the FactSet database (hereafter "FactSet") (FactSet, 2021) combined with regionalized industry emission factors from the Environmentally Extended Multi-Regional IO (EEMRIO) database EXIOBASE (Stadler et al., 2018a).

Previous literature has adopted various techniques for estimating missing corporate GHG data. One stream of literature employed econometric and machine-learning techniques for scope 1 and scope 2 emissions (CDP, 2020; Goldhammer et al., 2017; Nguyen et al., 2021). However, the cited papers acknowledge that same methods are not yet considered reliable for scope 3 estimates, due to the unavailability of trustworthy self-reported data to validate the models. The other stream of estimation models builds on the IOLCA methodology. As such, with our proposed methodology, we aim to contribute to this category of models.

Life Cycle Assessment (LCA) is a best practice tool in the sustainability assessment field and is used to evaluate the impact of project-based financial instruments, such as green bonds (Gibon et al., 2020). For macro-scale assessments, Input-Output LCA analysis (IOLCA), based on EEMRIO databases, is used to trace the generation of global environmental impacts at industry level (Goldhammer et al., 2017; Moran and Kanemoto, 2016; Wiebe, 2018). Investment funds are a collection of economic activities spread across geographies and sectors. Thus, IOLCA can be used to estimate environmental impact at fund level, where asset owners and regulators do not have the means to reliably measure full life cycle holding-level impacts (Goldhammer et al., 2017).

Previous IOLCA-based methods for estimation of corporate carbon footprints, developed by private data providers, are not yet widely used, are fee-based and opaque (Inrate, 2020; Trucost, 2019b). In academia, two studies have used IOLCA models for investment products (Koellner et al., 2007; Ritchie and Dowlatabadi, 2014). Their models use US-based IO tables for all companies, independent of their location, and are thus unable to account for regional differences. In addition, they assign companies to a single industry. Our proposed model is thus achieving greater accuracy in a company's emissions profile, by using detailed regional and sectorial emission factors.

To show the model's applicability for end investors and financial stakeholders, we conduct a case study on a large cross-section of investment funds. We define a sample of 1,340 Europe-domiciled sustainable (SRI) and conventional funds and their 11,275 unique holdings for the year 2019.[5] We also select a sample of funds which are self-classified as Article 8 or 9 under the EU Sustainable Finance Disclosure Regulation (SFDR). As of 2021, the EU, through the SFDR regulation, mandates asset managers to classify their SRI funds into Article 8 (funds promoting ESG characteristics) and Article 9 (funds with sustainability objectives). Thus, we test whether Article 9 funds show stronger environmental performance, on a life cycle basis, when compared to other SRI funds.

To better capture the exposure of SFDR-labelled funds to carbon-intensive sectors, for both direct and indirect emissions, we link detailed holding-level data with the climate-policy-relevant sectors (CPRS) classification introduced by Battiston et al. (2017) and present results for two SFDR-labelled funds. Reassuringly, we observed that the selected Article 9 fund was exposed to less climate-risky sectors than the Article 8 fund, for both direct and indirect emissions.

We provide the results for the whole sample of companies and funds in a Supplementary Excel file available with the online version of the article. The goal is to understand to what degree SRI funds perform better on GHG emissions than conventional peers. This case study contributes to previous literature (Boermans and Galema, 2019; Koellner et al., 2007; Monasterolo and de Angelis, 2020) by assessing a much larger sample of funds (1,340 funds, compared to cited papers: 44 pension funds, 26 investment funds, and 12 market indices, respectively) and by extending GHG emissions assessment from direct to life cycle.

[5] We use the terms *SRI* and *sustainable funds* to refer to funds considering environmental and social criteria or having an environmental investment objective.

To quantify GHG emissions at fund level we use two measures. The relative carbon footprint (RCF) captures the responsibility in emissions generation of a one million USD investment. The weighted average carbon intensity (WACI) quantifies the carbon intensity of companies held in a fund, relative to their revenue, thus measuring the portfolio's exposure, independent from holdings' market value. Companies with a high carbon intensity are more exposed to regulatory and transition risk, which translates to risks for the investment portfolio as well (Monasterolo et al., 2017). As explained in section 3.2, the RCF allocates a holding's emissions based on share ownership. Therefore, it is a way to divide responsibility between different shareholders. For both measures, we find that accounting for scope 3 emissions doubles or even triples the total GHG emissions attributable to a fund, for both conventional and SRI funds. Moreover, while SRI funds do reduce their relative holding in carbon-intensive-companies, achieving a lower RCF than conventional funds, they have similar WACI.

We then benchmark the results for our sustainable funds sample against conventional market indices, such as MSCI Europe, and then compare SRI funds under different sustainability topics. We find that 25% (38%, respectively) of the sampled Europe-domiciled SRI mutual funds are more exposed to life cycle carbon emissions than the ETFs tracking the conventional market index MSCI Europe (MSCI World, respectively).

Our paper fits in the rather limited research related to fund-level sustainability performance (Allevi et al., 2019; Boermans and Galema, 2019; Koellner et al., 2007). With our model, we aim to further enlarge and enhance input-output life cycle assessment-based (IOLCA) methodologies for sustainable investing and to offer a transparent, replicable, and usable metric for sustainable finance stakeholders.

3.2 Data and Methods

We first compute the impact at company level: we derive the detailed sectorial and regional revenue breakdown of a company, and for each sector-region combination we assign the matching GHG emission factors, estimated from the IOLCA database (scope 1, scope 2, scope 3 respectively) and sum all values. Then, we use fund information on holdings and stock market value to aggregate the impact at fund level. Table 3.1 summarizes all variables used.

3.2.1 Estimating GHG emissions factors

The main novelty of our model is the matching between detailed corporate revenue-based data and science-based GHG emission factors based on EEMRIO tables. Since their theorisation by Wassily Leontief (Leontief, 1951), input-output tables have been extensively used in economic applications. Multi-regional input-output (MRIO) tables capture all transactions between sectors and economies and thus enable the definition of a "production recipe" for any output of a sector. By having an additional matrix of environmental stressors, EEMRIO data make it possible to compute the environmental impacts due to production and consumption in all industries (Huang et al., 2009; Stadler et al., 2018a). A detailed explanation of the methodology can be found in section B.1 of the Appendix.

There are different databases for conducting sustainability analysis using input-output data augmented with environmental satellite accounts, such as EXIOBASE (Stadler et al., 2018a), EORA (Lenzen et al., 2013), WIOD (Dietzenbacher et al., 2013), or country-specific databases, such as the US IO tables from the Bureau of Economic Accounts (BEA, 2021). While all of them use the same source data to build the database (namely tables built according to the UN System of National Accounts standard), there are differences in results, due to model construction strategy (for example, how allocation is done between sectors) and source of emissions data (satellite emissions by industry may differ across IO databases). Thus, users must be careful when interpreting results from carbon footprint analysis and acknowledge the assumptions, on which an IO database is built. Different choices in building an IO database influence the end results in a carbon footprint analysis and thus also emission factors for a similar sector across different IO databases.

Table 3.1 Definition of variables used in this Methods section.

Variable	Range	Unit	Definition
RCF_f	$\mathbb{R}^+$	tCO_2-eq/MUSD	Relative carbon footprint of fund f, for each 1 million USD invested in the fund
sh_{if}	$\mathbb{R}^+$	MEUR	Market value of the shares of company i held by fund f $sh_{if} \leq M_i, \forall f$
M_i	$\mathbb{R}^+$	MEUR	Market capitalization of company i
w_{if}	[0,1]	-	Weight of company i holding in fund f, $w_{if} = \frac{sh_{if}}{M_f}$
M_f	$\mathbb{R}^+$	MEUR	Market capitalization of fund f.
$WACI_f$	$\mathbb{R}^+$	tCO_2-eq/MEUR	Weighted average carbon intensity of fund f, based on the carbon intensity (per million EUR of revenue) at holding level
E_i	$\mathbb{R}^+$	tCO_2-eq	GHG emissions of company i
R_i	$\mathbb{R}^+$	MEUR	Total revenue of company i
R_{ijk}	$\mathbb{R}^+$	MEUR	Revenue of company i in industry sector j in country k
EF_{jk}	$\mathbb{R}^+$	tCO_2-eq/MEUR	GHG emission factor of industry sector j in country k

Past literature has sought to describe the difference in the goal, construction and results of these different databases. Owen et al. (2016) explain the main drivers between differences in carbon footprint calculations when using various IO databases. Moran and

Wood (2014) find that per capita carbon footprints for major economies show a deviation of 10% between four different IO databases: Eora, WIOD, EXIOBASE, and OpenEU. A deviation of 10% or similar is thus expected also in the case of emission factors and could translate into slightly different life cycle GHG emission estimates at company- and fund-level, depending on the IO model used.

Input-output databases are generally considered reliable sources to capture industry-level supply chain networks and comparability across IO databases is high (Moran and Kanemoto, 2016; Stadler et al., 2018a). However, as industry averages are used to feed the database, it is to be expected that the IO-generated supply chains may not match the reported supply chain of any given company (Tarne et al., 2018). While the overall matching in terms of industry and region should hold for a given country-industry supply chain network in an IO framework, higher deviations may be present at the deeper stages of the supply chain – raw material extraction and processing (Giljum et al., 2019). Nonetheless, using IO data to estimate supply chain impacts is recommended, despite potential limitations, e.g., by the GHG Protocol that lists IO analysis as a source for estimation of scope 3 impacts (GHG Protocol, 2015).

We use direct (scope 1 and scope 2) and indirect (scope 3 upstream) emission factors from the open source EEMRIO database "EXIOBASE, monetary, version 3.8.1" (Stadler et al., 2018a). We decide to use EXIOBASE for our tool development due to its detailed country-level split, as well as homogenous industry classification by country.

Scope 3 downstream emissions from the use of products and services of the company are excluded from the current analysis, coherently with the guidelines of the GHG Protocol (2015). The database is mapped on 163 industry sectors and 49 countries (including 5 "Rest of the World" regions) and contains respective GHG emission factors (in tCO_2-eq per million EUR of output). As indicator, we use the midpoint impact category "GHG emissions (GWP100) | Problem oriented approach: baseline (CML, 2001) | GWP100 (IPCC, 2007)", which accounts for a subset of GHGs responsible for global warming (carbon dioxide – CO_2, methane – CH_4, dinitrogen oxide – N_2O and sulphur hexafluoride – SF_6) weighted using their global warming potential over 100 years.

For countries where industrial output is small, balancing exercises at the level of the IO tables may lead to unreliable outliers, as discussed in previous EXIOBASE methodology papers (Agez et al., 2020; Merciai and Schmidt, 2018). We checked each of the 163 industries for the presence of outliers, generally numbers higher than 10 $ktCO_2$-eq/MEUR of revenue, which occurred in 16% of the country-industry factors, and we set the upper emissions intensity cap at either the 50th (median) or the 75th percentile for the industry. These outlier sectors are associated with very low total output values and are not representative in the aggregate breakdown of the various funds assessed. Details and examples of the adjustment exercise are provided in section B.2 of the Appendix.

3.2.2 Estimating GHG emissions at holding level

The final dataset of emission factors is then used to compute the emissions at company level. The emissions of company i are denoted as E_i, and are computed as:

$$E_i = \sum_j \sum_k EF_{jk} \, R_{ijk} \, , \quad (eq. 3.1)$$

where EF_{jk} refers to the emission factor from country j and industry k, while R_{ijk} refers to the revenue in MEUR for the specific company i, in country j and industry k.

For each holding, as improvement to previous methods developed in academic papers (Koellner et al., 2007; Ritchie and Dowlatabadi, 2014) which use only a company's main industry class, we compiled a detailed revenue breakdown by industry and by country using FactSet RBICS (industry) and FactSet GeoRev (region) databases, see FactSet (2021). We use the annual average exchange rate from FactSet to convert the 2018 revenue reported in original currency to EUR, to match the currency in EXIOBASE.

The drawback in using IO is that it assumes the same technology across companies in the same industry group or sector. Thus, more companies would have the same impact per unit of output generated, under identical corporate streams by classification, even if, in practice, one company may have more efficient processes than the other, for example. Nevertheless, we posit that differences in emissions between companies engaged in the *same* sector are smaller than differences in emissions between companies engaged in *different* sectors, as supported by Freiberg et al. (2020) who find that industry membership explains a majority of emission variation across companies.

The FactSet revenue breakdown at company level is very detailed – 250 countries and 1,603 sub-industry groups. One caveat of the revenue model is that a company will be given the same industry breakdown for each country, as we do not have specific by-country and by-industry revenue information. The increase in company revenue specificity comes with more challenges in finding the most suitable link between the different classification systems. We created a concordance between the FactSet RBICS and FactSet GeoRev classifications and EXIOBASE. The exercise was performed manually, as having a correct correspondence between the financial and environmental databases was essential.

We use revenue data as a proxy for production, similar to other estimation models from literature (Nguyen et al., 2021) and practice (CDP, 2020). Specific production data by region and country are very rarely available from company reports. Methodologically speaking, the sum of a multi-regional input-output table's column (intermediate consumption and value added) amounts to the aggregate annual revenue ("total output") of the corresponding sector of the economy (Miller and Blair, 2009). The Eurostat Manual of Supply, Use and Input-Output Tables equates "market output" and revenue, i.e., the sum of all production costs and profit (Eurostat, 2008) margin, which supports our revenue-as-production-proxy hypothesis. There is thus some uncertainty when allocating production to a specific country, but our assumption of using revenue as a proxy for production is tenable given that our model captures each step in the supply chain, i.e., the global value chain network of a company through the industry-specific input-output relations.

3.2.3 Defining fund-level carbon footprint measurement methods

Despite efforts to standardize carbon footprint methodologies, there is still widespread heterogeneity in how financial institutions adapt different existing metrics (Busch et al., 2020; Popescu et al., 2021). The main contribution of our proposed methodology is the addition of complete indirect, scope 3 upstream impacts to the calculation. In terms of data sources, existing methods generally use a combination of reported and estimated data (Trucost, 2019b). We use estimated data across all scopes to ensure consistent results within and across industries.

The Task Force on Climate-Related Financial Disclosures (TCFD) recommends the use of multiple metrics for a single impact category in order to ensure robustness (TCFD, 2017). We choose two different tools for carbon footprint measurement: i) the Relative Carbon Footprint (RCF), and ii) the weighted average carbon intensity (WACI) and compute impact on scope 1, scope 2, scope 3 upstream separately and, summed, as life cycle emissions.

RCF for fund f is defined as:

$$RCF_f = \frac{\sum_i E_i \frac{sh_{if}}{M_i}}{M_f} = \sum_i w_{if} \frac{E_i}{M_i} \quad (eq. 3.2)$$

and measures the GHG emissions attributed to a one-million USD investment in the given fund (Koellner et al., 2007). We use USD as currency, as this is used to report company and fund market value in FactSet. The tool attributes, on an ownership basis, emissions from company level to the investment fund level, assuming an investment fund is responsible for emissions of a held company proportional to the monetary amount held. The market value of companies held (M_i), and the respective weight $w_{if} = \frac{sh_{if}}{M_f}$ in fund f determine the RCF of the fund itself. Therefore, the contribution of high-valued carbon-intensive companies may appear reduced, due to the dilution effect of the high valuation.

WACI, our second metric, is defined as:

$$WACI_f = \sum_i w_{if} \frac{E_i}{R_i}, \quad (eq. 3.3)$$

where R_i are the total revenues, (i.e., "Sales") of company i. It quantifies the emissions intensity per unit of sales and measures the average "efficiency" of the companies in the portfolio. By weighting each company i in the portfolio f, WACI represents the average exposure of the fund to carbon-intensive companies.

RCF and WACI can both be used to compare funds, and while they are by construction positively correlated, it is possible for a fund with a low RCF to have a higher WACI, if it invests disproportionately in companies with a very high market valuation, *ceteris paribus* (i.e., keeping portfolio weights and company emissions constant). The tools are complementary: i) RCF is suited to assess distributed impact between shareholders and could be used, for example, to compute the total responsibility of an asset manager, and to see where it could act to "decarbonize"; ii) WACI is a better suited measure for capturing the real exposure of investee companies, as it is not influenced by fund size nor by company capitalization (Boermans and Galema, 2019; Monasterolo et al., 2017; TCFD, 2017). This metric is better suited for further developing climate risk exposure estimations (such climate risk scenarios computing potential losses of a fund due to investing in companies that are subjected to physical or transition climate risk). While a fund may minimize its holdings in climate risky assets, it is still exposed to potential losses. A more detailed discussion is given in Appendix B.3.

3.2.4 Retrieving fund-level data

There is yet no universally accepted and verified definition of a "sustainable" fund (Popescu et al., 2021). For this study, we use MSCI and Bloomberg classifications of sustainable funds. Both entities base their classification on fund prospectuses. Bloomberg offers a more refined classification of funds that go beyond the binary SRI / non-SRI classification of MSCI, which is why we conduct our main analysis using the Bloomberg classification (see section B.4 of the Appendix for a further discussion of fund classifications).

We retrieved the list of all SRI, Europe-domiciled, active equity open-end (OEF) and exchange-traded funds (ETFs) from the Bloomberg Terminal in June 2021, which have a sustainability attribute: "Climate Change", "Clean Energy", "Environmentally Friendly", and "ESG". We focus on Europe to avoid differences introduced by regional bias. Nevertheless, our methodology is applicable to any fund as long as its holdings, and the revenues associated to them, are available.

The search led to 1,488 funds. In the FactSet database, holding-level data for year 2019 was available for 895 of the funds. Similar to Elton et al. (2010), we excluded funds that had less than 90% assets under management (AuM) from cash and stock holdings or had less than 5 equity holdings. The final equity SRI funds sample contains 670 funds – 581 OEFs and 89 ETFs. We selected from FactSet a comparable sample of conventional funds to match the SRI funds sample in terms of funds' domicile, AuM, and fund type. The final sample contains 1,340 funds, half of them with Bloomberg sustainability attributes. Table 3.2 presents the distribution of funds' AuM in the sample. Compared to previous studies (Allevi et al., 2019; Boermans and Galema, 2019; Koellner et al., 2007), we have a much larger sample of funds and a more diverse geographical distribution.

Table 3.2: AuM Summary statistics for fund sample in 2019, based on author calculations, using financial data from FactSet and conventional/ SRI fund classification from Bloomberg.

Fund type		*count*	Mean	St. dev.	Quartile 1	Median	Quartile 3
			AuM (million USD)				
Conventional	ETF	*89*	349	447	67	195	432
	OEF	*581*	503	987	57	172	495
SRI	ETF	*89*	299	479	33	103	283
	OEF	*581*	555	964	67	199	590

We retrieved information on five ETFs tracking market indices, that we use to benchmark our results (S&P500, MSCI World, MSCI Europe, MSCI USA, Dow Jones Industrial Average (DJIA) and STOXX 600 Europe).

To showcase the usability of our method for regulators, we present a short case study on SFDR-labelled funds: we extract a sample of recent self-labelled SFDR Article 8 and

Article 9 funds, listed on the Luxembourg Stock Exchange. Data description is detailed in the Appendix B.4.

For each fund, we retrieved the holdings list from the FactSet Ownership database, for the most recent reporting date in 2019 (the most recent full year for which all the data were available when we started our study), together with market value and revenues information. The revenue information was retrieved for 2018, under the assumption that funds make their investment decisions based on accounting information from the previous year. The selected pool of fund holdings represents over 12,516 company stocks. We computed life cycle IOLCA-based emissions for 94.3% of the sample. For the remaining 6.7%, there revenues data were incomplete/missing in FactSet. As some companies are listed under multiple ISINs, we have defined the separate sample of 11,275 unique companies, by removing multiple listings for the same company. Information on the curation process is available in Appendix B.5.

3.2.5 Validation against company self-reported data

We first conduct a validation exercise using CDP data. We retrieved CDP emissions records for individual companies from Bloomberg Terminal. The availability of reported data is very low (see Appendix B.6): for scope 1 emissions, CDP covers 17% (i.e., 1,780) of the pooled companies; for scope 3 emissions, coverage in CDP is even lower, at 11% (reporting at least on category Purchased Goods and Services). The low availability supports the use of emissions estimates in order to offer a greater coverage of an investment portfolio. In previous research, it is discussed whether reporting companies are the ones having better sustainability practices and thus better emission intensities. If that is the case, one should use a precautionary principle when estimating emissions of non-reporting companies (Hoepner and Rogelj, 2021).

The first validation sample based on self-reported company data to CDP consisted of 400 companies (4% of the total company sample), after removing outliers and incomplete data. In a second validation exercise, we use the highest emissions intensity by sector from CDP, scaled by revenue, to obtain a different set of estimates, which assigns to all non-reporting companies the life cycle emissions intensity of the maximum or “worst” performing company that did in fact report emissions to CDP, by industry. This exercise addresses the finding by Hoepner and Rogelj (2021) that companies that do not report emissions are more likely to have above-average emissions. Across most industries, we find that average emissions are higher for the IOLCA sample than for the CDP-extrapolated sample, implying that only using the extrapolation of CDP data is not allowing for a complete coverage of emissions. For the Trade sector, including all companies makes the CDP and IOLCA data more comparable. The results of the first validation are presented in Figure 3.1, while the second validation exercise is discussed in the Appendix section B.6.

3.3 Results[6]

3.3.1 Holding-level carbon footprint estimates

Total scope 1 emissions for the sample of 11,275 companies amounted to 11.8 $GtCO_2$-eq (with an average of 1.05 $MtCO_2$-eq per company, computed across all companies), while scope 2 emissions reached 2.2 $GtCO_2$-eq (203 $ktCO_2$-eq average per company). Upstream scope 3 emissions were the largest part of emissions – 14.9 $GtCO_2$-eq (1.3 $MtCO_2$-eq average per company) – larger than scope 1 emissions in all sectors except Mining, consistent with findings from Hertwich and Wood (2018). Even if the scope 3 of one company may be the scope 1 of another, the risk does not cancel out, and thus investors should measure and manage scope 3 emissions. In addition, many supply chain companies are not publicly listed companies. By construction, our estimation method handles these issues. In Table 3.3, we show the mean values for company level GHG emissions intensity, using the Standard Industrial Classification (SIC) codes. Appendix section B.7 provides the detailed summary statistics.

Table 3.3. Mean GHG intensity for all individual companies in the fund sample in 2019.

SIC industry code	***Count***	**Mean GHG Intensity (tCO_2-eq/MEUR revenue)**			
		scope 1	scope 2	scope 3 upstream	life cycle
Mining	419	1,233	132	446	1,811
Transportation & Public Utilities	1,090	784	172	379	1,335
Agriculture, Forestry, & Fishing	87	418	32	529	979
Manufacturing	4,292	168	53	437	658
Construction	313	97	31	291	419
Wholesale Trade	368	98	28	190	316
Services	1,701	29	26	156	211
Retail Trade	630	35	29	114	178
Finance, Insurance, & Real Estate	2,375	27	18	96	141

3.3.2 Validation and Limitations of IOLCA-based estimated emissions

For life cycle emissions, the Spearman Rank correlation coefficient was 0.77 (0.68 Pearson correlation coefficient) between IOLCA-estimated and CDP self-reported data, while the correlation coefficients for scopes 1, 2, and 3 separately were 0.74 (0.81), 0.67 (0.39), and 0.69 (0.46), respectively (all significant, p-value <0.0001). Correlations of carbon measurements from previous literature are comparable to our results – between 0.59 and 0.85 – and are much lower for data based on estimates (Busch et al., 2020; Goldhammer et al., 2017; Stanny, 2018).

[6] *We disclose all holding- and fund-level results in a separate Supplementary Excel file, which can be accessed in the online version of the associated published article.*

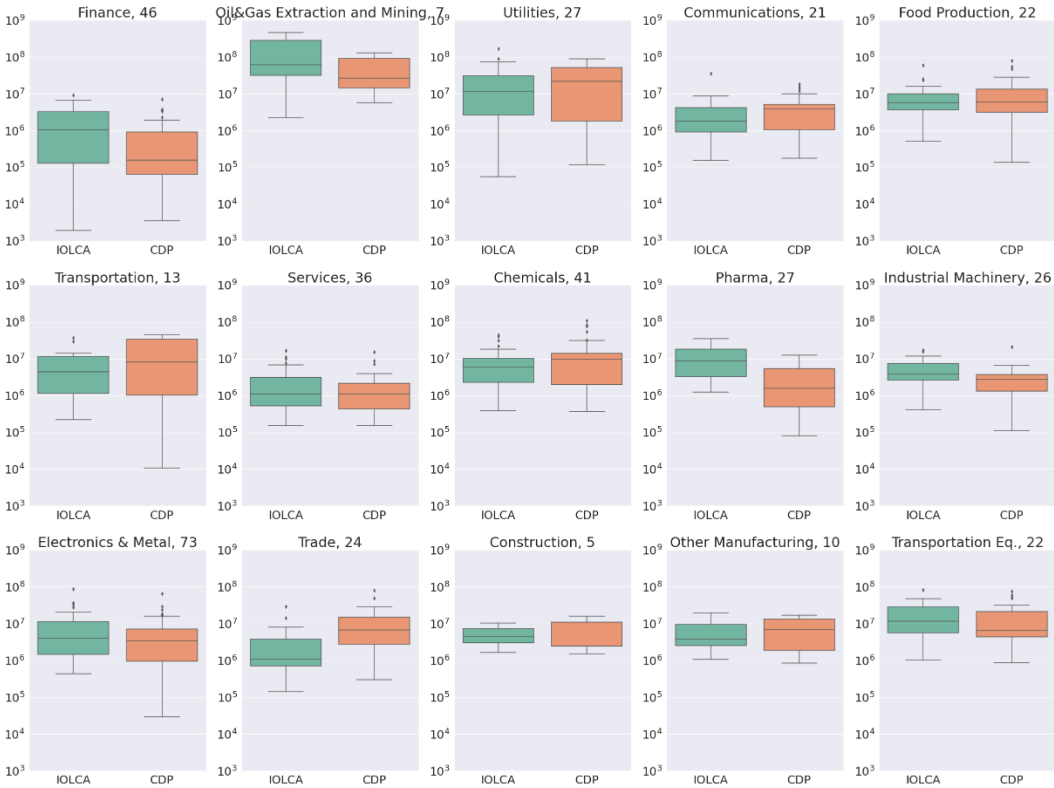


Figure 3.1. Boxplot charts showing CDP-reported vs. IOLCA-based estimated absolute life cycle emissions, logarithmic values. Industries have been reclassified by regrouping of similar industries. The number of companies by industry is shown next to the subtitle of each boxplot.

In Figure 3.1, we plotted the distributions of CDP-reported and IOLCA-based estimates by SIC industry code. For some industry groups, such as Utilities, Transportation and Transportation Equipment, our estimation method gave closer values to self-reported data. For the Trade sector, the impact estimated with the IOLCA-based method is significantly higher. This is due to an accounting difference for the companies represented in the small sample – in the IO table, the production of everything sold by a retail store is not accounted for in its impact (as it is not per se part of the supply chain – we could draw a parallel here with finance companies, whose scope 3 does not include the impacts of companies that they are financing), while companies reporting to CDP do report in scope 3 the life cycle impact of all the goods that they are purchasing and reselling. For industries *mining metals* and *oil&gas extraction* estimated values are larger than self-reported data. In this case, the companies have been linked to the EXIOBASE sector with a larger emission factor than the company per se, which is due to the lack of exact matching between FactSet and EXIOBASE classification.

3.3.3 RCF and WACI results for the fund sample

By reading the information contained in the fund prospectuses, summarized by the SRI labelling of Bloomberg, we would expect SRI funds to be exposed to less GHG emissions than non-SRI funds. We performed a Wilcoxon signed-rank test to determine whether the two samples of funds – SRI and conventional – come from distributions with the same location (Table 3.4). The null hypothesis of same distribution for SRI and conventional funds could not be rejected at all usual significance levels for WACI scope 2, scope 3 and life cycle, and could be rejected for all RCF measures and WACI scope 1. This indicates, once again, that investors are not necessarily considering life cycle carbon exposure when allocating funds between SRI and conventional portfolios.[7] If we look at the average RCF computed across all SRI funds (Figure 3.2), this is indeed significantly lower than the average RCF of non-SRI funds: 346 vs. 408 tCO_2-eq/MUSD invested, p-value = 0.000002. However, for life cycle WACI, the two samples were similar: the average WACI of SRI funds in our sample was 475 compared to 479 tCO_2-eq/MEUR for conventional funds (the difference of these means is not significant, p-value = 0.19).

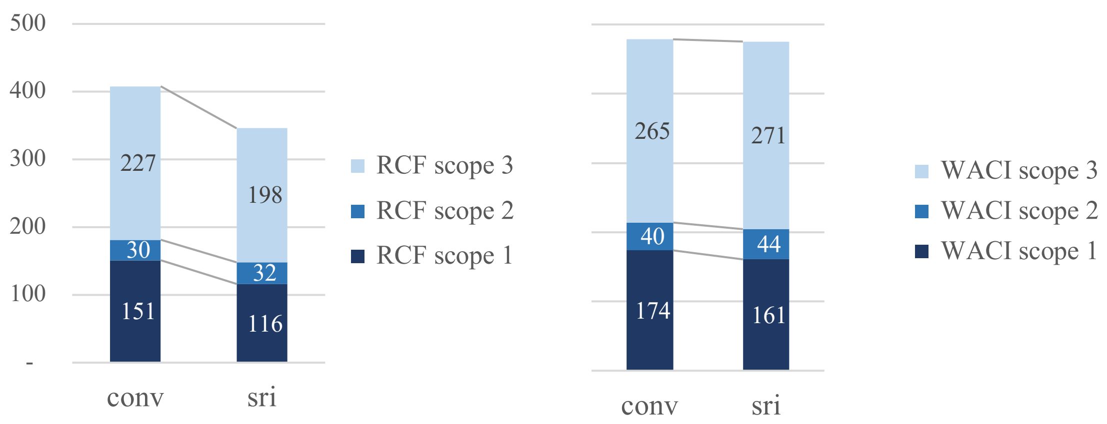


Figure 3.2. Mean RCF and WACI by scope, for conventional and SRI funds. The mean is displayed for each sample and indicator.

We look at a sub-sample of SRI funds – 159 funds with an SFDR classification (20 funds Article 9 and 139 Article 8 funds) and we reach similar conclusions as for the Bloomberg-sourced SRI funds sample: if we average results at fund level, Article 9 funds perform much better in terms of RCF, raising the trust in the self-labelling scheme proposed by the EU. For WACI, both Article 8 and 9 funds perform mediocrely, as seen with the bigger sample of funds, which could be due to holding less stocks from sectors like Finance or Tech for example. Article 8 funds perform similarly on WACI, while their RCF is much higher, meaning that they still hold proportionally higher shares in carbon-intensive companies (Figure 3.3).

[7] *The results for a paired t-test for the differences of the means of the two samples, a parametric alternative to the non-parametric Wilcoxon signed-rank test, are presented in Appendix B.8 and are in line with those presented in Table 3.4, except for RCF for scope 2 and WACI for scope 1.*

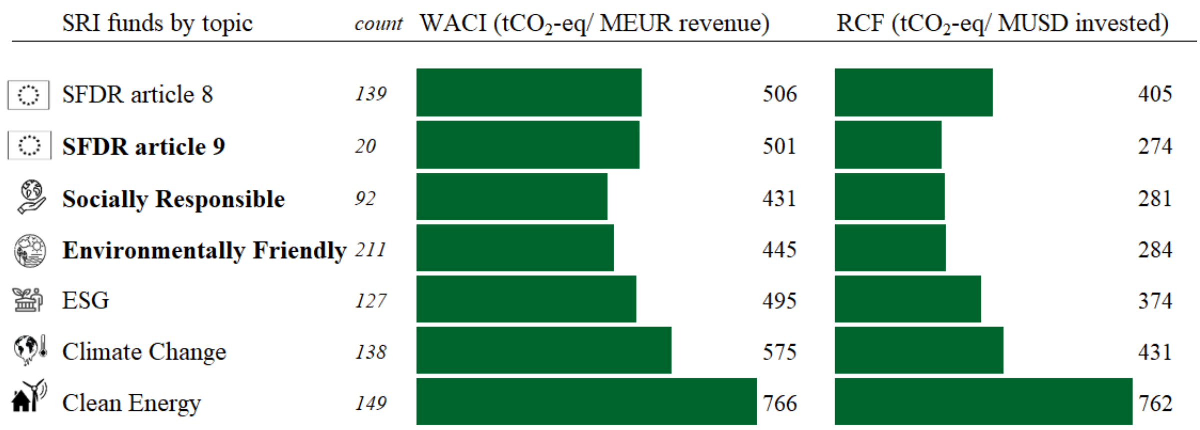


Figure 3.3: Mean life cycle WACI and RCF across different SRI funds

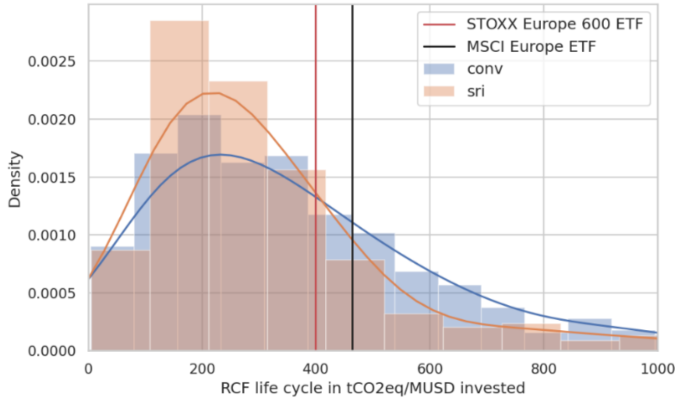
In Figure 3.3, we further grouped SRI funds by Bloomberg sustainability attribute. We found that "Socially Responsible" and "Environmentally Friendly" funds had the lowest RCF. "Climate Change" and "Clean Energy" funds had the highest footprint. As the latter funds tend to hold assets involved in economic activities that are linked to high emissions (e.g., resource extraction), they will be portrayed as "worse" performers from a carbon emissions perspective, even if clean energy is a key investment direction for the future. Conversely, "Socially Responsible" funds are investing in social-related issues and thus do not hold many production-intensive companies. Asking funds to report on their progress in reducing their carbon footprint may lead to the wrong incentive of seeking low carbon companies per se, instead of investing in solutions for decarbonization. For example, "Environmentally Friendly" funds may select stocks by carbon footprint in the first place.

Table 3.4: Results of Wilcoxon signed-rank test for SRI and conventional funds. If p-value is lower than 0.05, we reject H0 and say that the samples of SRI and conventional funds are different.

Metric	*variance (conv)*	*variance (SRI)*	*median (conv)*	*median (SRI)*	*stat*	*p-value*
RCF life cycle	**134,144**	**130,141**	**319**	**258**	**135,571**	**0.00**
RCF scope 1	27,383	19,490	109	84	140,525	0.00
RCF scope 2	1,132	3,480	21	18	124,242	0.01
RCF scope 3	38,583	45,718	181	148	132,703	0.00
WACI life cycle	***51,675***	***46,929***	***454***	***436***	***116,720***	***0.19***
WACI scope 1	25,060	21,454	151	132	126,757	0.00
WACI scope 2	***798***	***1,843***	***32***	***33***	***106,277***	***0.89***
WACI scope 3	***9,963***	***8,671***	***252***	***256***	***106,783***	***0.87***

Figure 3.4 shows that, even for the RCF measure, which features a statistically different mean between the SRI and conventional samples, 25% of SRI funds in our sample had a higher RCF than the market index STOXX 600 (16% for comparison against MSCI Europe index). SRI funds had a lower RCF than conventional funds across percentile intervals, while for the WACI measure no clear difference is discernible. In Appendix B.9, we show

similar distributions, by emissions scope. Similar to Koellner et al. (2007), but performing the analysis on a much larger sample, we observed that funds self-labelled as SRI can be found amongst funds with the largest life cycle carbon footprint in our sample. Worryingly, in top 50% funds with the highest WACI there are 47% SRI funds (44% for RCF). This result calls into question the SRI self-labelling of investment funds.



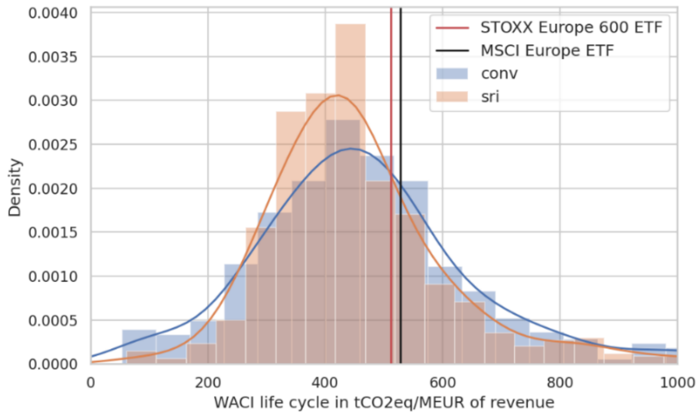


Figure 3.4. Density plots comparing RCF and WACI of conventional and SRI funds. The metrics are computed for the sample of 1,340 SRI and conventional funds, for year 2019.

To further understand the drivers of difference in RCF across SRI and conventional funds, we specify a (cross-sectional) regression model with different sets of explanatory variables and report the results in Table 3.5, where we also display results for the same regressions with WACI as dependent variable for comparison. We want to assess if the difference in RCF life cycle (and WACI life cycle) is explained by the SRI dummy and funds' AuM and type (OEF or ETF, as dummy variable). To control, up to a certain extent, for possible unobserved effects, in the main regression table we include dummy variables corresponding to the country of incorporation of each fund ("country fixed effects"). We also cluster standard errors by country of fund incorporation (we have 16 different countries of incorporation in our sample), to control for additional correlation in the residuals due to, e.g., omitted variables in our model capturing commonalities across funds investment decisions domiciled in the same country (for instance, some funds in our sample might have mandates imposing them not to deviate substantially from a local benchmark, that we do not observe directly in our sample).

Table 3.5: Results from regression of WACI and RCF on fund characteristics. P/S refers to the average price-to-sales ratio at fund level.

	(1) WACI life cycle	(2) RCF life cycle	(3) WACI life cycle	(4) RCF life cycle	(5) WACI life cycle	(6) RCF life cycle
SRI dummy	1.51	-57.424***	.409	-61.682***	18.064	44.98
	(14.633)	(17.653)	(14.689)	(19.286)	(25.18)	(41.463)
Env friendly dummy					-40.027**	-87.555***
					(18.519)	(16.15)
SRDR Art. 9 dummy					-6.916	-107.117***
					(5.382)	(4.917)
ETF dummy					-25.528**	-35.85
					(11.13)	(21.972)
AuM (MUSD)					-.004	.002
					(.003)	(.007)
P/S					-22.758***	-51.355***
					(3.762)	(3.029)
P/S X SRI					-6.986	-30.817***
					(5.552)	(6.211)
Growth style dummy					8.673	18.883
					(19.159)	(17.347)
Index style dummy					3.998	1.502
					(12.743)	(21.208)
Fund beta					-112.717***	-233.338***
					(21.59)	(35.584)
Fund beta X SRI					53.588	127.613***
					(33.404)	(40.466)
Intercept	479.014***	408.871***	479.617***	411.203***	628.293***	721.447***
	(5.421)	(11.39)	(8.049)	(10.567)	(15.535)	(24.849)
Observations	1471	1471	1471	1471	1282	1282
R-squared	0	.006	.017	.019	.103	.202
Country FE	No	No	Yes	Yes	Yes	Yes
Cluster country (16)	Yes	Yes	Yes	Yes	Yes	Yes

*Note: In columns (1) and (2) we show the results when running the regression only with SRI dummy as explanatory variable, and standard errors clustered at country of incorporation level. In columns (3) and (4) we include country fixed effects. In columns (5) and (6) we add a battery of control variables. Standard errors clustered at country of fund incorporation, where the more standard CV1 estimator of the variance covariance matrix as in MacKinnon et al. (2023) are in parentheses. The stars denote significance at *** p<.01, ** p<.05, * p<.1.*

Columns (1) and (2) and (3) and (4) confirm the results from the tests of the difference in means (t-tests) displayed in Table 3.4: the SRI dummy is significant (respectively insignificant) for RCF (respectively WACI), and a fund with an SRI label has lower RCF (respectively similar WACI) on average, compared to a non-SRI fund. Then, we add as regressors the average price-to-sales ratio at fund level, i.e., the weighted average of price-to-sales (P/S) ratios of the fund's holdings, and its interaction with the SRI dummy. The negative (and significant) coefficient of P/S in column (6) implies that if any fund, SRI, or non-SRI, invests in overvalued companies (high P/S), its RCF is smaller than that of a similar fund investing in undervalued companies (low P/S), on average. This is a mechanical result due to the definition of RCF, since an overvalued company would have lower emissions intensity per share, compared to an undervalued company with a similar emissions intensity per revenue. However, this could also indicate that there is a market premium on companies with a lower GHG emissions intensity. Moreover, the negative sign of the coefficient of the interaction term P/S x SRI shows that an SRI fund with a higher price-to-sales ratio will have a smaller RCF than a conventional fund, *ceteris paribus*. A possible explanation for this result is that SRI funds select, on average, companies which have low relative carbon footprint as they are overvalued. The price-to-sales variable is the only determinant of the difference between the WACI and RCF. In the regression specifications in the columns (5) and (6), we control for SFDR article 9, and environmentally friendly fund type and fund beta, and the main result is that the RCF of environmentally friendly funds (a subsample of SRI funds) is lower than the rest of the funds, even when accounting for the different types of regressors, such as the fund's betas to the market and investment style dummies. Our results are robust to all these different ways of computing standard errors (robust or with clustering) and additional regression tables are available in the Supplementary Materials to the online version of the associated article.

3.3.4 Comparing SRI funds with ETFs tracking conventional market indices

As it could be expected from the labelling of funds, we observed that the average European SRI fund was responsible for fewer emissions than MSCI Europe or STOXX 600 (Figure 3.5). Not surprisingly, it also had a higher emissions intensity than global (MSCI World) or US-based indices, as the latter have a higher concentration in Finance stocks than the European counterparts (Appendix B.9). Interestingly, if we only account for scope 1 emissions, the average European fund performs better than S&P500 Index and even MSCI World. However, relative scope 3 emissions for the average SRI funds are higher than those of S&P 500 and MSCI World and, as expected, of MSCI Europe and STOXX 600.

We find that 257 (38%) of the 670 SRI funds in our sample are more exposed to carbon intensive companies than the MSCI World ETF (24% when compared to MSCI Europe). This analysis is more precise when comparing funds tracking the specific index: we found that all 9 SRI funds tracking MSCI Europe (based on the fund title) have a lower WACI than the respective conventional index. This is reassuring for investors looking to invest in funds with a lower exposure than their regional conventional index. In Appendix B.9, we show a complete comparison between SRI and conventional funds, by fund investment objective.

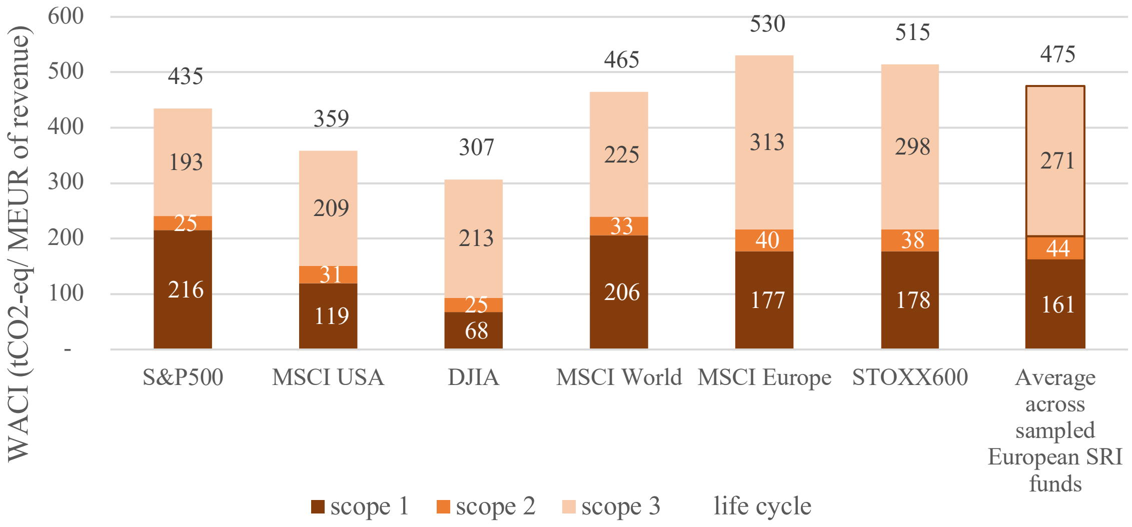


Figure 3.5: WACI by scope for six major indices. The values are computed for the year 2019 and for selected ETFs following the respective market indices.

3.4 Discussion

What drives the variation in a fund's carbon footprint? A fund can significantly reduce its carbon footprint as measured by RCF by investing in stocks with higher valuation and lower level of emissions (e.g., those belonging to Technology, Services, Real Estate Investment, or Finance sectors). At the same time, our results showed that funds with a sustainability label (SRI) are still exposed to highly emitting companies, even more so to companies that have a high indirect carbon intensity. While RCF divides absolute emissions from a company between its owners, it may wrongfully portray a fund that tweaks its holding amounts in carbon intensive companies without fully divesting from these. RCF and WACI are influenced by holdings' industry and valuation. Companies with high valuations contribute relatively less to the carbon exposure of a fund when this is measured by the RCF metrics. Instead, WACI reveals the real exposure to intensive companies, as it only accounts for company carbon efficiency – emissions per unit of sales. We consider that simply having a low carbon footprint should not be a measure of the overall sustainability of a fund, as it sends the wrong incentives to fund managers.

Why should we include scope 3 emissions in the estimation of fund's carbon footprint, despite lack of primary data? Separating by emissions scope the results in Figure 3.4, 155 (23%) funds have a higher scope 1 and 2 intensity than MSCI World (33% when compared to MSCI Europe), while more than double, 451 (67%) funds have a higher scope 3 intensity (only 22% for MSCI Europe). Therefore, if an investor only considers direct emissions, 23% of funds are worse than MSCI World, whereas, if one accounts for indirect emissions, 67% of the funds perform worse. When the comparison is done with MSCI Europe almost one out of four SRI funds are responsible for higher life cycle emissions. Considering scope 3 emissions allows to identify the sectors where the fund has a high indirect exposure. In addition, this type of analysis is more useful for end investors than simply communicating the final RCF or WACI, as it reveals the life cycle carbon exposure by industry.

To better understand the sectorial exposure of a fund, both to direct and indirect emissions, we employ the climate-policy-relevant sectors (CPRS) classification from Battiston et al. (2017). The CPRS regroups the detailed sub-industries from which companies in a fund derive their revenues. A similar analysis has been carried out by the European Banking Authority (EBA) in its recent report (EBA, 2021), but it is only taking into account main company industry code and direct emissions. We take as example one Article 8 and one Article 9 fund (Figure 3.6).

LU0250158358 Article 9 fund

CPRS2 sector	Holdings' revenue	MV held by fund	Scope 1 & 2 impact share		Scope 3 impact share	
	mEUR	*'000 USD*	*tCO2-eq.*		*tCO2-eq.*	
3-energy-intensive	287,629	144,364	7,644	*33%*	14,980	*62%*
9-other	222,974	66,754	834	*3.6%*	3,121	*13%*
7-finance	60,185	45,689	475	*2.1%*	1,116	*4.6%*
5-transportation	861	12,619	74	*0.3%*	170	*0.7%*
4-buildings	7,695	6,852	61	*0.3%*	283	*1.2%*
2-utility|electricity	34,757	4,510	13,865	*60%*	4,490	*19%*
2-utility|waste	377	2,403	9	*0.0%*	78	*0.3%*
1-fossil|oil	35	5	3	*0.0%*	1	*0.0%*
1-fossil|gas	14	2	3	*0.0%*	2	*0.0%*

LU0082087510 Article 8 fund

CPRS2 sector	Holdings' revenue	MV held by fund	Scope 1 & 2 impact share		Scope 3 impact share	
	mEUR	*'000 USD*	*tCO2-eq.*		*tCO2-eq.*	
3-energy-intensive	535,592	74,092	8,438	*27%*	10,499	*30%*
7-finance	513,047	33,346	419	*1.3%*	2,034	*5.9%*
9-other	244,320	22,360	575	*1.8%*	1,817	*5.2%*
1-fossil|oil	706,699	13,819	14,951	*48%*	28,341	*82%*
2-utility|electricity	156,778	12,249	12,296	*39%*	4,680	*13.5%*
4-buildings	75,471	11,051	409	*1.3%*	3,312	*9.5%*
5-transportation	322,840	8,527	908	*2.9%*	5,061	*14.6%*
2-utility|waste	5,626	2,744	461	*1.5%*	302	*0.9%*
5-transportation|air	5,040	2,699	389	*1.2%*	184	*0.5%*
1-fossil|gas	19,859	1,180	1,107	*3.5%*	844	*2.4%*
5-transportation|roads	9,156	423	9	*0.0%*	74	*0.2%*
1-fossil|coal	8,835	415	1,308	*4.2%*	520	*1.5%*
1-fossil-fuel	11,230	378	279	*0.9%*	358	*1.0%*
6-agric. etc|agriculture	2,133	166	32	*0.1%*	64	*0.2%*
6-agric. etc|forestry	320	36	3	*0.0%*	3	*0.0%*

Figure 3.6: Funds' exposure to Climate-Policy Relevant Sectors (CPRS). Table sorted by market value held, decreasing. The revenue exposure column sums all the revenue from companies held in the portfolio

For the Article 9 fund, the largest exposure comes from Utilities (scope 1) and Energy Intensive industries (upstream scope 3). On the other hand, the Article 8 fund is largely exposed to the Fossil Fuel industry (Gas and Coal), but it also has large scope 3 emissions from Transportation, which are not identified as a major contributor when only conducting a direct emissions analysis. We observe that the ranking of industries changes when considering indirect emissions. A fund manager can use this analysis to decide with which companies to engage on both direct and indirect emissions and reduce their climate risk. In Appendix B.9, we further describe the details of this analysis.

3.5 Conclusion

In this article, we aim to improve current IOLCA estimation methods for fund-level life cycle GHG emissions. We first estimate company-level GHG emissions, by adopting a more detailed holding-level mapping across economic sectors and regions, as compared to state-of-the-art (Koellner et al., 2007; Trucost, 2019b), that is then linked to regionalized sectorial GHG emissions factors from EXIOBASE.

To showcase the use of our model, we apply it to an equal sample of 1,340 SRI and conventional equity funds and their 11,275 unique holdings. Our tool allows for cross-industry comparison of direct and indirect GHG emissions and can be consistently applied on any equity investment fund to verify its climate-related performance. Thus, coverage and homogeneity in method are the two main strengths of using IOLCA for estimation of company-level GHG emissions. Moreover, we achieve a much larger coverage of companies, when compared to CDP company-self-reported emissions (95% vs. 17% coverage of the holdings' sample).

We highlighted the importance of accounting for scope 3 emissions, or supply chain indirect emissions, as these may even triple the total carbon footprint associated with a fund, compared to methods only accounting for direct impact. In addition, we find that SRI funds do not necessarily have a lower climate exposure than a market index, as 38% of SRI funds had a higher WACI than the index MSCI World.

In terms of practical contribution, our findings serve asset managers and retail and institutional investors as a benchmark for other existing impact assessment methods and as a methodology for reporting on life cycle impact under the new EU-level regulations for financial institutions (EC, 2019a). Moreover, our disclosed estimates of life cycle emissions for companies and funds are a step forward towards openly available and transparent ESG data, aiming to lift the veil on corporate and fund-level sustainability performance measurements.

In future research, we aim to investigate ways to better account for the contribution of industries to environmental positive impact creation, extending the metrics beyond the static, single-impact-focused RCF and WACI.

4 Input-output life cycle assessment extended to additional environmental and social indicators with identification of trade-offs between impact categories[8]

Abstract

As finance becomes a key lever in driving sustainability transitions, regulations that mandate impact reporting at financial product level are emerging, especially in the European Union (EU). However, without standardized, reliable and relevant indicators, measurement of sustainability at investment product level risks being watered down by greenwashing. Following an advised life cycle perspective, we designated 13 environmental and 13 social life cycle impact indicators ready-to-use and aligned primarily with the EU Sustainable Finance Disclosure Regulation. Using these indicators, we estimate the impacts of 230 investment funds representing all sustainable equity funds listed on the Luxembourg Green Exchange. These funds can be attributed substantial responsibility via the companies they invest in, with total estimated impacts varying between 2.1 and 28.4 million EU citizen equivalents, depending on the indicator. Trade-offs could be signaled between environmental and social indicators, with correlations from 0.01 to 0.67. Finally, most impacts can be traced to a small number of publicly listed companies, which investors could engage with, in order to drive change. The proposed framework could serve as a template for further alignment of sustainable finance regulations and life cycle assessment methods.

[8] Adapted from article under review as *Popescu, I.S., Schaubroeck, T., Gibon, T., Petucco, C., Benetto, E. Investment funds are responsible for substantial environmental and social impacts with trade-offs at Nature Communications Earth & Environment,* current preprint available online. https://doi.org/10.21203/rs.3.rs-3345219/v1

4.1 Introduction

Monetary flows towards so-called sustainable investment funds are projected to grow to one third of the global market by 2025 (53 trillion USD) (Bloomberg Intelligence, 2021). However, the effectiveness of sustainable finance in driving changes in the real economy is heavily scrutinized (Bingler et al., 2022; Dyck et al., 2019b; Kölbel et al., 2019) as there is no top-down, thorough assessment of their sustainability claims (Eurosif, 2022; Mazzucato, 2022), leading to an increased risk of greenwashing (Nature Catalysis, 2022). Nonetheless, this risk is being progressively compensated from a bottom-up perspective by the growing focus on measuring the sustainability of financial products such as investment funds. Investors' awareness is, among others, driven by the imminence of climate (but also other environmental and social) risks that can jeopardize the long-term profitability of investments (Dietz et al., 2016). Indeed, previous studies (Battiston et al., 2017; Dietz et al., 2016) highlighted the significant hidden exposure to losses in the financial markets due to climate change. Next to policy makers, investors are an additional lever to push for a sustainable economy, by exerting influence on the companies they invest in (Landier and Lovo, 2020).

Having access to reliable and complete sustainability information is vital to the integration of sustainability in investment decisions (Lauesen, 2019; Nature, 2021). Current environmental, social and governance (ESG) ratings, widely used as proxy for sustainable performance, are mostly unreliable and do not offer sound quantitative information to investors(Berg et al., 2022; Popescu et al., 2021). To tackle this issue, initiatives to standardize sustainability assessment at financial product level are emerging globally(SEC, 2021), with the regulations under the EU Sustainable Finance Action Plan being regarded as the most ambitious (EC, 2018; Sandner & Cherki, 2022). The Sustainable Finance Disclosure Regulation (SFDR) (EC, 2019a) is the piece of legislation addressed to financial institutions and is the driver of our research. However, indicators under the SFDR are not comprehensive enough, while at the same time reliable company data to aid in sustainability reporting is unavailable.

As fostered to a considerable degree in regulations (Becchetti et al., 2022; EC, 2019c), Life Cycle Assessment (LCA) can provide consistent estimation of sustainability impact at product and organisation level (Gibon et al., 2020; Hellweg et al., 2023; Popescu et al., 2021). Adopting a life cycle perspective to impact assessment is crucial in order to avoid shifting of impact to indirect stages of production and consumption. Moreover, environmental LCA methodology includes a comprehensive set of impact indicators, to avoid trade-offs between these (Laurent et al., 2012; Popescu et al., 2021). Importantly, social impact indicators can be retrieved using Social LCA (UNEP, 2020), which has not yet been broadly applied in this context.

Building on the approach of Popescu et al. (Popescu et al., 2023), which focused on climate change footprints of investment funds, in this study we expand the life-cycle-based sustainability assessment of investment funds by: (1) demonstrating that science-based, ready-to-use, environmental and social indicators aligned with regulations can already be operationalized in a coherent framework and (2) discussing the application of this framework to a considerable sample of equity sustainable investment funds by evaluating substantiveness, synergies, and trade-offs.

We begin by analysing sustainable finance reporting regulations, to identify links with indicators from best-practice sustainability assessment frameworks. Afterwards, we designate 13 environmental and 13 social life-cycle-based impact indicators that can be estimated at company and investment fund-level using input-output LCA (IOLCA) (Miller and Blair, 2009) analysis (Methods, Table 4.1 and Table 4.2).

We apply IOLCA analysis to estimate impact factors at country-sector level (Hertwich and Wood, 2018; Stadler et al., 2018a), and then at company level, using the country and sector distribution of a company's revenue. This data is then aggregated at investment fund level. This approach has been applied by ourselves and others in past work (Koellner et al., 2007; Popescu et al., 2023). For the case study, we assess all equity funds listed on the Luxembourg Green Exchange for which complete information could be retrieved. This is the biggest exchange for green financial products, which represent more than 13% of the assets under management (AuM) of all funds self-labelled sustainable under the EU SFDR (Morningstar, 2023) (so-called article 8 and article 9 funds).

4.2 Methods

4.2.1 Selection of life-cycle-based indicators

As starting point for proposal of the 26 environmental and social indicators, we had the so-called Principal Adverse Impacts (PAIs) proposed under the Sustainable Finance Disclosure Regulation (SFDR), which are defined under the SFDR's Regulatory Technical Standards (RTS). As shown in SI Figure S2, we have divided the SFDR PAI indicators between inventory (specific environmental flow) and impact indicators (translation of effect of environmental flows on a certain impact type). Furthermore, we looked at how the SFDR indicators match with the six environmental objectives proposed under the EU Taxonomy and its Minimum Social Safeguards. Afterwards, we analysed the Corporate Sustainability Reporting Directive (CSRD), which, via its European Sustainability Reporting Standards (ESRS), makes reference to science-based measurement methods and standards on greenhouse gases emissions (ISO, 2018), such as ISO:14046-1:2018, and on other environmental indicators, as the Environmental Footprint methods (PEF, 2021) (EF). More detailed analysis of the legislative framework around EU sustainable finance reporting can be found in Appendix C.1.

Table 4.1: 13 environmental impact indicators for sustainable finance reporting, based on Environmental Footprint version 3.1. and EXIOBASE. In the first column we list the EU Taxonomy environmental objectives. In the second column, we make the connection to SFDR PAIs. In the third column, we list the final set of 13 environmental indicators. In the last column we describe the environmental flows that are included to compute an impact indicator. An impact indicator is the sum of the impacts resulting from the environmental flows, calculated by multiplying each one of these with its corresponding characterization factor (i.e., the impact per unit of environmental flow estimated using different impact assessment models).

EU Taxonomy Objective	**SFDR PAI**	**Proposed EF impact category**	**Unit (environmental impact category indicator)**	**Source**	**Included environmental flows**
climate change mitigation	GHG emissions	Climate change, total	GHG emissions, GWP100 (kgCO_2 eq)	(Beylot et al., 2020, 2019)	CO_2, CH_4, N_2O, SF_6, HFC, PFC
climate change adaptation	n/a	n/a	n/a	n/a	n/a
the sustainable use and protection of water and marine resources	emissions to water; inorganic pollutants	Ecotoxicity, freshwater	Comparative Toxic Unit for ecosystems (CTUe)	(Beylot et al., 2020, 2019)	Benzo(a)pyrene, Indeno(1,2,3-cd)pyrene, PCDD_F, HCB, As, Cd, Cr, Hg, Cu, Ni, Pb, Benzo(k)fluoranthene, Se, Zn, B(a)P, Indeno, PCDD/F, NMVOC, PAH, B(k)F
	water usage and recycling; exposure to areas of high water stress	Water stress	Water stress (m^3 *of* H_2O *equivalents)*	(Cabernard et al., 2019)	Water consumption
	air pollutants	Eutrophication, freshwater	Fraction of nutrients reaching freshwater end compartment (P)	(Beylot et al., 2020, 2019)	NH_3 - air, P
	emissions to water; air pollutants	Eutrophication, marine	Fraction of nutrients reaching marine end compartment (kg N eq)	(Beylot et al., 2020, 2019)	NH_3, N
the transition to a circular economy	n/a	Material footprint	*Material footprint (tonnes of cultivated biomass, extracted mineral ore and fossils)*	(Cabernard et al., 2019)	Extraction Used
pollution prevention and control	air pollutants	Acidification	Accumulated Exceedance (mol H+ eq)	(Beylot et al., 2020, 2019)	SOx, NOx, NH_3
	air pollutants	Eutrophication, terrestrial	Accumulated Exceedance (mol N eq)	(Beylot et al., 2020, 2019)	NH_3, NOx
	emissions of inorganic pollutants	Human toxicity, cancer	Comparative Toxic Unit for humans (CTUh)	(Beylot et al., 2020, 2019)	Benzo(a)pyrene, PCDD_F, HCB, As, Cd, Hg, Ni, B(a)P, Pb, PCDD/F
	emissions of inorganic pollutants	Human toxicity, non-cancer	Comparative Toxic Unit for humans (CTUh)	(Beylot et al., 2020, 2019)	HCB, As, Cd, Cu, Hg, Ni, Pb, Zn
	emissions of inorganic pollutants	Particulate matter	Impact on human health (DALYs)	(Cabernard et al., 2019)	$PM_{2.5}$, CO, SOx, NH_3, TSP
	air pollutants	Photochemical ozone formation, human health	Tropospheric ozone concentration increase (kg NMVOC eq)	(Beylot et al., 2020, 2019)	CH_4, SOx, CO, NMVOC

EU Taxonomy Objective	SFDR PAI	Proposed EF impact category	Unit (environmental impact category indicator)	Source	Included environmental flows
the protection and restoration of biodiversity and ecosystems	activities negatively affecting biodiversity-sensitive areas; natural species and protected areas; deforestation; land degradation, desertification, soil sealing	Land-use related biodiversity loss	(global m3 PDF years)	(Cabernard et al., 2019)	Land use, crop, forest, pasture

Afterwards, we have considered current state-of-the-art in terms of life-cycle-based indicators. Especially for the environmental dimension, the difficulty in choosing a sufficient and comprehensive set of indicators, lies in the existence of multiple methods to assess the same impact category, even for established impact categories, like climate change. We preselected the Environmental Footprint (EF) version 3.1, updated in 2022 is proposing a set of 16 impact indicators and underlying methods and characterization factors, as (1) it is based on latest literature developments, (2) can be linked to ready-to-use indicators built using EXIOBASE (Beylot et al., 2020, 2019) (the selected environmentally extended input-output database) and (3) it is brought forward by EU policy. From these 16, we only selected 13 environmental indicators (Table 4.1), with exclusion of two EF indicators that are not covered in the IOLCA data (ozone depletion and ionizing radiation), and the summing of two resource use indicators into represent the material footprint indicator. While the EF is considerably up to date in terms of impact indicator assessment methods, it does not integrate aspects like the difference in impact magnitude caused by the location where the impact takes place, which is highly relevant, especially for water stress (Pfister and Bayer, 2014), pollution (P. Fantke et al., 2017), toxicity or biodiversity. Therefore, for water use, particulate matter, and land-use impact indicators in the EF methods, we use impact factors corresponding to location-specific impact indicators of water stress, particulate matter, and land-use related biodiversity loss, that are built using EXIOBASE. These are obtained from the work of Cabernard et al. (Cabernard et al., 2019). For social issues, the SFDR proposes rather qualitative indicators, some even only concerning due diligence & compliance (for example, "monitoring compliance to OECD Guidelines for Multinational Enterprises") instead of quantitative ones, focused on impact. We provide a set of rather quantitative impact indicators matching the SFDR's PAIs, that are also linked to the social issues identified by the EU Taxonomy and the CSRD. To ensure that one can estimate impact at financial product level, we analyzed indicator availability from PSILCA (Maister et al., 2020)[, 29], the social input-output life cycle assessment database which contains over 90 indicators. We selected a set of 13 social indicators (Table 4.2) related with the social indicators categories proposed by UNEP Social LCA Guidelines (UNEP, 2020). Yet, we did not consider the indicator values expressed in raw units, but their translation in so called "medium risk hours equivalents" (mrh), as proposed in the PSILCA documentation

(Maister et al., 2020). The raw indicator unit, while easier to interpret, cannot be extended easily to estimate life cycle impacts. For example, in the case of a raw unit in percentages, one cannot extend that to the estimation of life cycle impacts, as the percentage unit does not function like a physical unit, when the direct percentage is known. Medium risk hours equivalents unit is the multiplication of the hours worked in the sector with a factor that represents the extent of risk based on predefined criteria, where a medium risk has a factor 1. The mrh unit can be used to derive the life cycle impacts and allows for comparison between indicators.

Table 4.2: 13 social impact indicators for sustainable finance reporting, based on PSILCA. The indicators are compiled using two different literature sources. In the first column we list the EU Taxonomy environmental objectives. In the second column, we make the connection to SFDR PAIs. In the third column, we list the final set of 13 social indicators.

EU Taxonomy minimum social safeguards	**Connected SFDR PAI**	**Social indicator (raw unit from PSILCA database)**	**Unit considered in the analysis**
corruption	Cases of insufficient action taken to address breaches of standards of anti-corruption and antibribery	Active involvement of enterprises in corruption (%)	medium risk hours (mrh)
fair competition	Cases of insufficient action taken to address breaches of standards of anti-corruption and antibribery	Presence of anti-competitive behaviour or violation of anti-trusted monopoly legislation (score of ordinal 0-3 scale)	mrh
human rights	Operations and suppliers at significant risk of incidents of child labour	Children in employment (%)	mrh
	Unadjusted gender pay gap	Gender wage gap (%)	mrh
	Operations and suppliers at significant risk of incidents of forced or compulsory labour	Frequency of forced labour (cases per 1,000 inhabitants in the country)	mrh
	Lack of processes and measures for preventing trafficking in human beings; lack of due diligence	Presence of sufficient safety measures (Cases per 100,000 employees)	mrh
		Trafficking in persons (Trier)	mrh
	Rate of accidents	Rate of fatal accidents at workplace (#/yr and 100,000 employees)	mrh
	Number of days lost to injuries, accidents, fatalities, or illness	Rate of non-fatal accidents at workplace (#/yr and 100,000 employees)	mrh
	Violations of UN Global Compact principles and Organisation for Economic Development (OECD) Guidelines for Multinational Enterprises (Respect for core labour standards - e.g., freedom of association and collective bargaining; non-discrimination in employment and occupation)	Evidence of violations of laws and employment regulations (cases per 10,000 employees)	mrh
		Right of Association	mrh
		Right of Collective bargaining	
		Right to Strike	
taxation	n/a	n/a	n/a

4.2.2 Methodological framework

Input-output life cycle analysis (IOLCA) allows to estimate regional and sectorial impacts per monetary unit, making it suitable for assessments at organisation/company level, and has been previously used to this aim. IOLCA is particularly suited, as at company level reliable and complete data is available currently only in monetary terms in the form of revenue streams. Moreover, this type of analysis is useful for the assessment of indirect or supply chain impacts, as companies do not have visibility over their indirect suppliers, even if it is usually where the majority of impacts take place. Finally, IOLCA has been previously adapted to estimate impacts of financial portfolios, both in academia (Koellner et al., 2007; Popescu et al., 2023), and in the development of proprietary models by different data providers (Garel et al., 2023; Trucost, 2021). At the level of financial portfolios, impacts from many companies have to be aggregated, and thus using IOLCA as a uniform method across all companies in a portfolio ensures consistency and additionality in the assessment process.

Crucial in our framework is the consideration of IOLCA-based impacts as averages per country and sector, following an organizational LCA approach, and not per sectorial product, following a conventional product-oriented LCA approach, for which additional transformations are needed (Majeau-Bettez et al., 2018). Although a consequential aim can be envisioned, trying to address what the consequences are of investing in a certain fund at the inventory level, there is a lack of a consequential IO-based life cycle database at sector-level. Hence, conventional attributional modelling has been applied, and can be regarded as an approximation. In the rest of this manuscript, we do not come back on this distinction between attributional versus consequential (Schaubroeck et al., 2021).

The step-by-step schematic representation of the IOLCA framework for assessment of impacts at financial product level is shown in Figure 4.1. Technically, the calculation of impact factors is based on the conventional input-output modelling using matrix calculation. In a first step (Module 1), we derived the IOLCA-based direct and indirect impact factors for the selected set of environmental and social impact indicators. In the case of environmental indicators, characterization factors (CF) are used as weighting proportions to define aggregated impact indicators, that group more environmental flows under the same impact category. Following the input-output nomenclature, the direct impact factors vector for each impact indicator contains impact factors for each country-sector combination and is obtained by dividing matrix F (total impacts by country-sector) by total output x:

$S = \frac{F}{x}$ (eq. 5.1).

Then, we have computed the total (life cycle) requirements matrix (L), or the Leontief inverse, from the original input-output table (A) , the direct requirements matrix:

$L = (I - A)^{-1}$ (eq. 5.2).

The Leontief inverse allows us to compute the life cycle impact factors M (or "multipliers"), by multiplying matrices S and L :

$M = S \times L$ (eq. 5.3).

With the life cycle impact factors vector we are only capturing direct and supply chain impacts (or upstream impacts). Given the use of an IOLCA framework, the computation of downstream impacts (impacts from use phase onwards) it not straightforward and cannot be derived directly from the IOLCA tables. However, it could be estimated using traditional LCA data, but it is not covered in this paper. The S and M vectors, explained above, are used to derive the database of country-sector direct, indirect and life cycle impact factors (IF), for each indicator and country-sector combination (impact factor by country j and sector k) (Popescu et al., 2021). The IFs are then linked with the revenue breakdown for a company i (R_{ijk}), as per equation 5.4 below. The quality and granularity of revenue-level data is a main driver of final reliability of company-level impact estimates.

$I_{ci} = \sum_j \sum_k IF_{cjk} R_{ijk}$ (eq. 5.4)

The next key step is defining the sector and country level correspondence (concordance matrix) between the financial revenue database and the input-output database (Module 2). The concordance matrix bridges the IOLCA sector and country dictionary for impact factors with the FactSet company-level country and sector dictionary for revenue breakdown. A company will be assigned the average impact factors of the general country-sectors combinations that constitute its revenue generation streams – for example, Chemicals, Plastics and Other Manufacturing sectors in the US, China, and Germany for company BASF. This allows to obtain a life cycle impact per company (e.g., kg CO_2 eq. per euro output for GHG emissions indicator), that is the weighted average of the underlying economic activities of the company (Module 3).

Finally, impacts at fund level can be expressed as absolute values in terms of owned impacts, for each impact indicator (category) c, by computing the share of a company's impact that an investment fund f is responsible for (Module 4) (Popescu et al., 2021). The impact is derived based on investment fund-level information: the list of its public equity investments and the amount invested. Practically, for one impact indicator, the total impact of a company (I_{ci}) is divided by the market value (M_i) – total shares multiplied by price per share. Each shareholder is attributed its share of the holding, per monetary unit of investment. For each company, the weight held by the fund in the company is accounted for (w_{if}), which is the invested amount by each fund in each of its company holdings. This measure accounts for the market valuation of a company, dividing the responsibility of impact between all its shareholders:

$Fund\ impact_{cf} = \sum_i w_{if} \frac{I_{ci}}{M_i}$ (eq. 5).

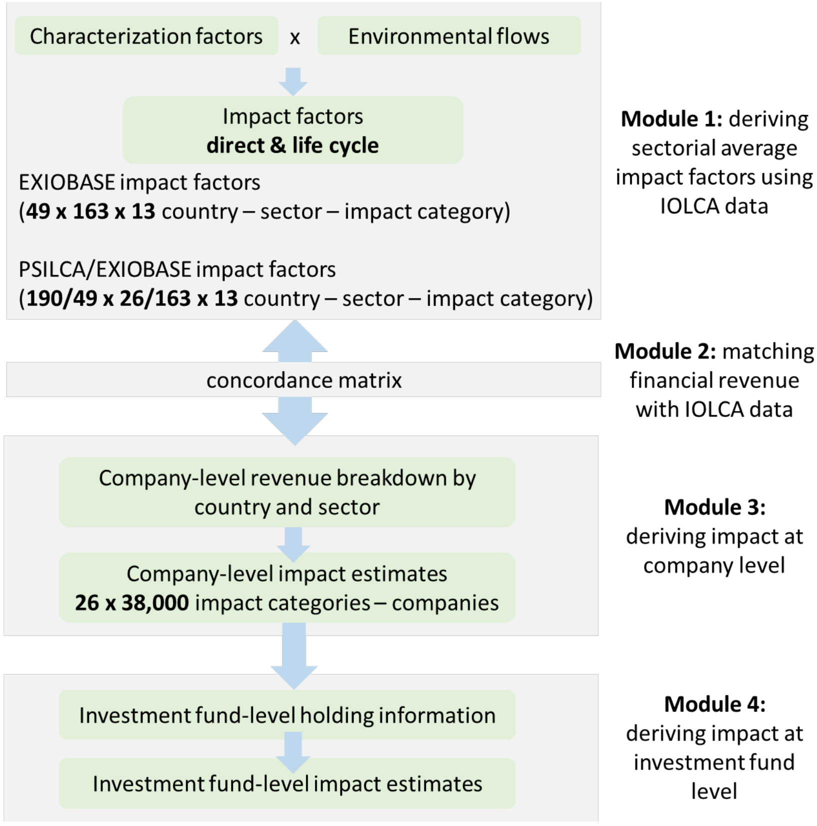


Figure 4.1: Schematic representation of the procedure to ready-to-use life-cycle-based impact assessment for financial products.

4.2.3 Database selection and handling

A suite of environmental and social input-output databases is available, each with distinct characteristics, but building on the same principles. Widely used databases for environmental assessments are EXIOBASE(Stadler et al., 2018a), EORA (Lenzen et al., 2013), GTAP and OECD (Giljum et al., 2019). The two main databases for social assessment are PSILCA (Maister et al., 2020) and the Social Hotspot Database (SHDB). While the environmental databases are fully free, or free for academic use, neither of the two social databases are freely available. Differences between databases are in the level of disaggregation available at country and sector level and in the impact extensions available. Deviations in data and results between input-output databases have been studied in previous work and the main drivers of variation are the structure of the economic flows and the environmental and social accounts data(Moran and Wood, 2014). As such, our results and coverage of proposed indicators and underlying environmental flows are influenced by our choice of primary IO database.

For the environmental analysis, we have chosen EXIOBASE, a IO database developed and maintained under a European research project(Stadler et al., 2018a), which has been widely used in academia and in practical case studies for environmental assessments (Bjelle et al., 2021; Stadler et al., 2018a). The choice of EXIOBASE has been previously detailed in the context of evaluating funds using IOLCA, but this was done solely for GHG emissions (Popescu et al., 2023). Compared to other input-output databases, it has a greater coverage of environmental accounts and a detailed coverage of European Union economies (Giljum et al., 2019; Moran and Wood, 2014) (49 countries/regions, 163 sectors and 1,114 environmental flows). The EXIOBASE is used to extract direct and indirect impact factors for the 13 environmental impact indicators. Data is reported at environmental flow level. We then needed to aggregate multiple environmental flows to form impact indicators, using their specific characterization factors as weighting proportion. The CF are based on developments from the Product Environmental Footprint 3.1 guidance and/or referenced literature, depending on the impact indicator. For the matching between environmental IO database and financial revenue, we use the concordance matrix developed manually in Popescu et al. (Popescu et al., 2023), based on finding the best match between the FactSet RBICS database used and the EXIOBASE nomenclature.

For the social assessment, we have chosen PSILCA, given the better accessibility and sector-level coverage. Social input-output databases have only been recently developed, to aid in accounting for the social impacts embodied in the global economy. Therefore, their reliability and use are lower. For the concordance matrix of the social database PSILCA and company-level data, the process was challenging, as there is not a common sector classification between countries in PSILCA. To ease the exercise, we have aggregated all the impacts at the level of the common 26 sectors classification (which is also the common classification of the EORA26 database), by computing the mean of the impact factors of all sectors linked to one EORA26 sector. For the final social concordance matrix, we linked the EORA26 classification to the sectorial classification from the database of financial revenue, in a 1-to-n linking – meaning that more country-sectors from the revenue database will receive the same impact factor, as they are part of the same aggregated EORA26 sector.

As source for financial information, such as holding amount at fund level and company-level revenue data, we use the proprietary dataset of FactSet (FactSet, 2021), that can be accessed by purchasing a license. The datasets are FactSet Ownership, for investment fund-level data, and GeoRev and RBICS, for information on the distribution of company revenue at country and sector level. Having data in monetary amounts about the revenue distribution of each company is the best available option. Ideally, companies would share information in physical units about the produced amounts and purchased products. However, companies seldom disclose this type of information and the most reliable and complete data available for produced amounts is revenue-level data, in monetary units.

4.2.4 Selection of funds' sample

According to market research by Morningstar (Morningstar, 2023), SFDR-labelled article 8 and article 9 funds amounted to 10,608 in December 2022, representing 37.8% of all the funds available for sale in Europe. Our initial sample, of article 8 and 9 funds listed on the Luxembourg Green Exchange, is of 1,389 funds. The assets under management of these funds represent 13.7% of the total AuM of SFDR article 8 and 9 funds (i.e., 630.23 billion USD out of 5.01 trillion USD). The total global pool of sustainability-labelled funds, which comprises all types of funds, not only equity funds, is estimated at around 5 trillion, 12 times higher than our sample (Morningstar, 2023). Our final sample is reduced to 230 funds, after removing funds with more asset classes (as it leads to double counting for impact intensity metrics) and removing non-equity funds (i.e., funds investing in fixed income or money market funds), as for these we cannot directly apply our proposed assessment model. The sample of equity funds is heterogenous in terms of investment theme and size, ranging from 4 million USD to 16.5 billion USD in Assets under Management (AuM).

4.2.5 Spearman rank correlation

We apply the Spearman rank correlation, as this is not sensitive to outliers and leads to more reliable results that the traditional, default correlation method used – the Pearson correlation. The Spearman rank correlation uses the rank of the observations on each variable, thus being described using a monotonic function (Schober and Schwarte, 2018).

4.2.6 Software and data availability

The data estimation, analysis, and output were performed in python and Jupyter notebooks. The *pymrio* package (Stadler, 2021) was used for input-output calculations, and the *mySQL workbench* for the financial data retrieval. The environmental impact data is sourced from EXIOBASE database, which is free for academic use, whereas the social impact data is obtained from the PSILCA database, for which a license is needed. Financial data comes from the proprietary database FactSet, and in order to reproduce the code, a licence from the data provider is needed.

4.3 Results

4.3.1 A set of consistent and ready-to-use environmental and social impact indicators

The three main pieces of regulations that mandate sustainability-level disclosures are: the EU Sustainable Finance Disclosure Regulation (EC, 2019a) (SFDR), the EU Corporate Sustainability Reporting Directive (CSRD) (EC, 2022), and the EU Taxonomy (EC, 2020). In our framework development for indicators (Figure 4.2), we first define the link between environmental and social objectives from the EU Taxonomy and then indicators proposed under SFDR (the so-called Principal Adverse Impact (PAI) indicators for investments in investee companies) and CSRD. We draw the (mis-)matchings between the sustainability indicators proposed. In a last step to define our framework, we link life-cycle-based indicators (Figure 4.2), that are ready-to-use and science-based, which could be thus used in reporting against the SFDR regulation.

The comprehensiveness and rigorousness of SFDR-proposed indicators is unsatisfactory, when compared to the state-of-the-art indicators in the sustainability assessment field. First, there is an inconsistent coverage of sustainability issues, as compared to widely accepted frameworks for sustainability assessment. Second, disclosure over the life cycle is not mandated. Finally, there is no clear methodology to underpin the indicators proposed, which may lead to reported data not being comparable between financial institutions (argumentation is further detailed in the SI).

The EU environmental footprint (EF) method (PEF, 2021) and the UNEP Social LCA Guidelines (UNEP, 2020) are chosen as guidance frameworks. These frameworks are among the most consensual at policy level and are relying on science-based sustainability assessment methods. The selection of ready-to-use, life-cycle-based indicators is restricted, in a first step, by the availability of raw environmental and social indicators in the IOLCA databases of choice. For environmental impacts, we use indicators that can be estimated using the environmentally extended multi-regional input-output database EXIOBASE, which was employed for similar purposes(Cabernard et al., 2021; Koellner et al., 2007) and has a detailed country and sector-level coverage. For the social impact assessment, the PSILCA database (Maister et al., 2020) is used, which has a large coverage of social indicators and detailed country and sector-level coverage for EU countries (Methods).

Life-cycle-based ready-to-use indicators have been found for almost all regulation objectives/indicators. Concerning well-matching environmental impact topics, climate change mitigation is the only objective with a one-to-one relationship between all standards, validating the maturity level and consensus on this main environmental issue. For SFDR PAI indicator "emissions of air pollutants" (like ammonia – NH_3), the EF method provides several impact indicators to assess their effects – namely terrestrial acidification and eutrophication (PEF, 2021).

Similarly, "emissions to water" and "emissions of inorganic pollutants" are represented by the corresponding life cycle impact indicators of *toxicity* and *eutrophication*. The SFDR PAIs of "land degradation" and "activities negatively affecting biodiversity-sensitive areas" can be grouped under the life cycle impact indicator of *land-use related biodiversity loss* (Cabernard et al., 2019). For "water use" and "exposure to areas of high water stress", we propose the alternative indicator of *water stress*, which weights water usage based on the characteristics of the region where it takes place – whether the area is more at risk of water stress or not (Cabernard et al., 2019). An exception is the EU taxonomy objective of climate change adaptation having no standardized equivalent indicator in LCA.

In the extended literature, there are however many examples of indicators specifically developed to measure adaptation, e.g., flood safety levels for a stormwater management system (Brudler et al., 2016) measuring the impact compared to a reference scenario. In some cases (e.g., electricity generation) the same indicators used for climate change mitigation can apply (EC, 2019c). Similarly, for the "circular economy" (CE) objective, indicators measuring circularity do not directly represent environmental impacts, instead they are a proxy (or not) for better (or worse) environmental performances which shall anyway be measured separately. Multi-dimensional scoring tools that serve as CE indicators have been previously developed and tested, such as the Circularity Potential Indicator (Saidani et al., 2019, 2017). Life-cycle-based indicators assessing resource use and scarcity(EC, 2021b) may be used to this aim, until better indicators based on reliable collected data will be developed(Muñoz-Torres et al., 2018; Saidani et al., 2019).

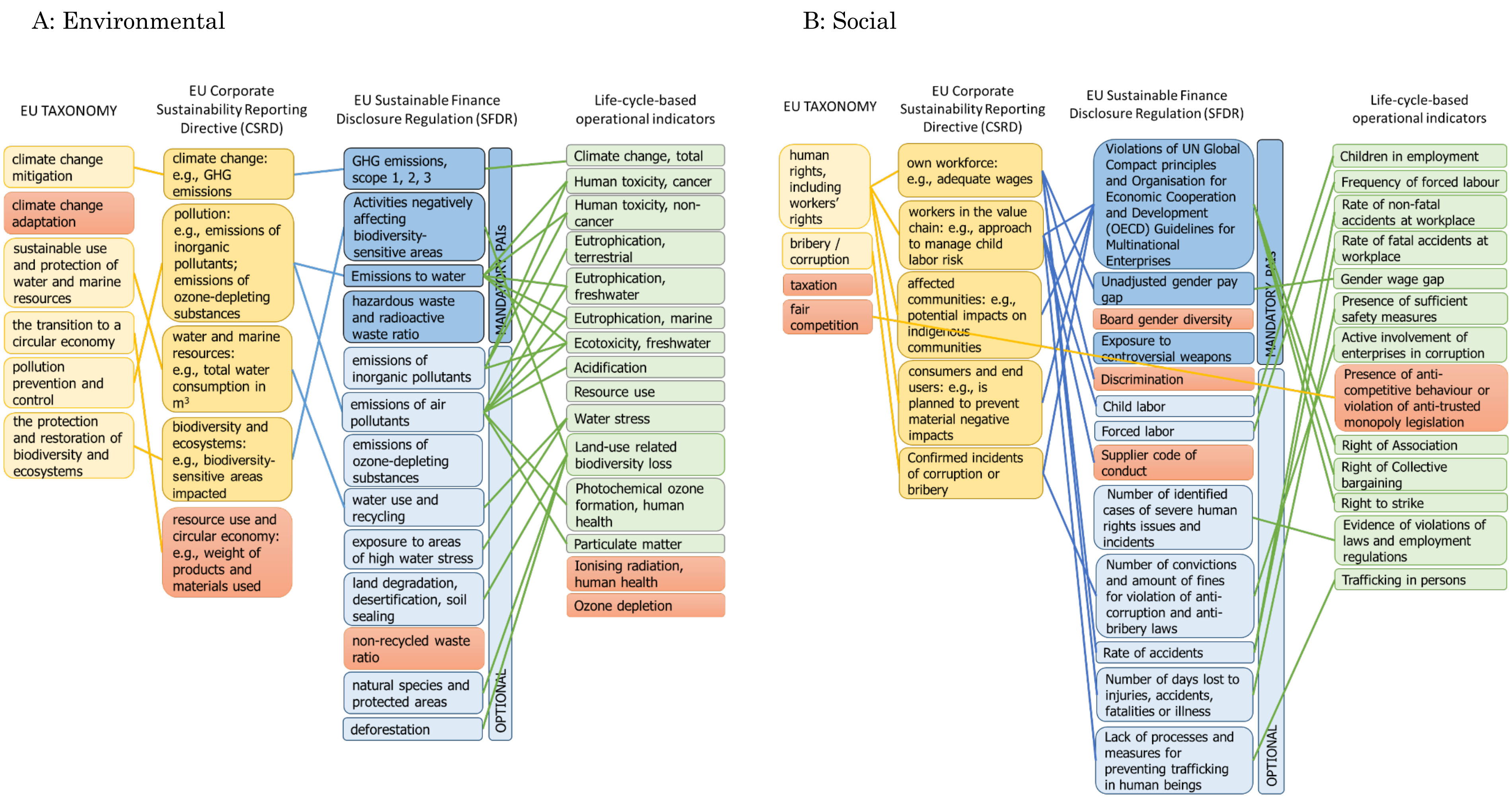


Figure 4.2: (A) Environmental impact indicators A and (B) social impact indicators, under the EU sustainable finance regulations and proposed life-cycle-based ready-to-use indicators. The indicators/objectives that are in orange boxes are not directly matched between the regulations and the life-cycle-based indicators. The darker-colored SFDR PAI indicators refer to the mandatory ones.

Social indicators from regulations tend to be qualitative (Figure 4.2 Panel B). For example, the scope of the SFDR-proposed indicator of "violations of UN Global Compact principles and OECD Guidelines for Multinational Enterprises" is too broad and would not give stakeholders a sense of the social impacts that underline a funds' portfolio. While social impacts are by default driven by more abstract characteristics of a company – such as employee policy – more quantitative indicators can be developed, that allow for a clearer assessment of a company or investment. Hereto, quantitative indicators by social impact category are being developed in social LCA (UNEP, 2020; Zimdars et al., 2018). We propose semi-quantitative risk-based indicators available in the social IOLCA database PSILCA, that can be estimated at sector, company, and financial product level. Examples of PSILCA indicators are rate of accidents, children in employment, right to collective bargaining.

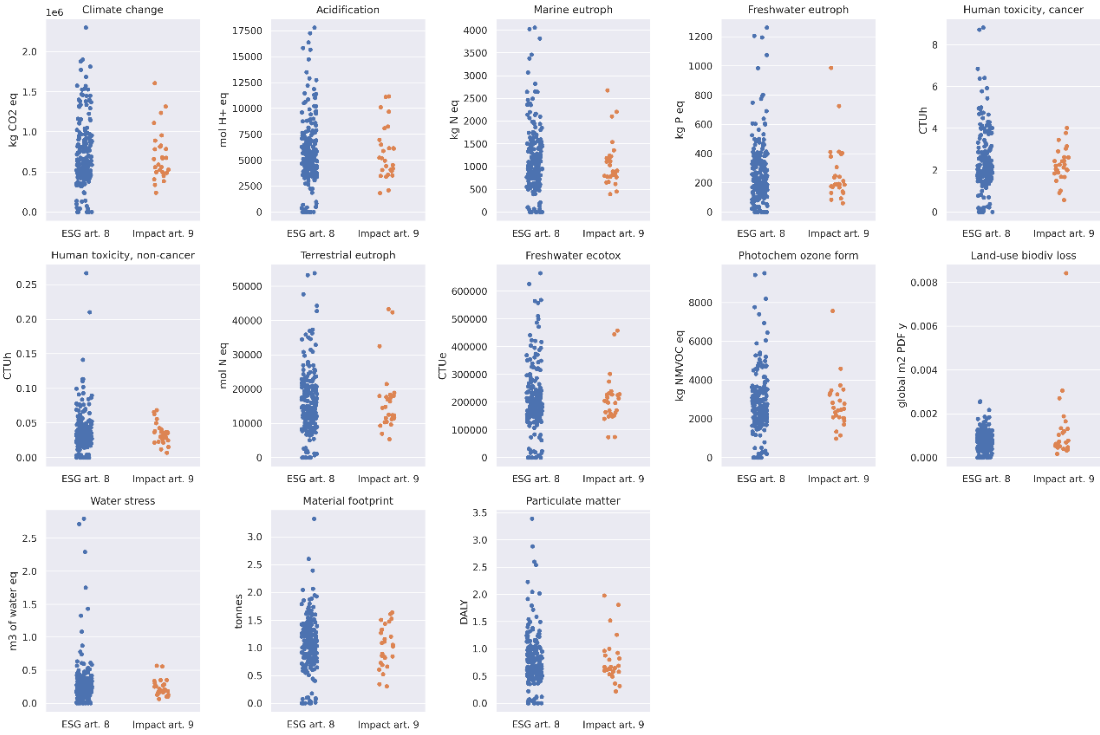
4.3.2 Application to a representative sample of sustainable funds

We applied the indicators framework to a representative sample of 230 equity funds, self-labelled sustainable under the SFDR classification, investing collectively in over 4,800 unique public companies worldwide. The sample represents the unique universe of SFDR Article 8 and Article 9 funds listed on the Luxembourg Green Exchange. The funds in the selected sample hold together 401 billion USD (US dollar) of investments, which, if compared to the size of an economy, is approximately as large as the gross domestic product (GDP) of Denmark over a year (398.3 USD billion in 2021, according to the World Bank data (World Bank, 2022)).

4.3.3 Widely spread impact distribution for the funds sample

For the environmental impact assessment, the results at fund level vary by indicator (Figure 4.3), with a widely spread distribution of impacts among Article 8 and Article 9 funds. Acidification, eutrophication and ecotoxicity impact intensities have highest spreads (for example, direct freshwater ecotoxicity impact indicator mean across funds is of 19.2 thousand CTUe/MUSD, with a standard deviation of 43.2 thousand CTUe/MUSD), while for the climate change indicator we see a smaller interval for the results distribution (245 tCO_2/MUSD mean, and standard deviation of 481 tCO_2/MUSD). All values are displayed in SI Table S1. For the set of social impact indicators, the impact range is more concentrated, especially for the Article 9 funds. Yet, outliers appear across all impacts. These can be driven by investments in companies which have activities in countries with large relative impacts, or be skewed towards specific industries, thus leading to a much larger result than the sample mean. Finally, these results show that choice between different funds may be associated with big differences in sustainability impact.

A: Environmental



B: Social

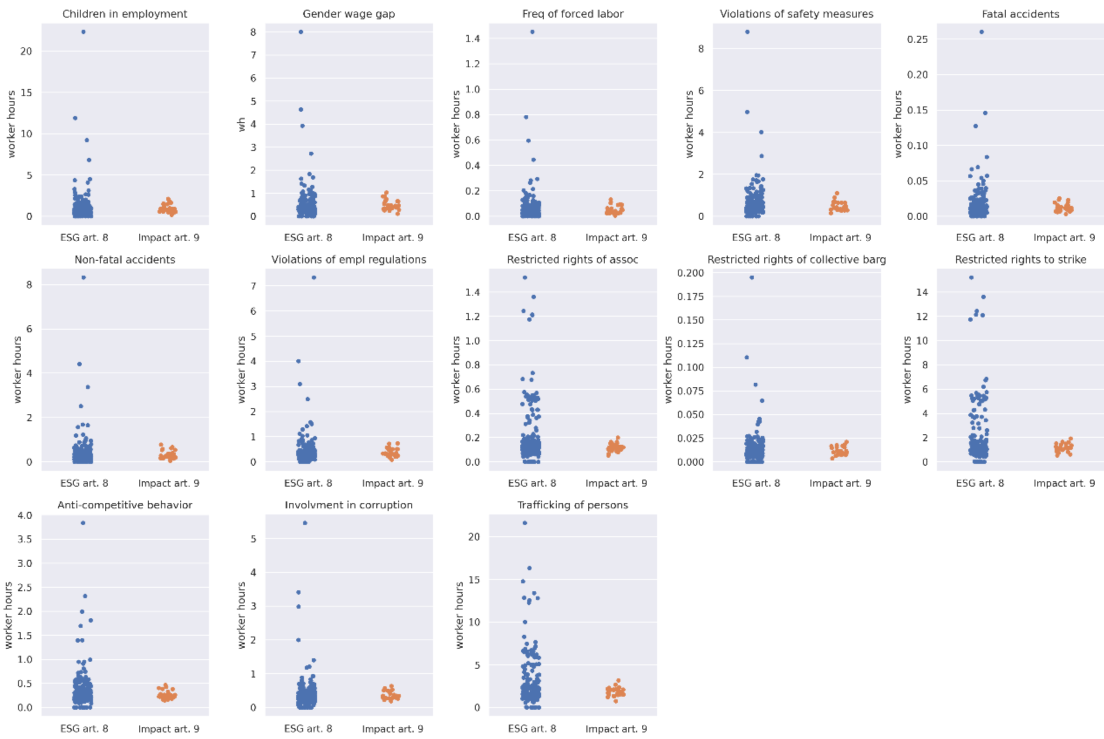


Figure 4.3: Stripplots showing the distribution of life cycle impact intensity of funds in the sample of year 2021 for fund-level holdings data and 2019 for company-level revenue data. The results are measured in respective impact unit per monetary amount of company revenue. Panel A shows results for the 13 environmental impact indicators, and Panel B, for the 13 social impact indicators.

4.3.3.1 Synergies & trade-offs between social and environmental impacts

Environmental and social impacts at fund level are not always strongly and positively correlated, as shown in the matrix of Spearman's rank correlation coefficients in Figure 4.4, implying that an investment fund or a company can rank highest for one indicator, while scoring lower for other indicators. In general, we observe high correlations within each distinct subset of social and environmental indicators, and low correlations in between the two, meaning that there are larger trade-offs in between environmental and social indicators than within the environmental or social indicators' groups.

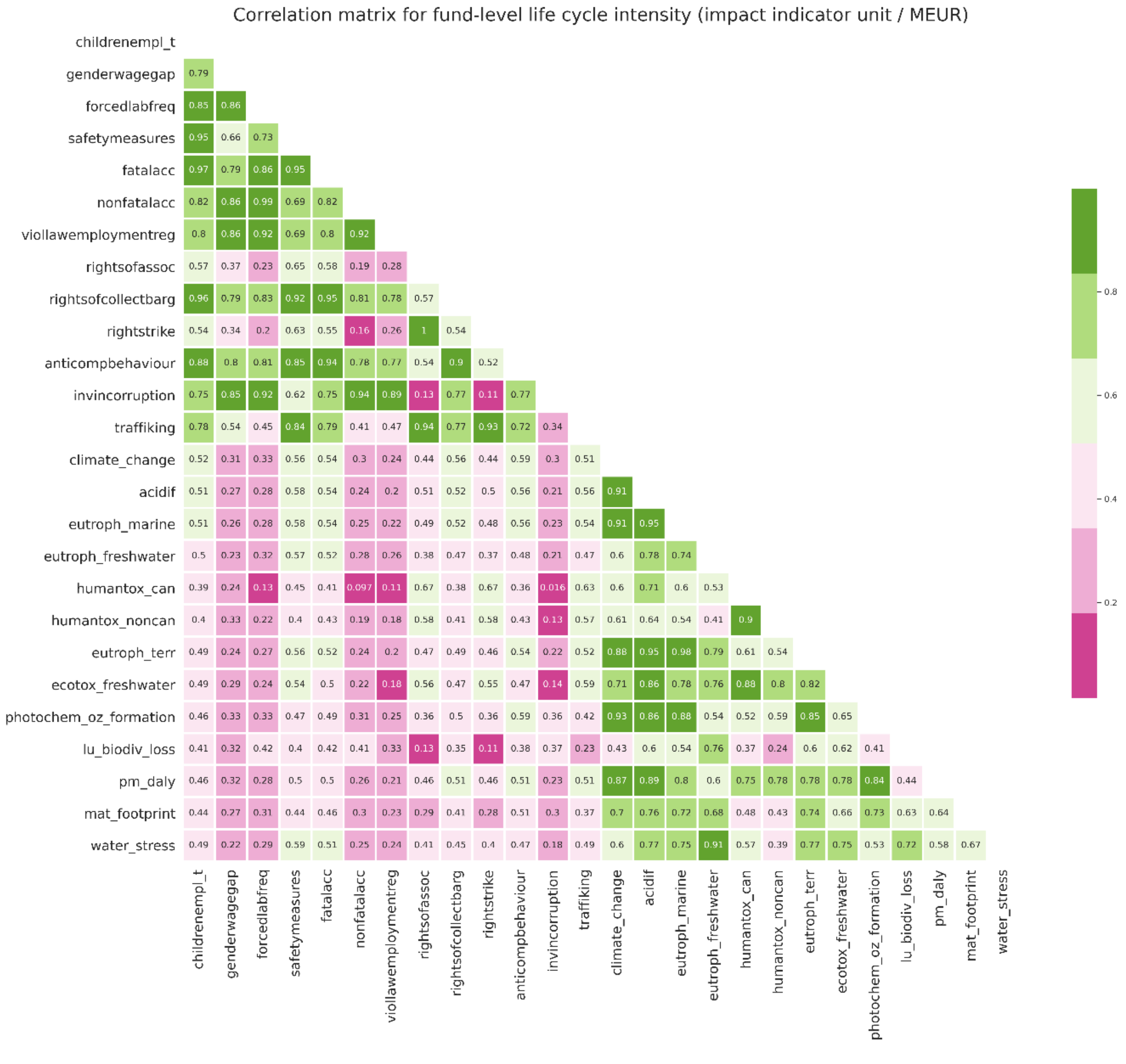


Figure 4.4: Spearman's rank correlation coefficients between environmental and social impact indicators.

Within the set of environmental indicators, some strong synergies are visible, whenever impact indicators are derived from common environmental flows. For example, acidification is highly correlated (coefficient larger than 0.9) with terrestrial eutrophication and photochemical ozone formation: expectedly so as ammonia emissions are contributing to all these three impact indicators. Human toxicity is correlated to ecotoxicity as heavy metals emissions are an important contributor to these impact indicators. At the opposite, for human toxicity we observe trade-off with water stress, given the low degree of similarity between the two impact indicators. Another trade-off observed at fund-level is for indicator climate change with land-use related biodiversity loss. Biodiversity loss would thus be a very important indicator to measure alongside climate change, in order to avoid causing more harm for biodiversity when investing with reduction of GHG emissions as main goal. Within the set of social indicators, there is a predominance of very high correlations.

At fund level, both the portfolio allocation and the sector-country distribution of the held companies' revenue drive the correlation coefficients. Given the fact that funds tend to have high similitude in portfolio allocation – if, for example, more funds follow the market index – correlation is higher at fund level. If we do the exercise at company-level, the inherent economic activities of the company drive the correlations. In Appendix Figure C.3, we show correlation matrixes between all impact indicators at company level, separately by main sector group. For Retail and Wholesale Trade sectors, there are strong negative correlation coefficients between most of social and environmental categories, signalling a high trade-off when investing in these industries. Indeed, the trade sector can be described as having low environmental pressures, while having a high impact on workforce. On the contrary, for Transportation and Utilities companies, we see a weaker negative relation between social and environmental indicators, while we observe more pronounced negative correlations between environmental indicators – especially between particulate matter and the other indicators, as companies with very high particulate matter impacts rank lower on other environmental indicators. Companies in the Mining industry are perhaps the most interesting, as they show strong trade-offs between social and environmental indicators, but also within environmental indicators (namely material footprint vs. the rest of environmental indicators).

4.3.3.2 Magnitude of direct and indirect impacts at fund level

We estimate the total life cycle impact of the funds sample, based on the amounts invested, and plot the proportion of direct and indirect impacts (covering the upstream life cycle chain) alongside absolute direct and indirect impacts (Figure 4.5). For all indicators, indirect impacts are considerably larger than direct impacts. However, results vary by impact indicator. Indirect proportion is lower for particulate matter, photochemical ozone formation and GHG emissions, where the contribution of direct impacts to the total life cycle impact is higher than 40%. Similar contribution is observed among the social indicators, namely for lack of rights of association and rights to strike.

To contextualize the estimated impacts of the funds sample, we express this in the population equivalents of the impact of EU citizens (assuming an EU population of 447 million citizens in 2019), based on the categories of the EU final demand in EXIOBASE (household and government consumption, inter alia). The funds' investments are equivalent to the impacts of between 2.1 to 28.2 million EU citizens, depending on the impact indicator chosen.

For example, for climate change mitigation, the total sample of investment funds is responsible for 62.2 million tons of CO_2-equivalents ($MtCO_2$-eq) direct emissions and 70.9 $MtCO_2$-eq indirect emissions. This is equivalent to the life cycle climate change impact attributable to the final consumption of Belgium in 2019 (11.5 million inhabitants), corresponding to 146.4 $MtCO_2$-eq, based on input-output calculations.

The variation in the million EU citizen equivalents is explained by the different drivers of impact for final demand versus funds' holdings. First, the investment pool of a fund investing in global public companies tends to be skewed towards companies from Finance, Services and Tech industries, as these are the companies with largest market valuation and largest share in the capital markets (Popescu et al., 2023). Companies in these industries generally have low direct environmental burdens (for finance companies, second-order impacts, via their investments, are not conventionally counted via the life-cycle-based method), compared to consumption goods, which may play a larger role in the final demand attributable to EU citizens, hence the lower citizen amount equivalent in terms of environmental impacts. Second, for some environmental and social categories, we expect European consumption to be more intensive than an average sample of global public companies (as one could describe the funds' holdings). For example, for the social indicators of trafficking in persons, restricted right to strike and restricted rights of association, the sample of funds has 20 times higher impacts than the total footprint of all EU citizens.

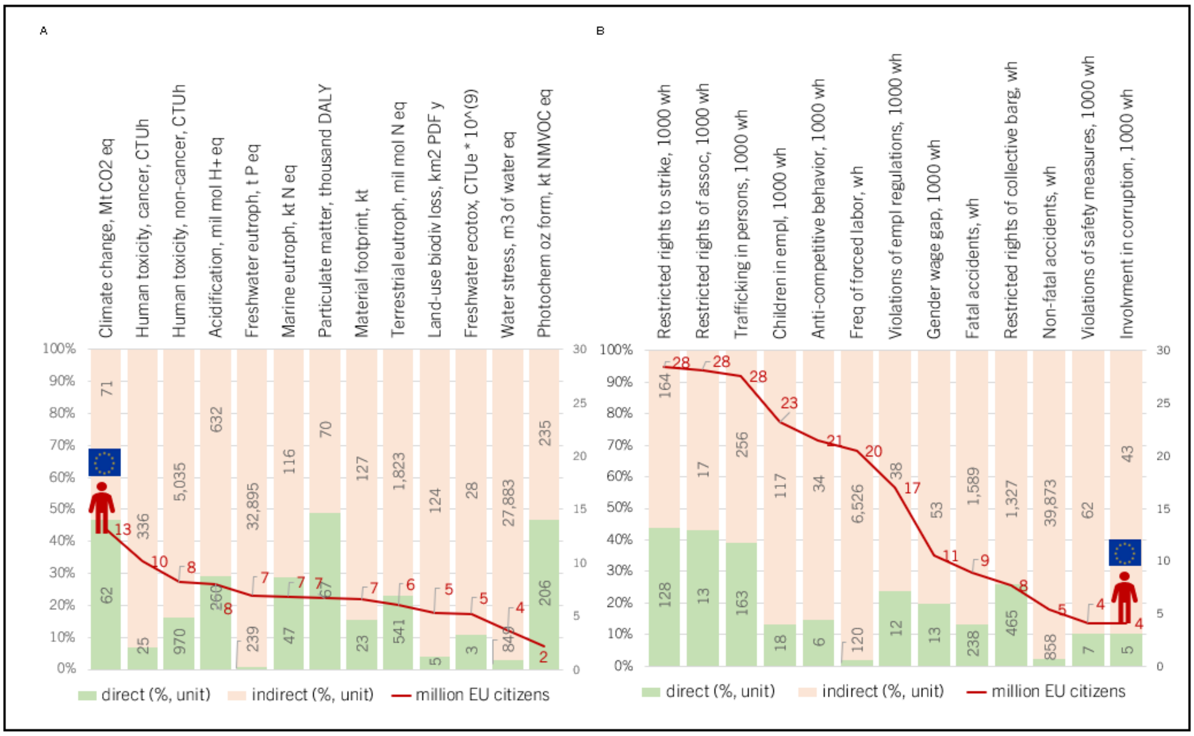


Figure 4.5: Estimation of the total direct and indirect environmental and social impacts of a sample of sustainability-labeled funds and equivalence in impact of millions of EU citizens. The stacked bars show the proportion between direct and indirect impacts, for A. 13 environmental indicators (with specific unit) and B. 13 social indicators (measured in medium worker hours across all indicators). The labels of the bars represent the actual values for the direct and indirect estimated sum of impacts for the sample of funds. The sample contains 230 sustainability-labeled funds. The impact at fund-holding level is computed for the year 2019. The red line shows the equivalent of the total estimated life cycle impacts in million EU citizens

4.3.3.3 Concentration of impact in key industries and large companies

We identify companies (grouped by main industry) that drive the lion's share of impact, by impact category. These companies drive in aggregate more than 50% of the total life cycle impacts estimated for the funds sample. In Figure 4.6, we show results only for a handful of impact indicators, with all the other results in Figure C.4. Fund-level allocation seems concentrated around a very small number of large corporations, meaning that the studied funds tend to hold similar large companies in their portfolios, with different holding amounts. The list of companies at the top varies depending on the impact category analyzed.

For water stress indicator, 50% of the life cycle impact can be traced back to only 27 large corporations (out of almost 5,000 different companies). Funds hold aggregated positions amounting to 28 billion USD in these 27 companies (representing only 8.3% of all positions held). The main positions driving impact being investments in Nestlé, Unilever, and Danone – all three large companies from the fast-moving consumer goods (FMCG) sector. It is expected to see FMCG companies to bear the largest share, as these depend on manufacturing of diverse products, but also cultivation and processing of raw materials, in the case of the food processing sub-sector. Similar importance of FMCG companies is seen for land-use related biodiversity loss indicator, while companies in the Paper sector also play a large role here (due to deforestation impacts).

For human toxicity impact indicator, companies in the Information Technology sector (IT) have, in aggregate, the highest contribution (largest companies being Schneider Electric SE, Samsung Electronics, and Siemens AG). IT companies, including semiconductor manufacturers, have large market values, hence the large exposure of funds. The high values for human toxicity are driven by the need of metals and other chemical compounds in the manufacturing phase.

For climate change impacts, companies from the Utilities and Oil & Gas sectors drive the largest share of impact (biggest contributors Enel SpA, China Petroleum, and Iberdrola SA).

For social impacts, there is a more even distribution of impacts between industries invested in. Surprisingly different to the environmental impacts is the prevalence of Finance and Services sector companies as high contributors to negative social impacts. This is because social issues tend to be more prevalent in finance and services-related sectors. Moreover, for indicators anti-competitive behavior and children in employment, companies from the Industrials sector also have a very high contribution.

4.4 Discussion

The literature on sustainability assessment of investment products is scarce, focused on GHG emissions (Bolton and Kacperczyk, 2021; Koellner et al., 2007; Popescu et al., 2023), despite the call for better alignment of capital markets with sustainability goals beyond reduction of carbon emissions (Karolyi and Tobin-de la Puente, 2022). Previous literature has assessed the climate performance of investment funds (Koellner et al., 2007) and the exposure to climate risk(Battiston et al., 2017; Dietz et al., 2016), but has not analysed in parallel multiple environmental and social impact indicators. In addition to previous literature studying connections between EU Taxonomy and LCA (Becchetti et al., 2022), we link specific indicators from EU SFDR requirements with ready-to-use life-cycle-based indicators.

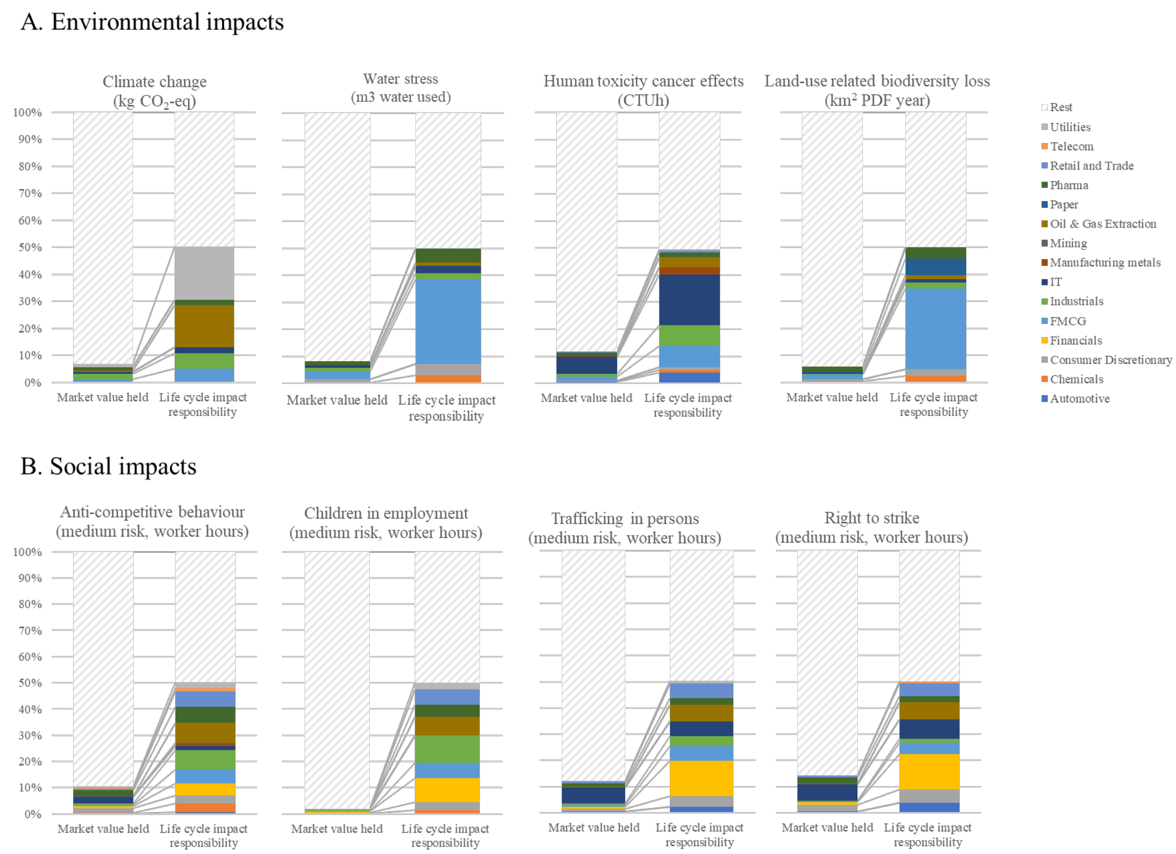


Figure 4.6: Identifying the holdings that drive 50% of the funds' impact. Holdings are grouped by main industry classification.

It is clear from our results that trade-offs between and within social and environmental impact categories occur. Focusing on one or a few impact indicators in the detriment of others, could lead to doing more harm than good. As stipulated by the EU Taxonomy, impact assessment should include both environmental and social considerations, in order to avoid impact shifting within environmental categories (for example, green electricity can lead to reduction in GHG emissions but may cause negative impact on biodiversity) or missing impacts on categories of stakeholders not considered when looking at social issues (for example violating the rights of indigenous people by approving construction/deforestation on native lands). When looking at company-level correlations in terms of impacts, we see more specific trade-offs. For example, investments in Utilities companies have better scores on social issues and worse score on environmental issues. Our results strengthen previous findings that climate change cannot be used as a proxy for all environmental impacts (Erhart and Erhart, 2023) contributing to the debate on indicator proxies (Huijbregts et al., 2010; Steinmann et al., 2017a).

Compiling a full set of ready-to-use indicators is delimited by the availability of input-output databases with associate impact assessment methods of adequate quality. IO databases, like EXIOBASE and PSILCA, and LCA methodology in general are under continuous improvement and future developments will likely lead to more accurate and complete estimates resulting from our proposed framework. Our modelled results are susceptible to uncertainty coming, among else, from the limited level of detail in revenue reporting – the coarser the level of reporting, the higher the risk to have under- or overestimated impacts. For example, this is the case for the company Iberdrola SA, where information on the type of electricity produced is not available in FactSet, leading to overestimation of impact for climate change indicator, as average electricity generation impact factors are then alternatively considered. Therefore, better reporting from the company side at the level of economic activities undertaken is necessary. In parallel, sustainability reporting requirements at investment level should develop to include more measurements of additionality and contribution, in addition to intensity metrics, in order to account for the transition plans of companies.

Our results provide evidence that impacts attributable to funds are substantial. The large share of indirect impacts, previously highlighted at industry level(Hertwich and Wood, 2018), is also to be observed at fund level. Moreover, if we regard investment funds as entities carrying the responsibility for their investment, their environmental and social footprints are comparable to that of EU consumers, albeit much larger given the high value of capital markets. Hence, we call upon a stricter approach to disclosure requirements in terms of indirect impacts. For example, measuring and setting indirect impact targets allows investment managers to exert influence over the companies in the supply chain, thus increasing the potential engagement opportunities (Landier and Lovo, 2020). In addition, we have observed a strong concentration of large publicly listed companies in the portfolios of analyzed funds. Depending on the impact category, the industry and companies contributing most impact are shifting. The large exposure to certain companies and impact hotspots can be a driver of engagement with companies, demanding improvements in environmental and social practices (Landier and Lovo, 2020).

Our analysis can serve as a baseline for harmonizing sustainable finance regulations and science-based sustainability assessment and its impact indicators. Standardization would facilitate comparability and reliability of indicators. Main strength of our approach is that impacts are estimated using the same background methodology data for all environmental indicators; for social indicators, similar methodology but a different underlying input-output database are used. Irrespective of the type of reporting requirements or their location, our proposed set of indicators is embedded in international practice related to sustainability assessment and can thus serve as a general framework for sustainability assessment at financial product level.

While outside the scope of the current paper, we acknowledge the importance of assessing the state of governance, at investment fund and company level. A robust governance policy at entity level would ensure the implementation of policies and activities that are helping advance the environmental and social agenda. A long-term perspective in value creation for stakeholders (Schoenmaker and Schramade, 2018) is in harmony with pursuing environmental and social objectives that usually have a much larger time frame to materialize than financial objectives (Flammer and Bansal, 2017).

5 Life cycle vulnerable employment and carbon emissions of companies – a detailed comparison[9]

Abstract

Sustainable finance is booming and with it the practice of impact washing – sustainability claims of investment managers that cannot be supported by real evidence. Despite recent regulatory pushes, notably the EU Sustainable Finance Taxonomy, measurement and reporting on social impacts is not yet standardized and lags behind environmental impact reporting in the financial investment field. As source for social indicators, we propose using country-industry social impact factors, built on input-output life cycle inventories, and linking these to companies and their financing instruments, using revenue as proxy for economic activity. "Persons in vulnerable employment" is just one of the many quantifiable indicators from the life cycle assessment methodology that can be used to measure social impacts of companies and investment funds. Using a sample of over 17,000 stocks, we study direct and indirect (supply chain) impacts and trade-offs between life cycle (cradle-to-gate) GHG emissions and vulnerable employment. We find that the 17,000 publicly traded companies are responsible for almost 300 million people in vulnerable employment, a number that more than doubles when adding supply-chain exposure to vulnerable employment. Our measure of direct and indirect vulnerable employment only poorly correlates with existing social impact scores of rating agencies that tend to focus on the social performance of direct company operations rather than their human rights performance in their supply chain. A more complete accounting of social impacts in supply chains would increase the true sustainability of companies and is particularly important as investors react to the poor treatment of workers uncovered during the COVID19 pandemic and as investments are being redirected to support the transition to net-zero emissions.

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[9] Adapted from published book chapter, available as *Hitaj, C., Popescu, I.S., Schaubroeck, T., Gibon, T., 2023. Social dimension of green finance, in: Falcone, P.M., Sica, E. (Eds.), Sustainable Finance and the Global Health Crisis. Routledge, pp. 241–277.* https://doi.org/10.4324/9781003284703-14

5.1 Introduction

Sustainable finance has moved from niche to mainstream, accounting for 36% or 35.3 trillion USD of total assets under management in capital markets (GSIA, 2021). There is an increasing risk of greenwashing in the market, as investors and regulators alike seek the best tools for measuring the sustainability of environmental, social and governance (ESG) investment products. With the threat of climate change and more recently health crises like the global COVID19 pandemic, investors look for resilient companies that create long-term value. For this, investors need reliable metrics, able to capture both environmental and social factors affecting and affected by publicly listed companies.

While ESG ratings were developed to cover all sustainability aspects, there is large criticism regarding their reliability (Berg et al., 2019). Quantitative tools are needed to measure the real impact of investment decisions. However, there is an over-concentration on methods measuring carbon-related emissions for both investment funds and green bonds (Gibon et al., 2020; Popescu et al., 2021). In the EU Taxonomy, the European Commission (EC) defined four other environmental-related goals, in addition to climate change, to tackle the complexity of environmental sustainably (EC, 2019c). At the same time, the Taxonomy extended impact measurement to social aspects, as financial products need to meet "minimum social safeguards" to be eligible for the sustainability label. Finally, the recently drafted EU social taxonomy (EU, 2022) discusses the importance of setting social objectives to consider in investment decisions.

Aside from the regulatory push to include the social dimension in sustainability claims of investment products, the COVID19 pandemic brought social impacts of companies and their supply chains to the fore and elevated the issue in the collective conscience. The pandemic negatively affected countries' ability to advance on the Agenda 2030 and the Sustainable Development Goals (UN, 2021). Aside from this more general effect, the pandemic shined a spotlight on how different companies were treating their workers, such as for example workers' access to measures to prevent the spread of the virus or pay during pandemic-related lockdowns and factory closings. With the renewed scrutiny, poor treatment of workers has risen in terms of the reputational risk it poses to companies (O'Connor-Willis, 2021), which is reflected in their stock market performance and ability to raise capital.

Despite this increased interest in social impacts, social indicators in the finance field are still largely under development. The European Supervisory Authorities (ESAs) were appointed to draft, inter alia, a set of indicators, on which financial institutions will have to report. One example indicator is "Violations of UN Global Compact (UNGC) principles and Organisation for Economic Cooperation and Development (OECD) Guidelines for Multinational Enterprises" (ESAs, 2021). The UNGC includes, for examples, Principle 3 (Businesses should uphold the freedom of association and the effective recognition of the right to collective bargaining) and Principle 4 (the elimination of all forms of forced and compulsory labor). These kind of binary indicators (participant or not a participant in the UNGC), however, yield little information on how well a company is doing in terms of social impacts, in particular as regards their supply chain.

For this reason, life-cycle assessment (LCA) methods are taking hold in sustainable finance impact measurement. LCA implies considering upstream and downstream processes of a company's activity, such as the production of an electric vehicle or a T-shirt from resource extraction, manufacturing, transportation, and distribution through end-of-life. A recent study analyzed the social risks associated with trade-based consumption in the EU27 (Pelletier et al. 2018). The authors found that using LCA gives a more complete picture of the global social risks of economic activities within the EU, as opposed to a simpler "country-of-origin" approach, in which indicators for the country of origin are considered without accounting for the flow of inputs from other countries to the country-of-origin. Finance scholars are also increasingly discussing the importance of looking beyond direct sustainably impacts and addressing value chain social wellbeing (Landier and Lovo, 2020).

In practice, few environmental assessment methods include the life-cycle perspective when evaluating investment funds (Popescu et al. 2021) or green bonds (Gibon et al. 2020). Social LCA is a more nascent field and has not, to our knowledge, been applied to investment funds, though some studies conduct a social LCA of certain sectors or global supply chains (Simas et al. 2014, 2015; Lèbre et al. 2020). Recently, UNEP (2020) published updated guidelines on S-LCA with the goal of furthering the application of social LCA to the assessment of companies. Our study fills this gap in the literature. The main aim and novelty of this work is the application of social LCA to the evaluation of public equities and investment funds, focusing on the social issue of "vulnerable employment".

We show the role that social life cycle assessment (S-LCA) can play in measuring the social impacts of investments. The advantage of metrics based on social LCA is that impacts along the whole supply chain of companies are considered. In the context of social impacts, we differentiate between direct and indirect or supply-chain impacts. When evaluating public equities or investment funds, social LCA relies on matching social life-cycle inventories with a financial database, so a company's performance on a social indicator can be tracked along their supply chain. In this study, we use the FactSet database for information on investments in publicly traded companies and the multi-regional input-output (MRIO) database EXIOBASE for information on life-cycle impacts. EXIOBASE is an environmentally extended MRIO database, but it contains several indicators that are relevant to social LCA, such as "vulnerable employment". By linking the two databases, we can determine the hours of labor in vulnerable employment compared to total employment per million euro invested in a particular company and separate the vulnerable employment into the direct or indirect (supply-chain) stages.

Previous social LCA studies have been applied to economic sectors, but they have not focused on the explicit link with financial investments. Some discussed the social risks embodied in global supply chains (Simas et al., 2015, 2014). Others looked at social trade-offs associated with the material needs of the climate transition (Lèbre et al., 2020). We particularly aim to advance this literature by further linking social impacts to capital markets, through publicly listed companies and their reach. As a first objective, we identify the sectors that are most affected by vulnerable employment, and, as a second objective, assess vulnerable employment and GHG emissions in publicly listed companies and study the apparel and mining sectors in greater detail. We assess the extent to which social and environmental impacts are negatively or positively correlated, as some sectors have low climate impacts but greater vulnerable employment risks, while risks are reversed for other sectors or are high/low across both dimensions. Cobalt and lithium mining, for example, play a key role for lithium-ion batteries and the ability of the global economy to transition away from fossil fuels and towards electrification of transportation, but are also known hotspots for poor working conditions (World Economic Forum, 2020).

The International Labor Organization (ILO) finds that vulnerable workers were hit hardest by the COVID-19 pandemic, which has worsened pre-existing inequalities (ILO, 2021). Going forward, corporations and their investors will have to reconcile social and environmental aspects in order to attract funding, in particular as the pandemic put renewed focus on working conditions across the globe.

5.2 Data and Methods

5.2.1 Input-Output Databases for Social and Environmental Life Cycle Inventories

Large-scale life cycle assessment (LCA) relies on life cycle inventory (LCI) databases. These databases are environmentally extended or socially extended input-output databases of economic activities. They are capable of linking an economic activity to its underlying suppliers and associate those production activities with environmental or social impacts. Whereas conventional input-output tables of economic accounts track the flow of goods and services through the economy in monetary units (euros), an environmentally extended LCI, such as EXIOBASE (Stadler et al. 2018), contains additional information in physical units of the environmental impact of these activities. EXIOBASE's input-output based LCIs are multi-regional, which means they contain information specific to economic subsectors across various countries or regions.

While EXIOBASE contains a few indicators on social impacts, such as vulnerable employment or low/medium/high-skilled employment by gender, its main purpose is to measure environmental impacts. It is therefore primarily used in environmental LCA or e-LCA. The most recent version of EXIOBASE (Stadler et al. 2018) covers 44 countries and 5 Rest of World regions (Table D.1 in the Appendix), 200 products, 163 industries, 3 employment skill levels per gender, 417 emission categories, and 662 material and resources categories (Table 5.1). For example, the emission categories cover the combustion emissions of CO_2, CH_4, N_2O, SO_x, NO_x, NH_3, CO, and other pollutants[10]. Non-combustion emissions of chemicals from various processes are also covered, as are agriculture-related air, soil, and water emissions, land use, extraction of minerals, and blue and green water consumption.

The two most comprehensive social life cycle inventories are the Product Social Impact Life Cycle Assessment database – PSILCA (Ciroth and Eisfeldt, 2022; Mancini et al., 2018) and Social Hotspot Database – SHDB (Benoit-Norris et al., 2012). PSILCA is developed by Green Delta, based in Germany, while SHDB is developed by New Earth, a non-profit based in the United States.

[10] *Namely: benzo(a)pyrene, benzo(b)fluoranthene, benzo(k)fluoranthene, indeno(1,2,3-cd)pyrene, polychlorinated biphenyls, dioxins (PCDD and PCDDF), hexachlorobenzene, non-methane volatile organic compounds, particulate matter (PM_{10} and $PM_{2.5}$), total suspended particulate, and heavy metals (As, Cd, Cr, Cu, Hg, Ni, Pb, Se, and Zn).*

Table 5.1: EXIOBASE version 3.

Property	Description
Base-years	1995 - 2011/16
Products	200
Industries	163
Countries	44 (EU28 plus 16 major economies)
Rest of the world regions	5 (Europe, Asia, Africa, America, Middle East)
Water accounts	194 (water blue and green per source, including final demand)
Material accounts	189 (energy products, including final demand)
	222 (used extractions)
	222 (unused extractions)
Land accounts	14 (including build up land for final demand)
Social accounts	14 (employment per skill level and gender, vulnerable employment)
Emissions	28 (from combustion including final demand)
	410 (non-combustions)
	3 (HFC, PFC, SF_6)

SHDB contains social risk and opportunity information that can be used to quantify the social performance of a product supply chain and life cycle. To model global supply chains, SHDB uses the Global Trade Analysis Project (GTAP), a global economic equilibrium model. SHDB contains data on 57 sectors across 113 countries and regions. Next to the inputs for each sector and the trade flows between countries expressed in monetary units, SHDB contains information on working hours by sector and region, which serve as the weights for the social issues examined. The social issues of labor rights and decent work, health and safety, human rights, governance, and community infrastructure are grouped into 22 social themes that are measured by one or more indicators. These include, for example, child labor, excessive working time, poverty, labor laws, toxics and hazards, gender equity, drinking water, sanitation, and children out of school.

Similar to SHDB, PSILCA covers 14,838 sectors for almost 189 countries, though for one-third of those countries only a basic set of 26 broad sectors is available. The 90 indicators in PSILCA are grouped into 23 sub-categories, such as child labor, forced labor, fair salary, workers' rights, health and safety, migration, and corruption. PSILCA is based on the multi-regional input-output model of the Eora database.

EXIOBASE is available free of charge, while both SHDB and PSILCA require the purchase of a license. For this study, we use EXIOBASE to compare companies' and funds' performance on GHG emissions and vulnerable employment, since it allows for comparison of environmental and social performance using a single database and since it has a higher resolution of sectors and is more up to date on the economic transactions side. A broader, multi-indicator analysis of social impacts along supply chains would benefit from using a dedicated social life cycle inventory, such as SHDB or PSILCA. Linking the inventories to a financial database can be more cumbersome than for EXIOBASE, since PSILCA uses different industry classifications depending on the country or region. For the United Kingdom and the United States, for example, the industry classification of demand is very detailed.

However, these industries do not match the industries used to classify demand in other countries. Any matching of the hundreds of sectors/industries with those in a financial database would need to be performed separately for the different classification systems available in PSILCA. Thus, PSILCA retains granularity in favor of a unified sector/industry classification across all countries. PSILCA does well for specific case studies but requires more work when looking across all countries and sectors. As we need to link the entire database (all country-sector/industry combinations) to a financial database, we use EXIOBASE, which also allows us to include environmental impacts.

One important drawback of using input-output-based databases to track life cycle or supply chain social and environmental impacts is that the data in the inventory are not company specific and represent the average performance of companies in the same sector and country. The advantage of conducting an LCA of a company or investment fund is first and foremost that detailed information on supply chain impacts can be tied to each company and that the data are external, independent, and transparent and are not self-reported. These gains in information stand opposite the non-negligible drawback of losing information on impacts that is specific to companies. Until a hybrid methodology is developed the relative merits of one or the other approach is a topic of debate. Currently, though, most rating agencies rely on information provided by the companies themselves that can only be verified to a certain extent. As such, our study provides a necessary robustness check to the information on company- and fund-level performance on social and environmental impacts.

5.2.2 Financial Database: FactSet

FactSet provides absolute revenue information for the full universe of publicly listed companies, as well as company revenue breakdown (FactSet, 2021). We use the FactSet Databases Revere Business Industry Classifications System (RBICS) and Geographic Revenue Exposure (GeoRev) for a detailed revenue breakdown for each company, by industry (FactSet RBICS database) and country (FactSet GeoRev database). The FactSet RBICS database is very detailed, with 1,603 separate sub-industries. This level of detail allows us to build a rather unique company profile, that we further link with environmental and social indicators available at the country-industry level.

5.2.3 Linking the input-output database EXIOBASE to the financial database FactSet

To estimate the environmental and social impact of public companies, we need, first, information on the economic activities undertaken by the company (from FactSet) and, second, impact factors by economic sector that we extract from the environmentally extended multi regional input-output (EEMRIO) database EXIOBASE.

To define the correspondence link between the two databases, we established concordance tables. For the regional classification the FactSet to EXIOBASE correspondence was a n:1 relationship. FactSet has a 250 countries classification and EXIOBASE has 49 geographical categories: 45 countries and 5 rest of the world (RoW) regions. For the sectorial classification, the matching was more cumbersome. In some cases, FactSet had a more detailed sectorial breakdown (e.g., for financial sector) and for others, EXIOBASE (e.g., a separate category for each renewable source of production of electricity for each renewable sources). Thus, the sectorial matching was either a 1:1 relationship, 1:n, n:1 or n:n.

We build on the methodology proposed by Koellner et al. (2007) and improved in (I. S. Popescu et al., 2022). A concordance matrix is established between different industry-level classifications in EXIOBASE and FactSet (Figure 5.1), allowing us to make a regionalized profile of all economic activities of a company and to allocate respective impact factors, thus building company-level estimates for the chosen sustainability indicators. At the company level, we extracted the revenue breakdown for the year 2020. This was then linked with the adjusted impact factors from EXIOBASE.

5.2.4 Choice of social and environmental indicators

Measuring social impact is more challenging than environmental impact, as measures tend to be qualitative rather than quantitative and the choice of measurement unit is not straightforward. EXIOBASE uses hours and number of persons (1,000 persons), to measure the number of people affected by the respective social stressor. PSILCA uses working hours as the default method. However, the activity variable has its limitations and does not cover all stakeholders. In the literature other units are proposed, such as "biophysical pressure" (Zimdars et al., 2018).

For this study, we use the vulnerable employment indicator, measured in 1,000 persons. The choice of our indicator is strongly supported by the draft EU social taxonomy (EU, 2022), as "decent work (including for value-chain workers)" is the first of three objectives under the taxonomy.

Vulnerable employment is defined by the ILO (ILO, 2013) as workers without employee status, as explained in the Supplementary Information of Stadler et al. (2018). People in vulnerable employment are classified as own-account workers and contributing family workers, i.e., workers without formal employment bonds. The measure is indicative of informal employment - workers not covered by social security or without access to paid leave and work stability or security (Simas et al., 2014).

The labor accounts extension in EXIOBASE is based on data sourced from the International Labor Organisation, Eurostat and OECD Statistics, as detailed in the database seminal paper (Stadler et al., 2018a). The labor data is updated to year 2011, and we use the 2018 economic accounts from EXIOBASE, the latest available year of data aside from extrapolations to 2019 and 2020, as using the 2018 data ensures higher reliability of data based on collected rather than extrapolated data.

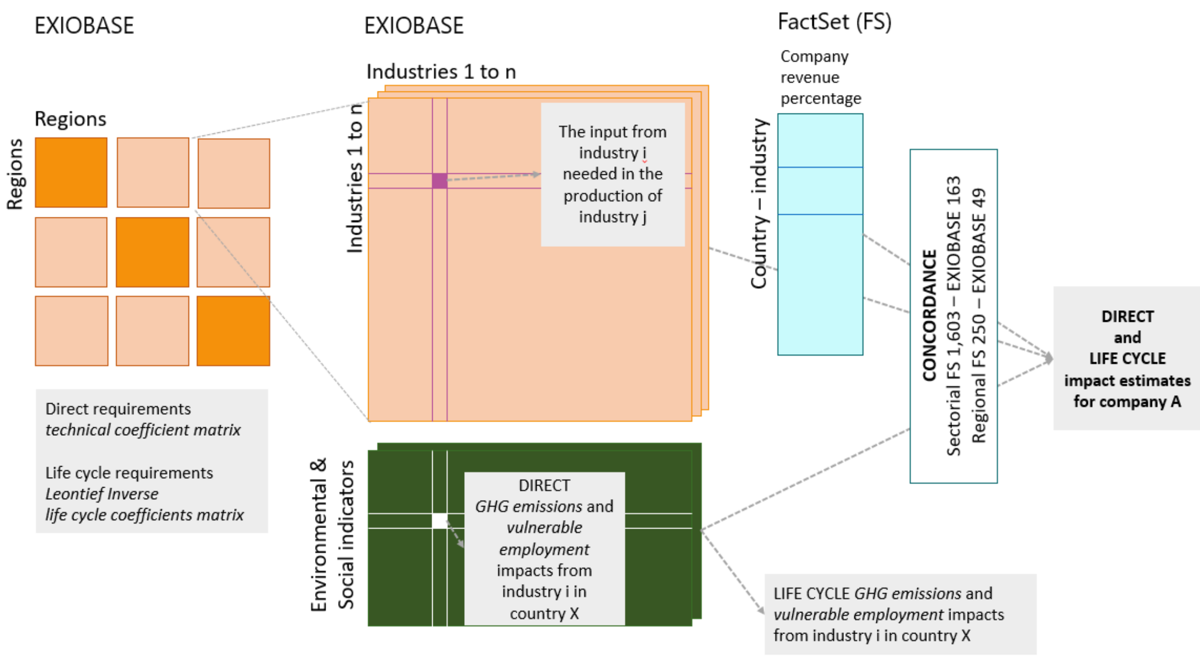


Figure 5.1: Linking input-output database EXIOBASE to the financial database FactSet.

For comparison and as proxy for green indicators, we also use GHG emissions, measured with the indicator "GHG emissions (GWP100) | Problem oriented approach: baseline (CML, 2001) | GWP100 (IPCC, 2007)", accounting for carbon dioxide and other greenhouse gases based on the global warming potential (GWP) over 100 years.

5.2.5 Social scores from Rating Agencies

We retrieve ESG indicators related to social and environmental issues from the Bloomberg database. Specifically, we retrieve, at company level, the MSCI ESG rating, Social Disclosure Score (developed by Bloomberg) and Social and Environmental dimensions rank score, from the Corporate Sustainability Assessment (CSA) methodology of RobecoSAM. The latter was acquired by S&P Global (S&P Global, 2020) and are available in Bloomberg. The description of each of the fields are presented in Table 5.2. The different measures did not cover all companies.

5.2.6 Company-level: Sample of public companies and market indices

Capital markets are increasingly looking at the sustainability profiles of investable companies. Over 40,000 companies are listed on stock exchanges around the world, where they attract investments by different actors, such as insurance companies, pension funds and asset managers. We select the full sample of available public companies in FactSet for 2020, the year of the pandemic. Choosing the year 2020 may lead to a reduced sample, as revenue collection in FactSet is not complete. However, analyzing specifically year 2020 allows us to understand the real exposure of companies in the year of the COVID-19 outbreak. The selection leads to a final sample of 17,529 companies, with combined estimated revenues of over 30 trillion EUR.

Table 5.2: Selection of ESG indicators available on Bloomberg. In the "Data Availability" column we show for how many of the sampled companies we find a valid score/rating. Retrieved in January 2022.

Indicator	Source	Scale	Description	Data availability
SOCIAL DISCLOSURE SCORE	Bloomberg	0.1 – 100 (100 is the best)	Proprietary indicator from Bloomberg, based on the extent of a company's social disclosure.	541/673 (80%)
ESG RATING	MSCI	AAA – CCC (AAA is the best)	Considers different social issues, like "Supply Chain Labor Standards" or "Access to Health Care" and it is calculated for each company, based on position relative to industry peers.	187/673 (28%)
ROBECOSAM ENV DIMENSION RANK	RobecoSAM (S&P Global)	1 – 100 (100 is the best)	covering up to 10 environmental (social, respectively) material themes, based on data collected from the RobecoSAM CSA survey.	573/673 (85%)
ROBECOSAM SOCIAL DIMENSION RANK				574/673 (85%)

Next to this full sample of companies, we consider subsamples of companies engaged in specific industries as well as companies held by a climate transition market index (Table 5.3). The five sectors of interest due to high shares of direct or indirect vulnerable employment include Apparel (486 companies), Chemicals (1,514 companies), Food Manufacturing (534 companies), IT&C (354 companies), and Mining Metals (253 companies). In a second step, we focus on the Apparel and Mining Metals sectors, as they have received particular media attention after recent disasters, such as the 2012 Dhaka garment factory fire in Bangladesh or the 2019 collapse of a cobalt and copper mine in Kolwezi in the Democratic Republic of Congo. Both sectors are labor-intensive and have a high share of vulnerable employment – indirect (supply chain) in the case of Apparel and more direct in the case of Mining Metals.

Another sub-sample we consider includes the 1,281 companies that comprise the MSCI Climate Transition Index and we analyze the related investable exchange-traded fund (ETF) Amundi MSCI World Climate Transition CTB UCITS ETF. The Climate Transition ETF invests in companies compatible with the below 2°C warming scenario, companies that would be positively affected by the climate transition. We look at how the fund evolved from 2018 to 2020, both in terms of GHG emissions and vulnerable employment.

Table 5.3: Sample of companies and investment funds.

Sample	Description	# listed companies	Year
Full	All publicly listed companies in FactSet, with available revenue information	17,529	2020
Apparel	All publicly listed companies in FactSet in this sector	486	2020
Chemicals	All publicly listed companies in FactSet in this sector	1,514	2020
Food manufacturing	All publicly listed companies in FactSet in this sector	534	2020
IT&C	All publicly listed companies in FactSet in this sector	354	2020
Mining metals	All publicly listed companies in FactSet in this sector	253	2020
Climate transition index fund	Amundi MSCI World Climate Transition CTB UCITS ETF DR USD (C) (LU1602144492)	1,281	2018-2020

5.3 Results and Discussion

5.3.1 Vulnerable employment by sector

Today, the total number of vulnerable workers worldwide is estimated at around 1.48 billion – around half of the total global workforce (International Labour Organization, 2018). According to EXIOBASE, for which the most recent vulnerable employment estimates are from 2011, the values are a bit higher than the up-to-date statistics, at 2.14 billion people in vulnerable employment across the globe, with 800 million people in China alone.

The sectors with the highest intensity in terms of workers in vulnerable employment per million euros (MEUR) of output include Agriculture and Farming, Mining, and Services (e.g., Sales). Intensity values in the top 100 sectors exposed to vulnerable employment range from 100 to over 6,000 persons per MEUR of industry output generated. As intensity values are highly influenced by different pricing across sectors, we also analyze values for absolute vulnerable employment exposure from direct operations of all sectors.

"Agriculture and Farming" has the highest vulnerable employment exposure at the global level with 60% of total employment (Table 5.4). "Retail and Trade" and "Services" sectors come next with by-country values between 5% and 30%. Manufacturing industries, such as "Apparel" and "Computers and Communication Equipment" have on average more than 5% of total employment classified as vulnerable. While these values represent global averages at sector level, regional variation is a larger driver of differences in vulnerable employment.

Indirect, supply chain vulnerable employment contributes, on average, more than 70% to total exposure to vulnerable employment for sectors related to Processing of Raw Materials (Food Processing or Metals Production), but also Textiles Manufacturing, Chemicals, and Computers and Equipment Manufacturing.

Table 5.4: Total vulnerable employment in absolute values (measured in 1,000 persons) and as percentage from total employment for the sector. The industry classification is a manual regrouping, by larger industry group, of EXIOBASE 163-industry classification.

Industry classification	Vulnerable employment (in 1,000 persons)	As a percentage of all sectorial employment
Agriculture and Farming	1,012,041	59.6%
Services	365,527	14.4%
Retail and Trade Activities	168,704	17.9%
Construction	152,836	24.5%
Processing of agricultural and meat products	63,015	11.0%
Other transport	56,923	13.3%
Mining	53,893	3.4%
Other manufacturing	49,539	7.2%
Computers and Communication Equipment	39,217	8.2%
Apparel manufacturing	38,709	8.0%
Metal production	36,438	7.7%
Chemical Manufacturing	17,625	7.3%
Automobile manufacturing	17,197	8.4%
Plastic manufacturing	14,027	7.4%
Utilities	11,799	2.6%

5.3.2 Vulnerable employment across countries and regions

The countries with the highest proportion of vulnerable employment out of total employment, averaged across sectors, are mostly in Asia (Table 5.5). India is the country with the highest mean – 89% of workers are classified as under vulnerable employment. China has the largest exposure to vulnerable employment mainly in the Agricultural sector as well as Construction and Hotels and Restaurants (336 million workers).

Table 5.5: Total Vulnerable employment, direct (scope 1), across countries and regions. We sum all the sectors in a country. The first 10 countries/regions have the highest direct exposure to vulnerable employment, while the last 10 countries/regions presented have the lowest direct exposure. The table is a sample from the full 49-region EXIOBASE classification. Values are based on data extracted from EXIOBASE v3.8, year 2018

Ranking from highest to lowest *direct* exposure to vulnerable employment	EXIOBASE Country/Region	Direct vulnerable employment (in 1,000 persons)	Direct vulnerable share of total employment
1	China	799,479	42%
2	India	616,645	89%
3	RoW Asia and Pacific	317,302	41%
4	Indonesia	85,124	40%
5	RoW Africa	78,937	19%
6	RoW Europe	42,004	18%
7	RoW America	41,732	32%
8	Brazil	24,769	23%
8	Mexico	19,852	24%
10	RoW Middle East	14,189	27%
40	Croatia	359	17%
41	Denmark	229	9%
42	Slovenia	210	14%
43	Lithuania	199	11%
44	Norway	182	10%
45	Latvia	112	10%
46	Estonia	77	7%
47	Cyprus	75	20%
48	Malta	49	18%
49	Luxembourg	32	14%

5.3.3 Company-level analysis: Vulnerable employment and GHG emissions of publicly listed companies

We computed vulnerable employment accounts for the complete universe of publicly held companies with revenue breakdown available in FactSet. Summary statistics for the sample are shown in Table 5.6. All companies are responsible for more than 295 million people in vulnerable employment, only from direct operations (about 14% of global vulnerable employment, according to the ILO statistics presented above). The number more than doubles when adding scope 3 upstream (supply-chain) exposure to vulnerable employment. the share of vulnerable employment across companies is highly skewed. The top 50 companies (0.2% of sampled companies) generate 50.05% of the direct vulnerable employment. Scope 1 GHG emissions for the same sample account for almost 8 $GtCO_2$-eq (roughly 20% of the global total GHG emissions). The average direct intensity of vulnerable employment for the sample of 17,529 public companies is 10.7 persons per MEUR of revenue output, while supply chain vulnerable employment is an additional 17.8 persons per MEUR for a total of 27.9 persons per MEUR (Table 5.6). The distribution is skewed to the right, as the median total (direct and indirect) vulnerable employment intensity is 9.10 persons per MEUR.

Table 5.6: Summary statistics for absolute and intensity measures for the sample of 17,529 public companies. Vulnerable employment is measured in number of persons.

Vulnerable employment	absolute (total)			intensity (per MEUR)		
	scope 1	scope 3 upstream	life cycle	scope 1	scope 3 upstream	life cycle
mean	17,055	21,210	38,288	10.71	17.18	27.91
std	325,688	121,006	400,412	52.07	31.76	66.71
min	0	0	0	0	0.026	0.034
10%	4	31	45	0.11	0.84	1.23
25%	42	187	280	0.41	1.92	3.15
50%	361	1,208	1,846	1.81	6.37	9.10
75%	2,823	7,304	11,186	7.17	17.77	27.20
90%	14,618	32,392	50,776	27.57	42.91	76.88
99%	214,596	366,528	588,061	95.11	165.34	262.73
max	35,254,804	5,055,269	40,314,679	4,385.86	384.05	4,429.80

In Figure 5.2, we plot the top 25 companies by vulnerable employment (those with the greatest absolute number of vulnerable workers) from the total sample of companies alongside their revenues in million euros. A look at the list of top 25 companies shows that the problem of vulnerable employment is not a side issue, but one affecting global companies, many of which most consumers in developed economies have come into direct or indirect contact with. Petrochina based in China tops the list, followed by Jardine Matheson, a British multinational conglomerate based in Hong-Kong and domiciled in Bermuda whose holding companies are active mainly in Asia in construction, transportation, automotive, hotels, restaurants, and real estate. China Petroleum & Chemical Corporation or Sinopec, engaged in oil and gas exploration, refining, and the production and sales of petrochemicals, fibers, and fertilizers, rounds out the top three. Three mining companies, Glencore, an Anglo-Swiss commodity trading and mining company, Vedanta, a global mining company headquartered in London, and Hindustan Zinc, an Indian mining company and subsidiary of Vedanta, take up the next three spots.

Aside from these oil, gas, and mining companies, food manufacturers (Charoen Pokphan Foods, JBS), automotive companies (SAIC, Toyota, Mitsubishi), e-commerce and retail giants (Walmart, Amazon, Alibaba), and electronics (Apple, Samsung) figure prominently in the top 25 companies.

Six companies most exposed to life-cycle vulnerable employment are also in the top 25 for GHG emissions (PetroChina Co., Ltd., China Petroleum & Chemical Corp., China Railway Construction Corp., China Communications Construction Co., Glencore, and Toyota Motor Corp.). However, we observed that companies often included in environmentally friendly investment funds (e.g., IT&C companies like Apple) and leading in sustainability rankings (e.g., Unilever), do have a significant involvement in vulnerable employment, while they are considered leaders in terms of climate change management.

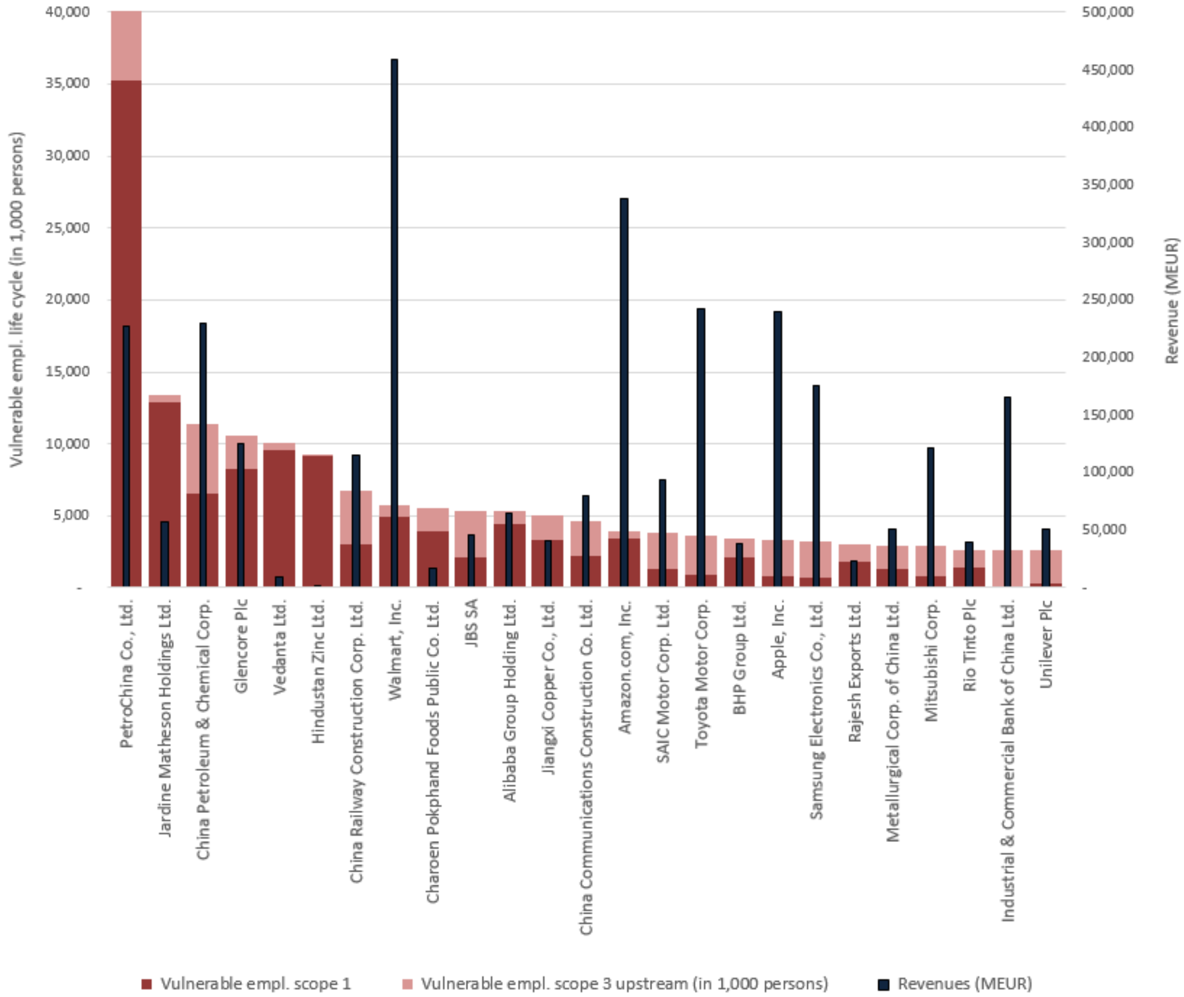


Figure 5.2: Top 25 public companies by life cycle vulnerable employment exposure, for year 2020. Results are estimated using the EXIOBASE vulnerable employment impact factors and FactSet revenue breakdown.

5.3.4 Impacts along supply chains: Direct and indirect vulnerable employment and GHG emissions

The reason SRI and sustainability labels exist is because consumers themselves cannot verify how something has been produced. This is particularly true for products that have been produced abroad, as labor and environmental protection laws can vary substantially across countries. Labor-intensive industries tend to concentrate in regions with low cost of labor, in part due to lax labor laws compared to OECD countries. Similarly, energy-intensive industries concentrate in regions with low-cost electricity, oil, or natural gas supplies. Metrics that track supply-chain impacts are important, since for most global, public companies, vulnerable employment, if any, is more likely to occur indirectly in the supply chain rather than directly in the main operations of the companies.

Figure 5.3 shows the mean indirect and direct impacts on vulnerable employment and GHG emissions for the selected sample of companies belonging to one of the five sectors (apparel, chemicals, food manufacturing, IT&C, and mining metals) chosen for their relatively high or low impact on the two indicators. Mining Metals has the highest life cycle impacts, both social and environmental, while for the social impacts, namely vulnerable employment, more than 80% of the impact is from direct operations. Apparel and IT&C are similar for social impacts, while Apparel has lower environmental impacts. The difference between sectors for the different indicators is mostly visible for the scope 3 upstream impact: we observe that IT & C has the second-highest supply chain GHG emissions, but the lowest supply chain vulnerable employment. When normalizing mean vulnerable employment by revenue, the apparel and food manufacturing sectors have higher vulnerable employment per million euro in revenue than the mining metals sector, with most of these impacts occur indirectly in the supply chain.

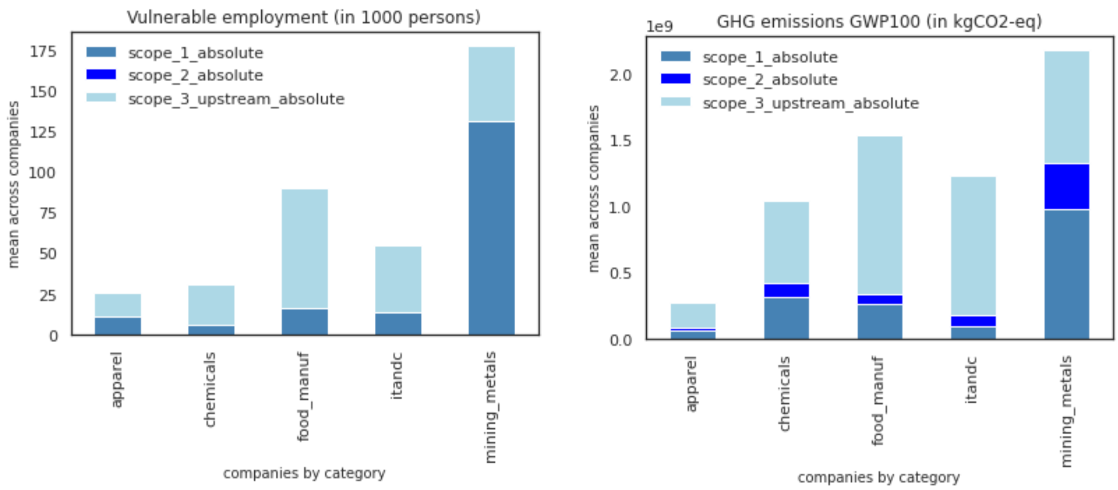


Figure 5.3: Mean vulnerable employment and GHG emissions across listed companies, by sector, estimated for year 2020, using EXIOBASE for impact factors and FactSet for the revenue data.

5.3.5 Correlation of social life cycle with available social scores from rating agencies

Our life-cycle measure of vulnerable employment has the benefit of considering impacts in both the direct and indirect (supply-chain) stages but comes with the drawback of using industry/country-averages without considering company-specific information. Social scores from rating agencies, in contrast, have the advantage of being company specific. However, they often rely on self-reported data from companies and the coverage is not as complete. In theory, some elements of the social scores of rating agencies are based on impacts that occur in the supply chain, e.g., "supply chain labor standards" in MSCI's ESG score. However, MSCI's ESG score had only 28% coverage.

Table 5.7: Correlation coefficient between our vulnerable employment estimates and Bloomberg's SOCIAL DISCLOSURE SCORE and ROBECOSAM SOCIAL DIMENSION_RANK. The upper table shows "Apparel" companies and the one below companies in "Mining metals"

APPAREL	SOCIAL DISCLOSURE SCORE	ROBECOSAM SOCIAL DIMENSION RANK
Number of companies	114	122
Scope 1 absolute	0.37	0.50
Scope 2 absolute	0.32	0.33
Scope 3 upstream absolute	0.32	0.33
Life cycle absolute	0.36	0.45
Scope 1 intensity	0.24	0.41
Scope 2 intensity	0.09	0.15
Scope 3 upstream intensity	0.02	0.18
Life cycle intensity	0.09	0.28
SOCIAL DISCLOSURE SCORE	1	0.64
ROBECOSAM SOCIAL DIMENSION RANK	0.64	1

MINING METALS	SOCIAL DISCLOSURE SCORE	ROBECOSAM SOCIAL DIMENSION RANK
Number of companies	75	83
Scope 1 absolute	0.11	0.19
Scope 2 absolute	0.12	0.18
Scope 3 upstream absolute	0.09	0.17
Life cycle absolute	0.11	0.20
Scope 1 intensity	0.08	0.13
Scope 2 intensity	0.25	0.27
Scope 3 upstream intensity	-0.01	0.11
Life cycle intensity	0.07	0.14
SOCIAL DISCLOSURE SCORE	1	0.58
ROBECOSAM SOCIAL DIMENSION RANK	0.58	1

RobecoSAM's Social Dimension Rank score had a higher coverage of our sample at 85%. It is a composite score of labor practices indicators, human rights, human capital development, talent attraction & retention, corporate citizenship & philanthropy, and some industry-specific indicators (S&P Global, 2021). The indicators are based on a company's responses to a Corporate Sustainability Assessment questionnaire. Most of the questions are measured mainly at the level of the company rather than its supply chain. This includes questions about whether the company has a non-discrimination and anti-harassment policy in place, the gender balance of the workforce, what share of the workforce is represented by an independent trade union or covered by a collective bargaining agreement, and whether the workforce has access to training. Only the human rights questions delve into the supply chain, as they focus on whether the company has a human rights policy in place and ask whether Tier 1 suppliers have been assessed for human rights issues in the last 3 years.

Social issues in the supply chain are thus but one component of a larger social score that is mainly determined by activities at the level of the direct company operations. It is thus of interest to assess how well our life-cycle measure of vulnerable employment correlates with the Social Disclosure Score of Bloomberg (80% coverage) and the RobecoSAM social dimension rank, for the two sectors of interest, apparel and mining (Table 5.7). A higher Social Rank indicates a better performance.

We observe that the selected market ESG measures are poorly correlated with our vulnerable employment estimates. As higher values in both the Social Disclosure Score and Social Dimension Rank indicate better performance, while for our measures higher values indicate worse performance, a negative correlation is expected. Instead, we find almost no correlation, or if any, then positive correlation. A positive, albeit not very strong correlation of 0.58 and 0.64 is observed between the two social ESG scores of the rating agencies for the Mining Metals and Apparel sectors, respectively.

There are several possible reasons for the poor correlation. As our social LCA methodology uses industry-country-average impact factors instead of company-specific factors, some degree of effort at the company level to do better than the industry-country average is lost. Another more disconcerting explanation for this incongruity is that larger companies have more resources at their disposal for sustainability marketing, which can lead to a false conception that the company actually does better on social issues. The Social Dimension Rank score of RobecoSAM is a weighted composite of different indicators, most of which focus on direct operations of the company and only one of which considered the assessment of human rights issues in Tier I suppliers without considering Tier II and III suppliers. The final score thus provides little insight into a company's social impacts along its supply chain.

5.3.6 Focus on the apparel, clothing, and textile sector

We selected the top 10 companies from the Apparel sector with the largest amount of direct and indirect vulnerable employment and plotted the direct and indirect vulnerable employment as well as the remaining employment, for reference (Figure 5.4). For Apparel companies, we find that LVMH Louis Vuitton Moët Hennessy directly and indirectly employs the most vulnerable workers, with supply chain impacts three times as large as direct (scope 1) impacts. Fiber producing companies, like Toray Industries or Texhong Textile Group also show high indirect vulnerable employment, due to the importance of raw materials (cotton and synthetic fiber production) in their supply chains. Industria de Diseño Textil SA (Inditex), known for its brands Zara and Massimo Dutti and often criticized for its fast-fashion philosophy (Aftab et al., 2018), has high vulnerable employment exposure.

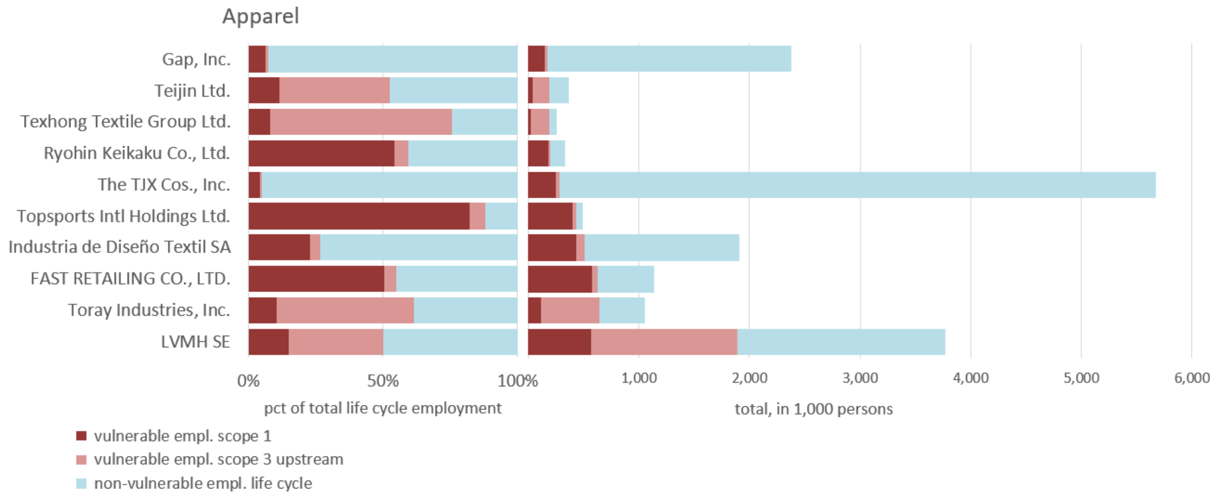


Figure 5.4: Top 10 companies most exposed to life cycle vulnerable employment, in the Apparel sector. The graph on the left side shows the percentage share of vulnerable employment in total employment, and the relationship between direct and indirect impacts. The right-side graph plots the total number of workers for a company.

The apparel sector has a long history of opaque supply chains and the use of vulnerable employment. The recent outbreak of the coronavirus disease (COVID-19) has in fact exposed the vulnerable employment of the clothing supply chain operating in South Asian countries, with millions becoming jobless (Majumdar et al., 2020). Specific S-LCA case studies confirm the general issue of bad job conditions, and this also for the same region, even for clothing delivered in Europe (Herrera Almanza and Corona, 2020; Van Der Velden et al., 2017). Initiatives and labels exist to counter these issues, such as the "Goodweave" label (GoodWeave, 2022).

5.3.7 Focus on the Mining Metals Sector

We conduct a similar analysis for the Mining Metals sector. We observe that direct vulnerable employment is higher than indirect, for all companies (Figure 5.5). Companies that are often held by climate-transition investment funds, such as Rio Tinto, Glencore, or BHP Group are associated with high vulnerable employment.

The Mining sector is booming but is particularly susceptible to vulnerable employment, especially in certain developing countries where "women and sometimes children often work in or around mines for less pay or status than their male and adult counterparts, without basic safety equipment" (Sovacool et al., 2020). Yet, even in the EU-28, among raw material industries, Mining and quarrying displays the worst social performance (Di Noi et al., 2020). The COVID19 crisis, in particular, may have caused job losses in the mining sector. The crisis disproportionately affected lower-income countries that tend to have a larger share of workers in the informal sector (Ramdoo, 2020), which is related with vulnerable employment. Moreover, as the products of the mining sector are used to manufacture electronics, electric vehicles, solar panels and wind turbines (Sovacool et al., 2020), the issue of vulnerable employment in mining needs to be addressed to ensure that the products we need for the climate transition are produced in a socially just way. Fortunately, there are certain initiatives that aim to counter types of vulnerable employment, such as the "Fairmined" initiative for gold (Fairmined, 2022).

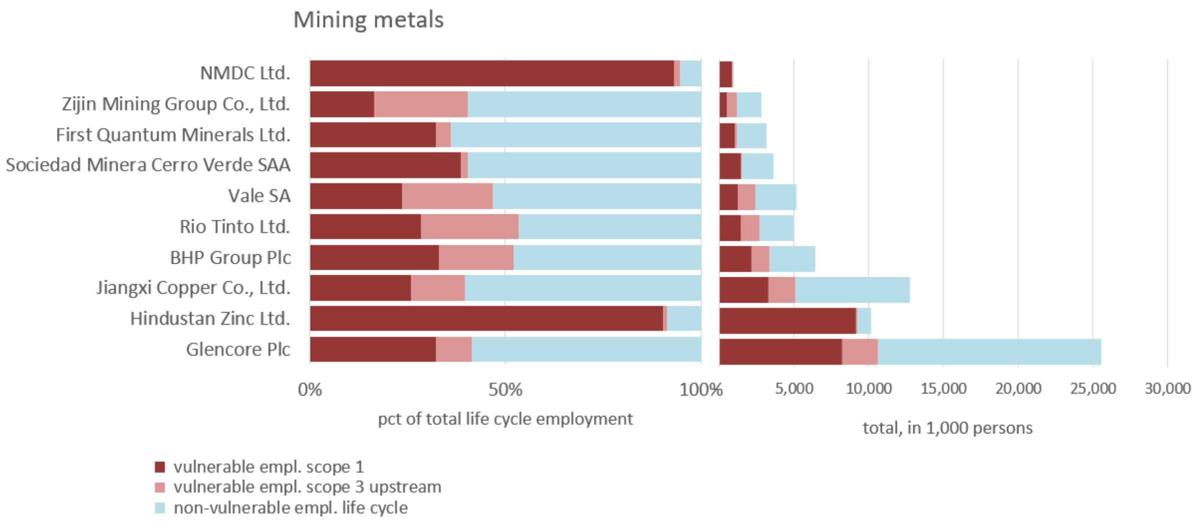


Figure 5.5: Top 10 companies most exposed to life cycle vulnerable employment, in the Mining of metals sector. The left graph shows the percentage of vulnerable employment in total employment, and the relationship between direct and indirect impacts. The second graph plots the total number of workers for a company.

5.3.8 Focus on climate transition indices investable universe: Trade-offs between social and environmental impacts

Climate-focused financial market indices seek to build portfolios aligned with the climate transition, following, for example, the guidelines of the EU Climate Transition Benchmark. However, the selection methodology for companies in such an index is not straightforward and social impacts may be overlooked when the focus is solely on climate. Figure 5.6 shows the life cycle GHG emissions and vulnerable employment attributable to the sample of 1,281 companies in the MSCI World Climate Transition Index. We extract detailed revenue information for the constituents of the Index and compare their exposure to GHG emissions and vulnerable employment, in order to understand which are the companies that show a positive or negative correlation between social and environmental impacts.

Companies in different regions are exposed to vulnerable employment to a different extent. For the regions of Asia/Pacific and Africa & Middle East, the vulnerable employment tends to be generally higher, as expected from the information we have at country-industry level from EXIOBASE.

Trade-offs between social and environmental impacts can be clearly identified for some companies and industries. For example, Utility companies have very low vulnerable employment impact factors but high GHG emissions (especially those companies generating electricity from fossil fuels). The same is valid for the Oil & Gas Extraction companies. The inverse relation holds for companies in the Services sector: Health and Social Work companies have a high vulnerable employment but low emissions, due to the type of activity performed.

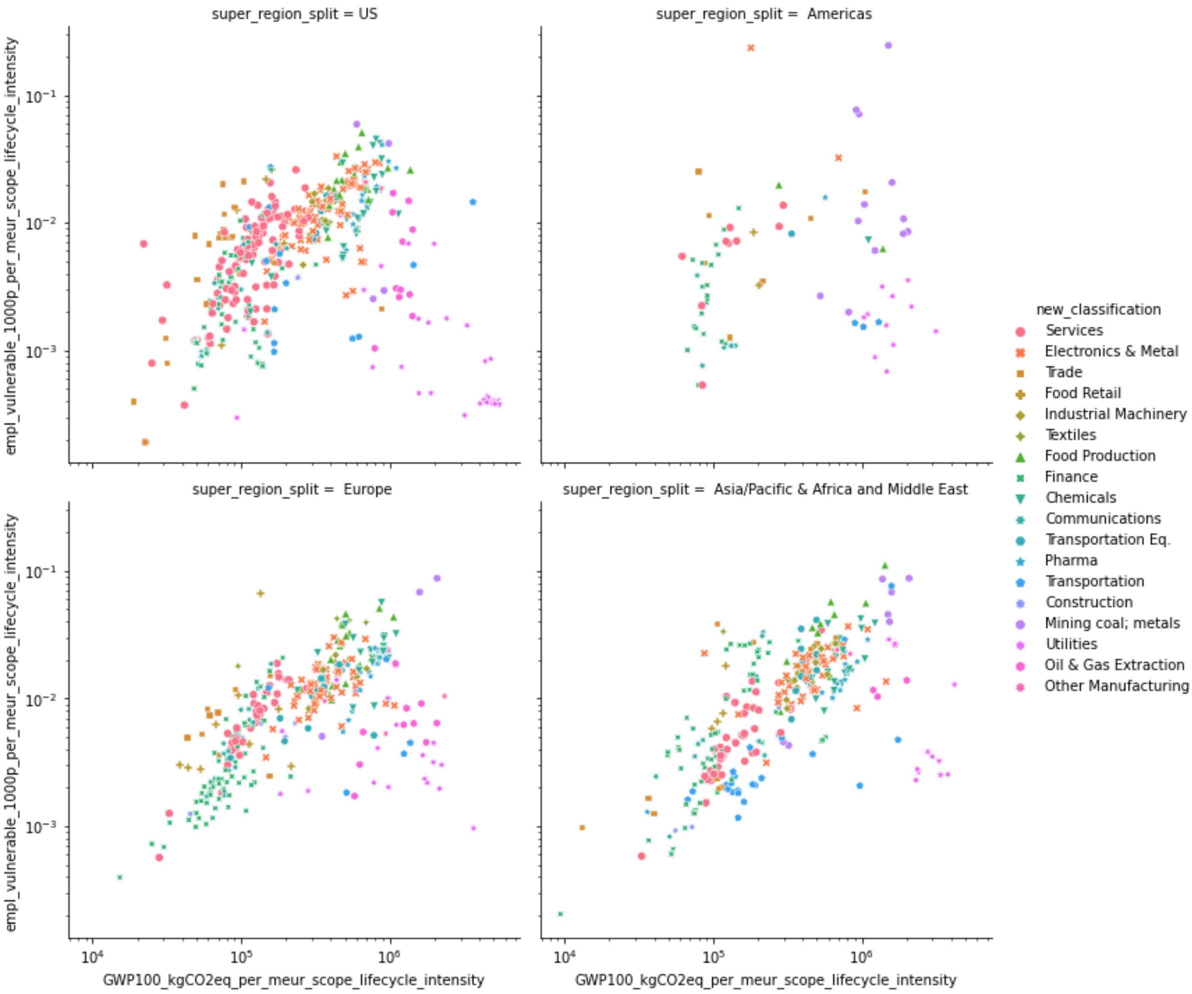


Figure 5.6: Scatter plot showing the trade-off between vulnerable employment and GHG emissions (GWP100) for companies in the MSCI Climate Transition Index. Each scatter plot illustrates companies domiciled in different regions (US, Americas, Europe and Asia/Pacific & Africa and Middle East). The symbols represent the main industry class of each company. There are a total of 1,281 companies composing the index in year 2020.

There are high trade-offs across companies in particular sectors. For example, retail companies like Walmart, AEON Co. or FAST RETAILING CO. rank high for direct, scope 1 intensity for vulnerable employment. In general, for scope 3 upstream, vulnerable employment is more correlated with GHG emissions. When looking at the intensity of vulnerable employment in the supply chain, we find companies producing electronic equipment as ranking high, while having low indirect GHG emissions. For example, QUALCOMM, producing communication equipment, or Nitto Denko Corp. from Japan, involved in manufacturing of semiconductors have high supply chain exposure to vulnerable employment – between 20 and 30 workers per million EUR of output produced, or about 200,000 workers in total.

For other sectors, such as Chemicals, we see that environmental and social impacts are correlated, when looking at the impact over the life cycle. Companies with high values for vulnerable employment can pass as good environmental investments. For example, food giants like Danone or Unilever and automobile manufacturers like Daimler and Toyota are often included in the portfolios of sustainable investment funds, like the MSCI World Climate Transition Index. However, their supply chain impacts in terms of vulnerable employment are very high. It is unlikely that social standards for supply chain workers will improve unless these companies are scrutinized by investors for allowing poor working conditions in their value chain.

The difference in social versus environmental impact implies that green investment is not necessarily socially responsible investment and special attention needs to be placed on green sectors associated with negative social impacts. Policy makers need to design different solutions to target both social and environmental improvements.

5.3.9 Investment in mutual funds

As a case study related to the mutual fund industry, we compare how the investable MSCI Climate Transition ETF performs on vulnerable employment (Figure 5.7) and GHG emissions (Figure 5.8), over three different years – since its inception in 2018 to the year of the Covid-19 pandemic, 2020. In order to have holdings amount information, we select an investment fund available to retail clients, offered by Amundi, an asset manager.

Worryingly, the Climate Transition fund, despite significantly decreasing its carbon emissions exposure from 2018 to 2020 (from almost 450 to 320 tCO_2-eq per million euros in output generated (MEUR)), has a stable exposure to vulnerable employment (11 persons/MEUR the mean value for the entire sample of companies but still 3 times larger than the median, as the distribution is skewed). This finding is critical for the development of the sustainable finance field. Investors cannot focus solely on carbon emissions as the main sustainability performance proxy. The climate transition cannot be achieved at the expense of worsening working conditions for persons more exposed to vulnerable employment. We can attribute more than 6,000 workers in vulnerable employment to this fund (and 200 $ktCO_2$-eq of GHG emissions).

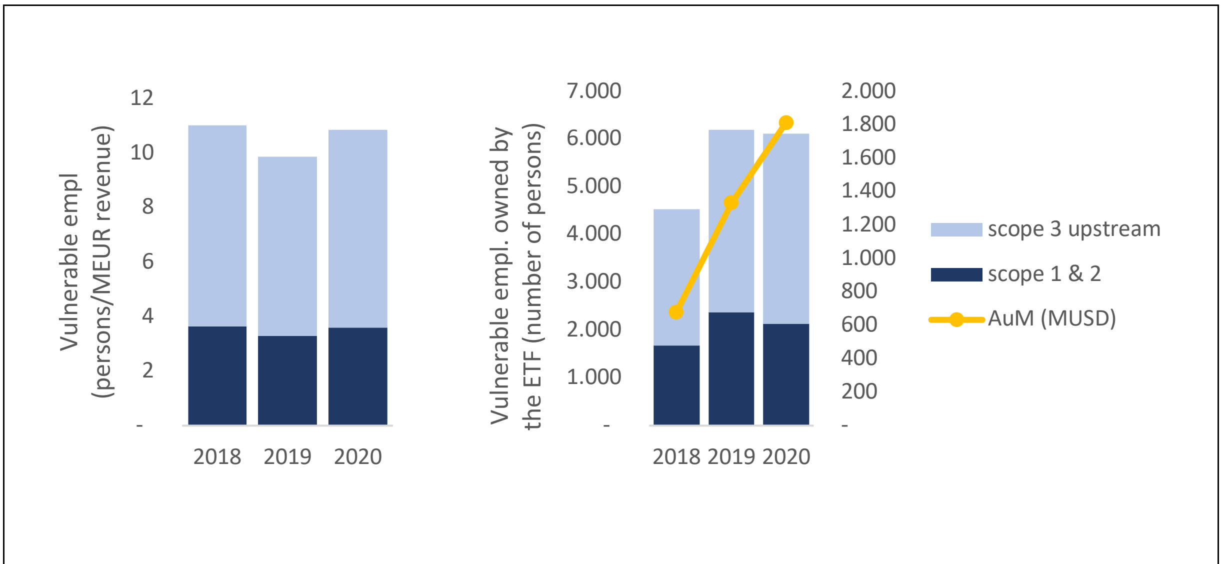


Figure 5.7: Vulnerable employment as intensity and absolute, attributable to the Climate Transition Index, for 2018, 2019 and 2020

Moreover, being included in a Climate Transition fund can serve as an endorsement of the fund for the sustainability practices of the company, assuming that no shareholder activism is conducted by the asset manager in order to change company practices. Holdings in the fund that show high supply chain vulnerable employment can be traced back to blue chip companies that tend to be held in any major mutual fund. For example, Apple, Daimler, BASF, each have estimated vulnerable employment exposure in the supply chain of more than 1 million workers. If investment managers start demanding more action and more reporting on supply chain social standards, they can trigger change in company practices.

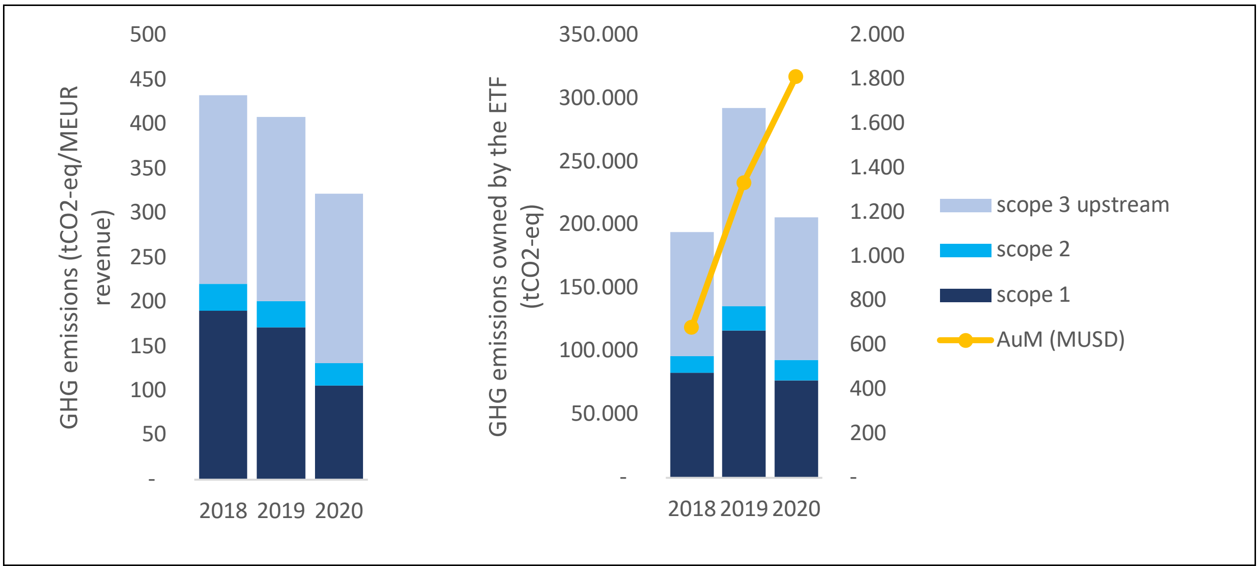


Figure 5.8: GHG emissions as intensity and absolute, attributable to the Climate Transition Index, for 2018, 2019 and 2020

5.4 Conclusion

The social dimension of green finance is of critical importance, despite being mostly overlooked in current sustainability assessments of green financial instruments. Recent regulations have put a renewed focus on social impacts, including the EU Sustainable Finance Taxonomy and national legislation, such as Germany's Supply Chain Due Diligence Law (*Lieferkettensorgfaltspflichtengesetz*) that was passed in 2021 and will take effect in 2023 and will hold large companies accountable for human rights in their supply chains. These efforts have gained traction after news stories highlighted the plight of workers without work protections during the COVID19 pandemic. With our study, we aim to highlight the importance of considering social impacts when making investment decisions for the climate transition.

Sustainability assessment tools like life cycle assessment (LCA) offer a basis for defining measurable social indicators for sustainable finance stakeholders. We introduced a first application of an environmentally extended multi regional input-output (EEMRIO) database, EXIOBASE, to the assessment of social impacts of corporations and investment instruments by linking it the financial database FactSet. We focus on the indicators of GHG emissions and vulnerable employment as a proxy for both the environmental and social dimension of sustainability. Vulnerable employment is defined as workers without employee status and is indicative of informal employment and thus correlated with other social indicators, such as whether workers are covered by social security, have access to paid leave or work stability.

We find that the agriculture and construction sectors have high shares of vulnerable employment, globally, at 60% and 25%, respectively. Vulnerable employment occurs mainly in the supply chain. Indirect, supply chain vulnerable employment contributes, on average, more than 70% to total exposure to vulnerable employment for sectors related to Processing of Raw Materials (Food Processing or Metals Production), but also Textiles Manufacturing, Chemicals, and Computers and Equipment Manufacturing.

For the complete universe of publicly held companies with revenue breakdown available in FactSet vulnerable employment amounts to 10.7 persons per MEUR of revenue output on average, while supply chain vulnerable employment is an additional 17.8 persons per MEUR for a total of 27.9 persons per MEUR. This distribution includes companies with much higher shares of vulnerable employment in their own operations and their supply chain. Across all sectors, however, vulnerable employment is often hidden in the supply chain, and this finding is particular true for the apparel and food manufacturing sectors.

In the apparel sector, we find that for 7 out of the top 10 publicly listed companies in our sample in terms of vulnerable employment the total direct and indirect (supply chain) vulnerable employment made up more than 50% of their total employment. In the mining metals sector, the share was above 40% in all of the top 10 companies. Even when considering companies across all sectors, the top 25 companies in terms of vulnerable employment included many companies' consumers in developed economies are likely familiar with, such as Walmart, Amazon, Apple, Toyota, Samsung, Mitsubishi, and Unilever.

In general, we find that social impacts show a higher variation between regions than within the same region across different industries, while for environmental impacts the opposite is generally valid. Environmental impacts are technology and process-driven, while social impacts are rather a factor of societal norms. Nonetheless, there are sectors, such as Agriculture and Farming, that are more exposed to social issues like vulnerable employment, across more regions, independent of the development status of the country, just as there are sectors where environmental impact can be country-dependent, when, for example, one country has more restrictive regulations in terms of GHG emissions.

Our assessment of companies included in the MSCI World Climate Transition Index showed that companies selected for the good performance on climate change do not necessarily do well on vulnerable employment. While some companies exhibit both high GHG emissions and high vulnerable employment, we also found companies with low GHG emissions and high vulnerable employment, particularly in the Food Retail, Services and Trade sectors. This result is particularly concerning when it comes to industries that will likely see greater investment flows in the future, as they are necessary for the climate transition, such as electric vehicles and solar panels. Manufacturing in these two sectors requires metals, such as cobalt and lithium, that are susceptible to human rights violations in their mining. While the Climate Transition fund decreased its carbon emissions exposure from 2018 to 2020, its exposure to vulnerable employment remained unchanged and was 3 times larger than the median for the entire sample of companies.

The advantage of the life-cycle assessment methodology as applied to publicly listed companies and funds lies in quantifying impacts along their supply chain. While rating agencies, such as Sustainalytics and RobecoSAM, do consider social impacts along supply chains, only Tier I suppliers are considered, and the indicator is but one of several others that focus on the main operations of companies rather than on the extent of human rights issues in their supply chain. Our measure of vulnerable employment was poorly correlated with the Social Score of RobecoSAM and the Social Disclosure Score of Bloomberg for companies in the apparel and mining metals sectors. Our measure has the added advantage of offering 100% coverage, while the social scores of RobecoSAM, Bloomberg, and MSCI had lower coverage of 85%, 80%, and 28%, respectively.

Social-centered life-cycle inventories, such as Product Social Impact Life Cycle Assessment database (PSILCA) and the Social Hotspot Database (SHDB), are dedicated to measuring social impacts across multiple indicators. However, they cannot be readily linked to financial databases because industry classifications differ across regions within PSILCA and SHDB. More work is needed in harmonizing these databases and facilitating the correspondence to financial investment products. Future research could focus on facilitating this correspondence, since the results would serve to validate our present results on vulnerable employment using EXIOBASE and would expand the measurement of social impacts along supply chains beyond the single measure of vulnerable employment.

6 The relationship between stock returns of companies and sustainability characteristics estimated by means of input-output life cycle assessment[11]

Abstract

We test the relationship between sustainability characteristics of firms and their stock returns. We are using a unique dataset of estimated life cycle impacts, covering the period from 2012 to 2021, and more than 25,000 different companies. Specifically, we estimate greenhouse gas emissions, water use, particulate matter, toxicity, acidification, and vulnerable employment impacts at company level. For GHG emissions, we find a strong positive relation with stock returns, strengthening previous academic findings. Furthermore, we find water use and vulnerable employment to have positive and significant relation to stock returns, in addition to GHG emissions. The effect of water use regression is stronger in countries with higher water stress. We document that for the other sustainability variables, there is no significant relationship, suggesting that investors are yet to integrate complete sustainability information in their investment decisions.

[11] *Earlier version of this paper was submitted to and rejected from the Journal of Accounting Research.*
To ease the readability of this chapter, all figures and tables are added in the end of the chapter, as it is custom in the finance literature

6.1 Introduction

In the asset pricing literature, non-financial characteristics have been recently used to explain the variation in stock returns, in addition to traditional, financial drivers. The reason to explore this relationship is the underlying belief that companies who are more exposed to negative impacts, be it directly or indirectly, are more likely to face transition, physical, and reputational risks in the future (UN Global Compact, 2004). Moreover, the financial system has a large role to play in the transition to a more sustainable and just society by re-directing financial flows towards sustainable companies and projects. Starting with the Paris Agreement in 2015 (UNFCCC, 2015), where countries committed to make financial flows consistent with the low-carbon transition, to asset owner initiatives and banking initiatives (Net-Zero Alliance, 2020; NGFS, 2022), financial market players take steps to implement sustainable investment decisions.

However, unlike financial characteristics, sustainability-related characteristics are complex to measure and there isn't always a simple and straightforward numerical value to give to it (Escrig-Olmedo et al., 2019). Developing comparable and reliable metrics to assess performance at financial product level is a persistent challenge in sustainable finance (Popescu et al., 2021; Vörösmarty et al., 2018), as sustainability impacts are measured via thousands of different emissions affecting nature and human societies (Hellweg et al., 2023).

Non-financial characteristics of firms have been traditionally encompassed in so-called Environmental, Social and Governance (ESG) ratings. However, a major drawback of ESG data is that they are not consistent across different providers, according to both the financial economics literature (see, among others: Berg *et al.* [2019], [2022], Christensen *et al.* [2019], [2021], and (Dimson et al., 2020)) and the industrial ecology literature (see (Busch et al., 2020; Busch and Lewandowski, 2018; Rekker et al., 2019), and the references therein). The dispersion of similarly defined indicators for the same company in the same year from different data vendors has been found to be a significant determinant of stock risk premia (Avramov *et al.* [2022] and Gibson *et al.* [2021]). These inconsistencies, often due to methodological differences, are among the causes of the opposite conclusions reached by empirical studies on the relationship between performance and different sustainability measures of companies, investment funds and, in general, financial instruments. Even for other measures of sustainability, and especially for model-based (as distinct from self-reported) GHG emissions datasets, the differences can be substantial as discussed, e.g., in the recent work of Aswani *et al.* [2022].

Only data on climate change, and specifically GHG emissions is reported at a consistent rate in order to conduct large-scale studies (Bolton and Kacperczyk, 2023). Toxic emissions data reported by companies has also been used to study the pricing of pollution by investors (Hsu et al., 2022). However, the sampled data is limited to the US. The literature using carbon emissions and pollution data to study the relation to stock returns find a positive risk premium, and a higher expected return for companies with a larger footprint. Recently, a similar approach has been adopted for linking the biodiversity footprint of companies and their stock returns (Garel et al., 2023). The authors find that, in general, biodiversity is not priced in the markets. However, there is a small premium around biodiversity landmark meetings, where investors react to latest developments.

With our paper, we aim to extend the research on the relation between sustainability characteristics and stock returns by extending the current available large-scale datasets of ghg emissions to other environmental and social variables. Specifically, using input-output life cycle assessment (IOLCA), we derive annual company-level estimates of greenhouse gas (ghg) emissions, water use, particulate matter, human toxicity cancer effects, acidification, and vulnerable employment. IOLCA has been used as an estimation method previously, mainly to assess the sustainability footprint of a whole industry or country (Alsamawi et al., 2014; Bjelle et al., 2021; Cabernard et al., 2021; Hertwich and Wood, 2018). More recently, IOLCA has been used to estimate impact at company level, where reporting data is of insufficient reliability. For example, Trucost uses an IOLCA model to complement reported emissions data (Trucost, 2021) and Iceberg Data Lab (IDL) uses IOLCA to develop biodiversity footprint metrics (Garel et al., 2023). Nonetheless, there are no empirical finance papers exploring other quantitative characteristics of firm, beyond ghg emissions (Bolton and Kacperczyk, 2021) and biodiversity (Garel et al., 2023). Using our novel dataset, we explore the pricing of non-financial characteristics of firms in the cross-section of stock returns. We have a larger global sample than previous literature, that extends to a large time period: our sample contains more than 25,000 unique company data, from 2012 to 2021.

The debate on the link between sustainability and stock returns is still unsolved (Liang and Renneboog, 2020). Part of the literature finds a negative (or neutral) relationship between better sustainability performance and stock returns (Aswani et al., 2022; Cheng et al., 2012) and the other part finds a positive relation (Bolton and Kacperczyk, 2023, 2021; Pastor et al., 2021; Pedersen et al., 2021), sometimes using the same databases of emissions, but different samples of companies/dates, or measures of emissions (e.g. absolute emissions vs. intensity, defined as absolute emissions divided by sales) and different data cleaning procedures. Avramov *et al.* (2022) find that ESG ratings are negatively associated with future performance when data vendors agree on the rating of a company, while the same ratings are not associated to performance otherwise. Aswani *et al.* [2022], recognize the agreement of different data providers on self-reported emissions data, and the heterogeneity among vendor-produced, that is model-based, emission estimates for the same company.

Using our estimated impact indicators database, we first revisit one of the most debated questions in environmental finance, namely the association (predictability) of individual companies' stock returns and ghg emissions both internationally, and in different geographical areas, including the US and Europe. We hypothesise that:

H0: Investors positively price sustainability factors (greenhouse gas emissions, water use, particulate matter, human toxicity cancer effects, acidification, and vulnerable employment) in the cross-section of stock returns.

This hypothesis is consistent with investors asking for a higher return for holding companies that could be exposed to higher long-term sustainability risks in the future. We find that, generally, investors positively price sustainability impacts, when measured in absolute terms[12] (the level value of the sustainability indicator). If we use ghg emissions as an explanatory variable in the individual regressions with each additional sustainability impact,

[12] *As argued in Bolton and Kacperczyk (2023), the level of emissions (or any sustainability proxy in our case) is a better measure to capture long-term risk exposure, as intensity metrics are driven also by changes in sales, that could thus introduce noise in the study of the sustainability performance of a company towards its share price performance.*

we only find significance for water use and vulnerable employment. This could imply that investors are pricing water and vulnerable employment and consider these as valid risks for stocks, but do not take into consideration pollution impacts, no matter the type: acidification, human toxicity, particulate matter. We also find that significance is different depending on the country of incorporation of the company. In some cases, EU and US companies see less significance across indicators. A potential reason could be that investors already perceive the EU and the US as taking enough measures to mitigate the negative consequences on the economy and thus health of companies that sustainability issues may have in the future.

Our results hold internationally, and in different geographical areas, including the U.S. and Europe only, and we also find that the relationship is stronger after 2018, although it existed also before that date. First, we chose the 2018 break point because it allows to compare our results with those of (Aswani et al., 2022; Bolton and Kacperczyk, 2023), as 2018 is the last year in which they have complete emissions data from Trucost. Second, the first version of the working paper version of (Bolton and Kacperczyk, 2023) was available in mid-2019 implying that annual stock returns in 2019 and in the following years could have, in principle, already started reflecting that information, as investors trade on the predictability findings of that paper. Thirdly, investors face increasingly stringent regulations in terms of integration of sustainability criteria in their portfolio allocation decisions, as the European Commission's Sustainable Finance Action Plan (SFAP) set out in 2018, we expect this effect to be stronger with time, as regulations on sustainability integration enter into force and companies adapt to reform sustainability reporting requirements for investment products providers and companies alike (EC, 2018b). As the European Commission is considered at the forefront of environmental regulation, the 2018 date could be identified with the influence of European sustainable finance regulations on investors' expectation. We use this last argument to interpret our stronger regression results, as the start of European-wide ESG regulations has paved the way for a more stringent international action on sustainability disclosures, as seen by the developments of the Task Force on Climate-Related Financial Disclosures (TCFD, 2017a), International Sustainability Standard Board (ISSB, 2021) and, more recently, ESG disclosure regulation to be introduced by the Security and Exchange Commission (SEC, 2022).

Our first contribution is towards validating previous literature findings that investors positively price higher risks related to carbon emissions or pollution in the cross-section of stock returns (Bolton & Kacperczyk, 2023; Hsu et al., 2022). The novelty introduced comes from using an estimated dataset of sustainability data, that is based on latest science-based indicators from life-cycle assessment. For example, for toxic pollution, we use a more sophisticated indicator, that groups different kind of emissions under a sole indicator, depending on their toxicity potential – human toxicity, cancer effects – unlike an equal weighting of different emissions, as done in previous literature.

Our second and key contribution relates to extending the critical sustainability issues that are addressed by finance research to water, vulnerable employment, and different kinds of pollution. While water scarcity has been regarded as a main environmental issue for decades (Dinar et al., 2019), it has not gained sufficient traction between investment professionals and investment literature.

For example, the question of water issues in relation to financial profitability has been insufficiently explored, and mostly from the perspective of water companies and not companies who consume and thus are exposed to the water crisis (Piñeiro-Chousa et al., 2020). A study from CDP shows that one third of surveyed companies do not assess the exposure to water issues (CDP and Planet Tracker, 2022). A recent coalition of investors is aimed at increasing the attention to water issues by companies – Ceres's "Valuing Water Finance Task Force" incentivises corporate action on water scarcity and pollution issues (Ceres, 2021).

Social issues have been previously studied in relation to financial returns, but were using different proxies of social performance, unlike our quantitative measure of exposure to vulnerable employment. Using ESG scores as proxy, one article shows that socially responsible portfolios are tilted towards firms with higher S score on issues like community and employee relations (Statman and Glushkov, 2018). In another highly cited paper, Edmans (2011) shows that companies which foster a better work environment for their employees tend to win higher returns. We argue that, in exchange, companies that are exposed to higher vulnerable employment will experience higher expected returns, due to the higher risk associated with their social performance.

The rest of the paper is structure as follows. In Section 6.2 of this paper, we discuss in depth the data and the sample used, as well as all control variables employed. In Section 6.3, we detail the empirical specifications of our paper and discuss the results from the series of regressions. Finally, we conclude with key take aways.

6.2 Data and sample description

We start by constructing our sample of sustainability impact data at company level. The dataset is restricted to the years and companies for which revenue data and detailed revenue breakdown information is available in FactSet, namely 2012 to 2021 and around 40,000 companies. Stock-level data (price) as well as absolute revenue are individualized at ISIN level, while sectorial breakdown of revenue is presented at primary company level. The input-output database used for sustainability impact factors, EXIOBASE, has time-series information from 1995 to 2022, and thus allows year-on-year linking to the company-level data and computation of all measures of sustainability selected for the sample companies. We remove companies for which absolute GHG emissions are less than 1 tCO_2eq and GHG emissions intensity is lower than 10 tCO_2/MEUR, to adjust for outliers, and keep this sample for the rest of the impact indicators as well. Afterwards, we use FactSet to retrieve monthly stock price and number of shares per company, which are then used to compute stock return. We remove from the sample companies with a share price lower than 1 USD and market value lower than 1 million USD. We match this database with company-level monthly and yearly financial controls, that we retrieve from Compustat. We include in our study companies from the financial sector, as these are also included in previous literature (Table A.1., from Bolton & Kacperczyk, 2023).

After the linking and removing non-matched observations, our final database has 1,642,571 company-month observations: 27,345 unique companies for the period 2012 to 2021, spread across 113 countries (**Table 6.1** and **Table 6.2** Summary of data sample after matching with

Compustat data). The largest number of unique companies is available in year 2019 (19,087 companies). The sector that dominates by far the sample is Manufacturing (84,131 companies), followed by Services (21,240 companies) and Transportation & Utilities companies (12,663 companies). For the complete sample, most companies are domiciled in Asian countries (62,391 companies, area *Far East*), followed by US and Canada (25,279 companies). From the EU28 member states, there are a total of 18,006 companies sampled over the period.

6.2.1 Estimation of company-level sustainability impacts using EXIOBASE

Sustainability data, and in particular GHG emissions data is available from different data providers. Most of these data is proprietary and vendors' methodologies are based on a combination of monetary estimation, based on input-output data, econometric techniques, and company self-reported data (Popescu et al., 2021). While some argue that estimates are muddling the sustainability data universe (Aswani et al., 2022; Kalesnik et al., 2021), company self-reported data is unlikely to reach a good level of coverage in the near future, and companies themselves report using different methodologies, which makes aggregation at fund level cumbersome (Hoepner and Rogelj, 2021) and data based on estimation and calibration vital for quantification of risk coming from sustainability profile of companies.

We argue that IOLCA is a reliable, science-based and homogenous methodology for measuring impact across a large sample of companies and has been previously used to this aim in academia (Koellner et al., 2007; Popescu et al., 2023) and by data providers, to cover for the missing information on sustainability indicators (Garel et al., 2023; PRéSustainability, 2019; Trucost, 2021). For example, the Trucost GHG emissions database uses company data, sectorial models, and input-output data to compile a database for over 16,000 companies (Trucost, 2018). A main difference between the Trucost model and ours is that they apply the US input-output table to the entire world, while, in our model, we use the global input-output tables of EXIOBASE, which have specific data across 49 countries and regions of the world, thus achieving a greater differentiation in industry-level impacts.

We decide to only use estimated IOLCA-based sustainability data, as it allows to extend the impact categories considered beyond the overused GHG emissions, to adjacent and equally important environmental and societal issues. Specifically, we use the model prototyped in (Popescu et al., 2023) to build a dataset of company level impacts for indicators **GHG emissions**, **acidification**, **human toxicity cancer effects**, **particulate matter formation**, **water use**, and **vulnerable employment** (the single social impact indicator). The chosen environmental issues are a representation of impact categories that link to pollution, and that would have impacts on ecosystems and human health. To quantify the impacts of single substances to certain impact categories, so-called characterization factors are used as weighting factors, to group environmental flows that contribute to the same impact categories, but with a different level of contribution (Baumann and Tillman, 2004). For example, for the impact indicator human toxicity, emissions of different metals like nickel or mercury, and chemicals, are weighted based on their characterization factors, as not all metals contribute equally and with the same force to the impact category. The obtained values are then summed to derive the total impact factor for human toxicity, measured in CTUh (comparative toxic unit for humans). Impact assessment methods developed in the LCA field define values for the characterization factors. Depending on the methodology used, the characterization factors can vary. Some widely used impact assessment methods are ReCiPe (Huijbregts et al., 2017), CML 2001 (de Bruijn et al., 2001) or USEtox (E. P. Fantke et al., 2017), for toxicity. In **Table 6.3**, we show the composing environmental flows for each of the chosen impact indicators. These are based on the impact assessment methods proposed in the EXIOBASE environmental extensions, that draw upon widely-adopted guidelines, such as the EU Environmental Footprint Method (PEF, 2021).

The benefit of using our data is having a homogenous set of sustainability data estimates across years and companies from different sectors. To our knowledge, it is the only non-proprietary dataset for life-cycle-based company-level sustainability data and covers a much larger sample than datasets like CDP, which had less than 4,400 companies reporting, and only 70% of these also disclosing on at least one category of scope 3 emissions (Bain & Company, 2022). Besides covering a large sample of companies, our estimates are also transparent, and solely based on environmental and social data sourced from input-output environmental extensions, which are based on trusted sources for the specific emissions/stressors. This means that they are not subjected to the heterogeneity of disclosure and measurement methods that is characteristics to company self-reported data. In addition, our dataset is novel by offering company-level impact estimates across a series of different indicators, for which ESG ratings and other datasets have poor coverage or only qualitative data.

We validate our estimation method by using Trucost GHG emissions data – a known data provider for life cycle sustainability data. The correlation between Trucost data and our estimated emissions are shown in Table 6.10 Panel D and Panel E. Correlation coefficients for absolute emissions are between 0.7 and 0.79. For intensity metric, the highest correlation is for scope 3 GHG emissions, with a coefficient of 0.57. For the empirical analysis, for absolute levels of emissions, we did find similar significance, using the two datasets to run the same regression specification (see regression output in Table 6.13 Panel D), which strengthens our choice of estimation method for the sustainability data.

The estimation of impact followed a few main steps, detailed in the model prototype paper (Popescu et al., 2023) and summarized in this paragraph. In a first step, EXIOBASE was used as database for deriving direct and life cycle GHG emission factors by country-industry combination. For industries with a low output, or small countries, there could be outliers in the database, as explained in greater detail in (Popescu et al., 2023). In these cases, a special adjustment was conducted: (1) adjusting renewable energy sectors to have 0 for direct emissions, (2) adjusting country-sector combinations with industry output less than 10 million EUR – where most outliers are, and (3) to adjust any remaining inconsistencies, upper and lower outliers were winsorized (at 0.05 lower and 0.1 higher). Another option would be to use the regionalized mean by industry, thus grouping countries by main region, with the aim to avoid outliers. However, this would lead to less differences between estimates at company level, while also not completely solving the issue of outliers. Thus, we use the special adjustment to derive scope 1, scope 2 and scope 3 upstream GHG impact factors, for the set of FactSet country-industry (GeoRev – RBICS) combinations. The emission factors are derived for each of the years from 2012 to 2021. For each year, we are using a different annual version of the input-output database, which is available from 1995 to 2022 (Stadler et al., 2018b), thus capturing yearly differences at country-industry level. We have repeated the process for the other five indicators, using where needed characterisation factors embedded in the *impacts* extension of EXIOBASE (Stadler, 2021). The structure of the input-output tables is the same and only the extension vector of impacts changes, meaning that direct and life cycle changes in country-industry impact factors are driven solely by the intensity of different environmental indicators. In order to derive impact factors for impact categories that contain more environmental flows, the characterization factors are suggested under the Environmental Footprint 3.1. methods, as detailed in previous literature deriving LCA-based indicators from EXIOBASE (Beylot et al., 2020; EC, 2021c). The dataset we obtain thus contains a time-series of country-industry impact factors across different impact indicators. We use a simple set of rules to adjust for outliers: (1) sectors with industry output less than 10 million EUR use the indicator value for the sector median and (2) across all industries, we apply winsorization at 5% (both for upper and lower limits), to account for outliers.

In terms of scope, with our IOLCA-based model we estimate scope 1 (direct impact in regressions), scope 2, and scope 3 upstream impacts (summed together under indirect impact in regressions), leaving out scope 3 downstream impacts due to data availability, as detailed in the methodological paper of (Popescu et al., 2023). While EXIOBASE reports original data harmonized in EUR, in this study, all values have been converted to USD, to keep the same currency across control variables and dependent variables. For example, for GHG emissions, IOLCA estimated intensities are expressed in kgCO_2-eq per million USD (US dollar). Finally, for the regression, we define three types of IOLCA-estimated impacts – (1) absolute or level values (e.g., GHG emissions, measured in tCO_2-eq) and (2) intensities (e.g., GHG emissions intensity in tCO_2-eq per MUSD of company revenue). For the empirical analysis, intensities and change in level are both winsorized at the 2.5% level, to remove outliers.

In the following sub-sections, we summarize what each indicator is referring to and show summary tables by impact indicator. For the analyses that look at total impacts per year, we reduce the sample to only include one ISIN per company (entity), as some companies may have multiple associated ISINs, with different share prices, and therefore may appear multiple times in the final regression sample. In **Figure *6.1***, for each chosen indicator, the mean direct and indirect intensities, for all companies in year 2019, grouped by main industry group. In Table 6.4, we show the top 10 companies in terms of impact by impact indicator. We discuss the top companies under each indicator in the sub-sections below.

In Table 6.5 we show the yearly total impacts across all six environmental and social indicators, split by direct and indirect impacts, as a more detailed representation of Figure 6.1. As can be observed, year 2019 sees the largest total GHG emissions (16 GtCO_2-eq). Year 2018 and 2020 also see large impacts, as these are the years with more than 24,000 unique companies present.

Following, we show for year 2019 the total impacts by main industry category (Table 6.6). Specifically, we assign each company to its primary industry and sum the impacts under each industry category. Manufacturing sector has the largest number of companies, and thus also highest assigned aggregated sales, and shows largest impacts for all impact indicators and scopes with two exceptions: for GHG emissions, most direct impacts are associated to Transport and Utilities, while for vulnerable employment largest direct impacts are, in aggregate, attributed to companies from Retail sector and Trade in general.

In **Table 6.7** Panel A and Panel B we report summary statistics for the sustainability variables estimated with the IOLCA-based model. The values are transformed in natural logarithms, given the log-normal distribution of GHG emissions and other sustainability variables. We show mean, median, but also standard deviation of the data. In Panel D and Panel E we also report the distribution of the raw values for the sustainability variables.

6.2.1.1 GHG emissions

"GHG emissions" combine emissions of CO_2, CH_4 and N_2O, SF_6, HFC and PFC and their associated characterization factors. The indicator is measured in tCO_2-equivalents. The impact indicator is constructed using the characterization factors from the 2007 IPCC report, for GWP100 indicator (global warming potential for 100 years). Emissions of GHG increase the global temperature in the long term, thus the indicator of global warming potential. As widely known, global warming poses large risks for ecosystems worldwide, such as the heating of oceans and the melting of glaciers. Different GHGs have different warming potentials, expressed in equivalents of CO_2.

As per Figure 6.1, the largest emissions were for companies in the Mining and in the Transportation and Utilities sectors – for companies in these sectors, scope 1 emissions represent more than half of total emissions, and scope 2 emissions have the largest share for Transportation and Public Utilities companies. For the rest of the companies, scope 3 upstream emissions represent more than 50% of the total emissions. Largest direct and indirect impacts can be attributed to companies in Oil & Gas Extraction, and Transportation and Utilities (Table 6.4).

The mean sampled firm has scope 1 GHG emissions of 738.2 $ktCO_2$-eq, and a median of 10 $ktCO_2$-eq. There is a high variation between companies, as we observe a standard deviation of 6,943 $ktCO_2$-eq (**Table 6.7**) for scope 1 GHG emissions. For scope 2 GHG emissions, we have a mean of 137.5 $ktCO_2$-eq and median of 9.4 $ktCO_2$-eq, and for scope 3 GHG emissions, the mean is 943.5 $ktCO_2$-eq and the median is 94.8 $ktCO_2$-eq.

For comparison and validation against previous studies, we also use a sample of GHG emissions from Trucost, as it is the same data provider used in the BK study. Our sample covers the period of 2012 – 2021, for which we also estimate IOLCA-based sustainability data (the BK study has data from 2005 to 2018). We have data for scope 1, scope 2 and scope 3 emissions, in total 685,000 monthly observations, and 13,300 unique companies.

6.2.1.2 Acidification

Terrestrial acidification is due to the deposition of nutrients in the soil (mainly nitrogen and sulphur and ammonia). These lead to releases of hydrogen ions (H^+) which changes the soil properties, for example by decreasing the pH, and thus reducing soil fertility. A main cause of acidification is burning of fossil fuels in the industry, via emissions of NOx and SOx, that lead to the formation of acid rain (PRé Sustainability, 2021). In this paper, we measure acidification as proposed in the Environmental Footprint (EF) methods, using Accumulated Exceedance (AE), expressed in mol H^+ eq as unit of measurement. SOx, NOx, and NH_3 are considered under the indicator and AE measures the change in critical load exceedance for the composing substances (PEF, 2021). We are using characterisation factors from EF 3.1., and apply them to environmental flows from EXIOBASE, that are linked to country-sector outputs. However, we do not account for site-specific characteristics of the nutrient emissions. For acidification, location-dependent characterisation factors should be used, as local conditions such as geographical factors influence the degree of the negative impact (Seppälä et al., 2006).

For the companies in our study, the largest acidification impact was for Agriculture companies, as these industries are the ones for which information on environmental flows are available in EXIOBASE. Transportation and Utilities and Mining companies follow with large direct impacts, and Manufacturing companies with large indirect impacts (Figure 6.1). Largest direct and impacts can be attributed to utility companies, while indirect acidification impacts are large for companies in Oil & Gas Extraction, but also Manufacturing sector (Table 6.4).

The mean sampled firm has direct acidification impact of 5,922 mol H^+ eq * 10^3, and a median of 50 mol H^+ eq * 10^3. Indirect acidification impacts have a mean of 10,691 mol H^+ eq * 10^3, and a median of 1,103 mol H^+ eq * 10^3 (**Table 6.7**). There is a high variation between companies, as we observe a standard deviation of 66,638 H^+ eq * 10^3 for direct acidification and of 61,119 H^+ eq * 10^3 for indirect acidification.

6.2.1.3 Human toxicity cancer

Human toxicity, cancer effects indicator aggregates impact on human health from release of toxic substances. Intake of these substances (via air, food, water, skin) can increase the risk of cancer. The USEtox model accounts for thousands of substances emitted (E. P. Fantke et al., 2017), specific metals and chemicals. Each substance has an attributed characterization factor, which allows for the weighting of all substances under one indicator. The unit of measurement is comparative toxic unit for humans or CTUh. This unit expressed the estimated increase in morbidity for the total population normalized by unit mass of contaminant emitted.

Recent advancements in research have looked at the attribution of toxicity impacts to emitting companies, by using data on location of industrial facilities. For example, (Erhart and Erhart, 2023) rank European industrial facilities by toxicity and climate change impacts. They find electricity and sewage companies to have the largest impacts for toxicity, while mercury and zinc emissions are highly relevant for the total toxicity impacts. Studies like this one are key in developing more company-specific data.

For human toxicity cancer effects, there are very large indirect impacts from companies in the Manufacturing, Construction and Mining industries, with Agriculture having the highest direct and indirect impact intensity, for both direct and indirect impacts (**Figure *6.1***). The high emissions intensity of Agriculture companies is biased due to the omission of many toxicity substances from the basis environmental data that the environmental extensions of the EXIOBASE are constructed on. Largest direct impacts can be attributed to companies processing metals, such as steel, as the company with the highest human toxicity impact is ArcelorMittal. Indirect impacts are high in heavy construction industry, where a lot of metal processing is needed (Table 6.4).

The mean sampled firm has direct human toxicity cancer effects impact of 1,698 CTUh * 10^{-3}, and a median of 4.79 CTUh * 10^{-3}. Indirect human toxicity cancer effects impacts have a mean of 5,768 CTUh * 10^{-3}, and a median of 469 CTUh * 10^{-3} (Table 6.7). There is a high variation between companies, as we observe a standard deviation of 67,188 CTUh * 10^{-3} for direct human toxicity cancer effects and of 36,486 CTUh * 10^{-3} for indirect human toxicity cancer effects.

6.2.1.4 Particulate matter formation

The Particulate Matter formation (PM) indicator comprises emissions of carbon oxide (CO), sulphur oxide (SOx), ammonia (NH_3) and TSP – total suspended particulate, which are airborne particles that are higher than 10 in diameter and PM indoors and outdoors – $PM_{2.5}$ – and characterizes their influence on human heath using the indicator "disease incidence" (Fantke et al., 2016). Location of the emissions of PM is key in assessing the impact on human health (Fantke et al., 2016). We are however not using spatially differentiated characterization factors. Therefore, also for this indicator, more detailed and specific measurements are needed in order to have a more accurate impact estimation.

For PM impacts, the gap between averages at industry level is not so large as for the other indicators, with Mining, Manufacturing and Transportation and Utilities having the highest impacts. Mining is the only sector where companies have on average larger scope 1 particulate matter impacts, than on the life cycle (Figure 6.1). Largest direct impacts on particulate matter can be attributed, surprisingly, to companies in the construction sector, more precisely, cement manufacturing. Transportation and Utilities companies are also present. For indirect PM impacts, we see that auto manufacturers are dominant Table 6.4).

The mean sampled firm has direct particulate matter formation impact of 136 disability life-adjusted years (DALY), and a median of 0.74 DALY. Indirect particulate matter impacts have a mean of 202 DALY, and a median of 20 DALY (Table 6.7). There is a high variation between companies, as we observe a standard deviation of 1,571 DALY for direct particulate matter and of 1,146 DALY for indirect particulate matter.

6.2.1.5 Water use

The water crisis is more and more prevalent in discussions worldwide. For example, a recent report of the Water Commission from the OECD talks about the urgency to take collective action on better protecting and managing water, to avoid a water crisis (OECD, 2023). Water stress can affect the financial system at microlevel – incurring losses on banks, asset owners, due to risks on the assets that they finance or invest in – or at macrolevel – for example, by causing political instability (Bourassi and Thouement, 2023). Like pricing carbon emissions, there are calls for a cap-and-trade system for water use, as a financial mechanism to incentivize better use of water (Nugent, 2022).

Water stress is strongly associated with climate change, as effects of climate change are driving more pressure on water, such as droughts and floods. There are also high risks associated with water, as water is highly embedded in our economic trade. Even if one company may not be directly affected by water stress, it may be dependent on suppliers from countries exposed to high water stress, and supplier exposure would in turn inflict risks on the main company (Ding et al., 2021; Hoekstra and Mekonnen, 2012). For example, semiconductor companies have been affected by draughts in Taiwan (Bourassi and Thouement, 2023). Previous studies from the sustainability literature have highlighted the water use embodied in global trade (Cabernard et al., 2019; Hoekstra and Mekonnen, 2012), or specific in global food production (Mekonnen and Gerbens-Leenes, 2020) and humanity as a whole.

“Water Consumption Blue – Total” is measured in Mm3 (million m^3). The ”Water Consumption Blue – Total” impact indicator groups together all water consumption blue categories from EXIOBASE’s environmental extension table. These relate to water consumed during 104 specific processes – mainly agriculture and manufacturing. In scope 1, this would mean mainly water used by an Agriculture company in the irrigation of its plants, in scope 2, would mean water used in the generation of electricity purchased, for example, for running a coal power plant and, in scope 3 upstream, for example for a textile manufacturing company, could be the emissions from the cultivation of textile fiber, such as cotton.

For the estimated water use indicator, agriculture has disproportionately large impacts (direct water use), followed by the manufacturing sector (indirect water use). Companies from the Agriculture sectors are the only ones where direct consumption is more significant than indirect, and this is due to the high water needed directly in the process of agricultural production (Figure 6.1). Largest direct and indirect impacts can be attributed to companies in Manufacturing, especially food-related manufacturing, and agriculture. For example, the company with the largest indirect water use footprint is Nestlé (Table 6.4).

The mean sampled firm has direct water use of 3.1 Mm^3 and a median of 0.054 Mm^3. Indirect water use mean is 24.2 Mm^3, and median is 1.85 Mm^3 (Table 6.7). There is a high variation between companies, as we observe a standard deviation of 40 Mm^3 for direct water use and of 166 Mm^3 for indirect water use.

This indicator can be proxy for EU Taxonomy environmental objective of “Sustainable use and protection of water and marine resources”. Worldwide, there has been an irresponsible use of freshwater resources, and industry plays a large role. Yearly, 4 trillion m^3 of water are consumed, an unstainable level (Ritchie and Roser, 2018). Much of the water consumption is occurring in Agriculture sectors, but also energy-related sectors, and the impact can be indirectly attributed to final consumption or manufacturing sectors happening in different parts of the world. Therefore, it is important to account for the lifecycle perspective when allocating impact to companies (Mekonnen and Hoekstra, 2020; Wang and Zimmerman, 2016). As per Tukker *et al.* [2013]; Stadler *et al.* [2018] “blue water” represents the water extracted from surface water and groundwater bodies. “Consumption” refers to the difference between the water extracted and the water returned to the same water body or ecosystem. Raw data on water consumption is scarcer than for indicators like GHG emissions. The final database of country-industry impact indicators is thus less precise that for GHG emissions, but still offers a good first approximation of this impact. EXIOBASE developers are using diverse data sources, such as WaterGAP (Flörke et al., 2013) or other academic literature sources (Pfister and Bayer, 2014) to compile country-industry inventories of water consumption.

While water scarcity has been regarded as a main environmental issue for decades (Dinar et al., 2019), it has not gained sufficient traction between investment professionals and investment literature. For example, the question of water issues in relation to financial profitability has been insufficiently explored, and mostly from the perspective of water companies and not companies who consume and thus are exposed to the water crisis (Piñeiro-Chousa et al., 2020). A study from CDP shows that one third of surveyed companies do not assess the exposure to water issues (CDP and Planet Tracker, 2022). A recent coalition of investors is aimed at increasing the attention to water issues by companies – Ceres's "Valuing Water Finance Task Force" incentivises corporate action on water scarcity and pollution issues (Ceres, 2021).

6.2.1.6 Vulnerable employment

The indicator vulnerable employment is the only explicit social indicator available in the EXIOBASE database. It is measured in 1,000 persons. This indicator is built in the extensions of EXIOBASE. The underlying data comes from the International Labour Organisation, Eurostat and OECD statistics (Stadler et al., 2018a). Vulnerable employment is a proxy for workers without formal employment bonds and workers not covered by social security (Simas et al., 2015).

For vulnerable employment (Figure 6.1), companies in the Agriculture sector had the highest intensity, due to the high informal employment. Retail trade companies have a larger proportion of direct vulnerable employment, while Manufacturing has a very high share of indirect vulnerable employment. Companies in Retail Trade have more than 50% of vulnerable employment attributable to the direct operations phase, with Agriculture also showing a larger portion for direct impacts. For vulnerable employment, and in general social indicators, large variation can be seen at country level in addition to industry level, as country-level practices in terms of social norms and respect of human rights cut across sectors (Hitaj et al., 2023). Largest direct and indirect impacts can be attributed to companies domiciled in China, while main sectors are Oil & Gas Extraction, Retail Trade or Finance (for indirect impacts). Interestingly, the Switzerland-domiciled company Glencore active in the mining sector has one of the biggest impacts in terms of vulnerable employment (Table 6.4).

The mean sampled firm has direct attributable vulnerable employment of 11,700 persons and a median of 600 persons. Indirect vulnerable employment mean is 26,000 persons, and median is 2,870 persons (Table 6.7). There is a high variation between companies, as we observe a standard deviation of 122,000 persons for direct vulnerable employment and of 138,000 persons for indirect vulnerable employment.

6.2.2 Correlation between impact categories

The cross-correlations between different scopes for the same impact indicator are shown in Table 6.8. Generally, direct impacts are highly correlated with indirect impacts – highest coefficient being of 0.831 (between direct GHG emissions and scope 3 GHG emissions). For particulate matter formation, the correlation is lower – a coefficient of 0.694 between direct and indirect particulate matter impacts.

In Table 6.9, we show the autocorrelations between yearly measures of absolute impact. The strong correlation coefficients underline the importance of the size of a company in the total impacts it generates, while intensities may change more year-on-year.

In Figure 6.2, we show the correlation between all chosen indicators, for the sample of companies of year 2019 (more than 27 thousand companies). The degree of correlation varies considerably. Particulate matter impacts are positively correlated with acidification, both for direct (coefficient 0.68) and indirect impacts (0.75 coefficient). Interestingly, vulnerable employment impacts are correlated strongly with GHG emissions (0.5 direct correlation coefficient and 0.73 indirect correlation coefficient). For indirect intensities, vulnerable employment is also highly correlated with water use, while indirect particulate matter is strongly correlated with acidification indirect impacts (0.75) and human toxicity cancer effects (0.68). The correlations are highly driven by the elements composing the impact indicators – for example, both acidification and particulate matter aggregate emissions of sulphur oxides (SOx) and ammonia (NH_3). At the other end, GHG emissions show low correlation for direct impacts with acidification, human toxicity cancer effects, particulate matter, and water use. Vulnerable employment shows a weak but negative relation to human toxicity cancer. For indirect impacts, correlations are generally higher, implying that companies are more similar in terms of indirect and supply chain characteristics, than in terms of direct operations. The lowest correlation coefficient for indirect impacts is between human toxicity cancer effects and GHG emissions. The information on correlation coefficients between variables can help investors choose which impacts to address, in order to achieve the greatest reduction across all indicators. In Table 6.10, we show similar results as in the Figure 6.2 – the correlations between impact indicators, as absolute values, absolute values but as logarithmic values and intensity values. As observed, the correlations are much higher for logarithmic values of absolute emissions.

6.2.3 Control Variables

Companies' absolute level of emissions is highly influenced by earnings. Similar to previous literature (Bolton and Kacperczyk, 2023) we control for this by including earnings- and return-related independent variables. Summary statistics for controls and returns values are shown in **Table 6.7** Panel C. We account for: (1) sales growth (**salesgr**), computed as the yearly percentage change in company sales, (2) market capitalization (**logsize**), computed as the natural logarithm of the firm's market capitalization (mcap, shares outstanding multiplied by share price, at the end of year *t*), (3) return on equity (**ROE**), computed as net income divided by shareholders' equity (4) book-to-market value (**btom**), computed as the firm's book value (or shareholders' equity) divided by mcap, (5) leverage (**leverage**), computed as the value of debt (total liabilities) divided by the value of assets, (6) capital expenditures (CAPEX) as percent of total assets (**capextoassets**), (7) physical capital owned by the company (**logppe**), computed using the firm's value for property, plant & equipment (8) volatility (**volat**), computed as the standard deviation of returns, taking into account the returns from the past 12 months, (9) momentum (**mom**), expressed by the average of the most recent 12 months returns, up to month *t-1*, (10) MSCI World Index dummy (**msci**), and (11) industry concentration – Herfindahl–Hirschman Index (**HHI**), computed based on a company's EXIOBASE industry breakdown. Some variables are winsorized at 2.5%, in order to minimize the impact of outliers on the regression results (btom, leverage, volat, mom, salesgr, roe, capextoassets).

6.2.4 Drivers of impacts

In Table 6.11, we show the link between GHG emissions at company level and financial characteristics of the company. As expected, the firm's GHG emissions are positively correlated with size, but also with book-to-market, leverage, PPE, and ROE. We observe a negative correlation with HHI – meaning that companies in more concentrated industries tend to have lower GHG emissions. A negative coefficient is also observed for investment ratio (proxied via Capex/Assets ratio) – companies that have more capital expenditures tend to have lower GHG emissions, consistent with the idea that companies with a lot of physical assets and investments will naturally increase their footprint. We ran similar regression for all other impact categories. In Table 6.12 we show the drivers of water use impacts. Interestingly, for indirect water use impacts, adding GHG emissions in the regression leads to a very high R2, of 0.876, without fixed effects, while without GHG emissions, 0.668 of the variation is explained. For the direct water use, less of the variation is explained by including also GHG emissions (0.698), which further validates our previous assumption that indirect impacts are correlated stronger than direct impacts, between impact indicators.

6.3 Empirical results

Our main empirical question is whether investors are pricing in sustainability information at company level, via stock returns. We answer the question by looking at six proxies of sustainability, estimated with the IOLCA-based model, as explained in the *Data and sample description* section.

We construct a cross-sectional pooled OLS regression model and run regressions for absolute levels of impact (Eq. 1) and intensity (Eq. 2). We build on the assumptions of (Bolton and Kacperczyk, 2023) by adopting a firm characteristic-based approach to explaining returns of stocks. We run cross-sectional regressions which are motivated by the large variety of observations for the selected time period. Thus, we do not make any assumptions on the asset pricing model, as motivated by BK, as it would be difficult to set the assumptions for the pricing of complex sustainability issues.

$$ret_{i,t} = a_o + a_1 \times (Impact\ indicator\ absolute)_{i,t-1} + a_2 \times Controls_{i,t-1} + \mu_t + \varepsilon_t \quad \text{(Eq. 1)}$$

$$ret_{i,t} = a_o + a_1 \times (Impact\ indicator\ intensity)_{i,t-1} + a_2 \times Controls_{i,t-1} + \mu_t + \varepsilon_t \quad \text{(Eq. 2)}$$

For the second equation, we use intensity values for company-level impacts that are winsorized at 2.5% level. All yearly financial controls are lagged by one year, as per the custom in literature. Many of the independent variables have the same value over 12 months, as they are measured yearly. However, we use year-month observations, to account for the monthly changes in returns data. Impact indicators – our main independent variable – are lagged by one month. We cluster all regressions at company and date level. In all regression iterations we use company and date fixed effects. In some regression specifications we add industry and country fixed effects. For the industry classification, we use the SIC sector classification, that is provided in the FactSet database.

In our first set of regressions, we look at the relation between IOLCA-estimated company GHG emissions and returns. This regression analysis has two goals. First, we test the hypothesis from previous literature that GHG emissions are positively priced in the cross-section of returns, using a different data source and an extended sample of companies, spanning more years. Our analysis includes more years compared with previous research, studying also the three entire years from 2019 – 2021. This period is of particular interest when studying ESG-related asset pricing questions, as in 2018 the EU has published its EU

Sustainable Finance Action Plan (EC, 2018b) and started the implementation of the EU Sustainable Finance Disclosure Regulation (SFDR, EC, 2019). Second, we aim to validate our estimation model, by understanding whether our regression results and coefficients are similar to the previous literature. To make the validation step more precise, we also use a sample of Trucost GHG emissions, which is the source of the data in BK. We will run the regressions using Trucost and our measure of GHG emissions on the same sample of companies, which allows for a better comparison of results.

In our second set of regressions, we aim to test whether other impact indicators, beyond GHG emissions, are priced in the cross-section of stock returns. We perform the same regressions as in Eq. 1 and Eq. 2. Moreover, to control for the fact that the sustainability risk may be already fully captured by GHG emissions, and to separate the different effects of different impact indicators, we run all new regressions with GHG emissions as control variable as well, as per Eq. 3.

$$ret_{i,t} = a_o + a_1 \times (impact\ indicator)_{i,t-1} + a_2 \times ghg\ emissions_{i,t-1} + a_3 \times Controls_{i,t-1} + \mu_t + \varepsilon_t \quad \text{(Eq. 3)}$$

Finally, we introduce dummies related to environmental and social issues in the regressions, to test whether effect is stronger based on the country profile with regards to the specific sustainability issue (Eq. 4).

$$ret_{i,t} = a_o + a_1 \times (impact\ indicator)_{i,t-1} + a_2 \times impact\ interaction\ with\ dummy_{i,t-1} + a_3 \times Controls_{i,t-1} + \mu_t + \varepsilon_t \quad \text{(Eq. 4)}$$

6.3.1 GHG emissions and stock returns

In **Table 6.13** Panel A, we report the results for the cross-sectional analysis using GHG emissions as independent and explanatory variable of stock returns. For our full sample of GHG emissions, we find similar coefficients as BK, namely that GHG emissions are positively and significantly correlated with stock returns. Results are robust to the inclusion of country and industry fixed effects. The coefficient for direct GHG emissions is of 0.144, while for indirect emissions is of 0.298, meaning that indirect emissions are priced stronger than direct emissions. A possible explanation is that indirect emissions pose higher long-term risks to investors. Thus, we showed that investors are pricing in GHG emissions, even when looking at a larger sample of companies and for the period after 2018. We perform separate regressions before and after 2018, to understand to what degree results vary when we introduce additional years as compared to the time period used in BK (Panel C). Pricing is slightly stronger before 2018, but results are robust to the split between periods.

In Panel D of Table 6.13, we run the same regression but on a smaller sample, matching data that we could retrieve from Trucost. We run the same regression for our measure of estimated IOLCA-based emissions and Trucost scope 1, scope 2 and scope 3 GHG emissions that are provided. The Trucost data is based on a combination of company-reported data and estimations using IOLCA, but US-based IO tables. We do find similar results and same significance and sign of coefficients, as when using our measurements of GHG emissions, which is a reasonable validation of our modelled sustainability data.

We also run the regression by region, to understand whether there are differences in pricing of GHG emissions risk depending on the company domicile. In Table ***6.13*** Panel E, we show the results for the regressions separating companies by region/country: EU28, US, China, rest of the countries. For GHG emissions, we do not observe a change in significance depending on the country domicile. However, effect is strongest in the US.

6.3.2 Other sustainability metrics and stock returns

We continue testing the relation between company sustainability characteristics and stock returns. As for indicators acidification, human toxicity, and particulate matter we don't find strong significance, we don't report results in this thesis.

6.3.2.1 Water use

We find significance for both direct and indirect water use footprint (Table 6.14 Panel A). Companies with a higher water footprint have a higher stock return, consistent with the theory that investors are pricing in risks related to water use and water scarcity. The significance of water use variable is robust to including GHG emissions in the regression, across all scopes (Panel B). This finding implies that investors price in water use as a risk, in addition to having large GHG emissions.

We run the same regression using GHG emissions and water use, but by region: EU28, China, US, and Rest of the world (Panel C). In this case, we find no significance for the water indicator for companies domiciled in EU28 member states, neither for US-domiciled companies, but we do find high significance for companies in China and companies domiciled in other countries. This finding leads to test whether companies in countries with higher water risk price it stronger than rest of the countries.

To test to what degree the stock price reflects the regional differences in terms of availability of water (a region with less water would imply an increased long-term risk for investors, compared with another regions), we include in the regressions a dummy for water stress. Therefore, to control for regions where water stress is more important, given the limited availability of water and increased risk of draught we use the dataset of "water stress country rankings" (Luo et al., 2015) from the World Resources Institute (WRI). The dataset contains rankings from 1 to 5, with 5 being the highest exposure to water stress, of 167 countries. We use the year 2030 BAU scenario and the average country-level score.

All countries with scores above 3 are high and extremely high water stress. From score 2 to 3 we have medium-high water stress (Figure 6.3). From the figure we observe that Middle East countries are most exposed to water stress currently, alongside countries in North Africa, such as Morocco, but also European countries like Spain. US, China and Australia are projected to be much more exposed to water stress in the future (Luo et al., 2015).

We consider countries with score above 2 as highly affected by water stress and thus for these, the water stress dummy is equal to 1. These are 74 out of 167 countries, for the chosen scenario. In Table 6.14 Panel D we show the results from running the regression with the summed direct and indirect water use (life cycle water use). We do find a positive premium for water stress dummies, in countries with medium to extreme high water stress (dummy for water stress is 1, if the WRI score for the country is larger than 2), but only for life cycle water use variables, and only when including both country and industry fixed effects. When we run the same regression, but also include GHG emissions as explanatory variables (Panel

E), we find that indirect water stress and life cycle water use interacted with water stress dummy show a positive coefficient, but only when including both country and industry fixed effects.

To summarize, investors positively price in water use as a sustainability risk, in addition to GHG emissions. Water use is priced in not priced in by investors in specific regions (EU28 or US).

6.3.2.2 Vulnerable employment

Absolute vulnerable employment is positively correlated to stock returns and the coefficient is statistically significant in main regression, including financial controls and country and industry fixed effects (**Table 6.15** Panel A). If we run the same regression by regional split, we find that direct and indirect vulnerable employment impacts are not significant in the US but are positive significant in other regions (Panel B). When running vulnerable employment in addition to GHG emissions as explanatory variable (Panel C), we have similar results for vulnerable employment direct impacts. For EU28 indirect vulnerable employment impacts we see non-significant coefficients, while for US companies, there is a significant and negative coefficient for indirect vulnerable employment (Panel D). This could imply that investors in US companies expect lower returns from companies exposed to indirect vulnerable employment – these companies being thus less attractive for investors.

We further aim to test whether companies from countries where there is a concerning situation relating social issues (such as lower respect for human rights and lower health coverage) see a higher pricing of risk. To derive dummies for social impacts, we use the SDG indicators database, tracking country-level progress on specific indicators grouped under the 17 SDGs. The indicators are *universal health coverage* (UHC) index of service coverage (worst 0-100 best) and f*undamental labor rights are effectively guaranteed* (*rights*, worst 0–1 best). We use the median of the samples to define the dummies. If a country has a score larger than median, the dummy is 0, otherwise it is 1 – since a smaller score means a lower performance (dummy). For all indicators, the final set of data used is normalized between 0 and 100, with 0 being worst and 100 best, in terms of impact. Hence, dummies are 1 for worst values. In countries with better human rights, using the SDG-related indicator human rights coverage as source to define dummy, a higher vulnerable employment value performance is priced positively in the market (**Table 6.15** Panel E). This implies that investors see more risks for companies located in countries that care more about human rights. This is only significant for direct vulnerable employment.

Additionally, we use data from the World Values Survey on social and environmental issues that capture not the quantitative value but rather the perception of people. We select all countries, survey period 2017 – 2022 (https://www.worldvaluessurvey.org/WVSOnline.jsp). The two most interesting questions with satisfactory data are relating to preference towards *environmental protection versus economic growth and creation of jobs* and whether respondents perceive that *human rights are respected*. For the question regarding environmental protection versus economic growth, respondents had to choose between "Protecting environment" and "Economy growth and creating jobs". The total coverage is of 90 countries. In 69 of these, protection of environment is more important. We would define the dummy to be 1 if environmental protection is more important and 0 otherwise. The question from the World Values Survey most fitting to the social impact of "vulnerable employment" is related to the degree of respect for human rights felt in one country – "respect for human rights nowadays". For other questions related to employment, there were not enough countries surveyed. Out of 64 countries for which data is available, in 40 of them respondents considered that there is a great deal of or fairly much respect for human rights. For these countries, we allocated a dummy of 1. To match the countries in the "Environmental protection" question, if a country was not included in the "human rights" dataset, it would get value of 0 – meaning that there is importance for human rights. We combine the two indicators under one, as done in (Ding et al., 2021), as we also only find some significance for the combined dummy. WE set a dummy of 1 if both dummy for environmental and for social questions were 1. We thus hypothesize that in countries where there is more concern about values of environment and human rights, there is a higher pricing of negative impacts related to vulnerable employment.

In Panel F **Table 6.15** Panel F we show the results and significance of indicators when we interact with the WVS dummy. If we don't include fixed effects, we see a positive pricing of risk in countries that care more for values, but, on the inclusion of fixed effects we find the opposite result. In Panel G we find similar significance if we include GHG emissions next to vulnerable employment values. Interestingly, there is negative pricing when country fixed effects are also included in the regression.

6.4 Conclusion

The future prosperity of our planet and of humanity will depend on much more than limiting greenhouse gas (GHG) emissions. While climate change is the single most urgent crisis, water scarcity, toxic pollution, but also social issues are vital to be addressed for a sustainable and just transition. In literature, climate change and its respective indicator of carbon footprint have been extensively researched, albeit with mixed results in terms of relationship to capital markets. With our paper, we aim to add to the debate on integration of sustainability factors by capital markets and thus further study how additional sustainability issues, such, as vulnerable employment, water use, and pollution (air pollution or toxic emissions) are priced by investors.

Specifically, we study the relation between stock returns on a global and extended time series sample and their sustainability performance, measured on six key indicators used as proxies: GHG emissions, acidification, human toxicity cancer effects, particulate matter formation, water use and vulnerable employment. We hypothesize that investors positively price the five other sustainability characteristics, beyond carbon emissions. To measure these sustainability characteristics, we developed an input-output life-cycle-based model to estimate impacts for every company, using revenue data, that is widely available for every publicly listed company, unlike non-financial information. We find that all sustainability characteristics are positively priced, when considered as the sole explanatory sustainability variable. However, when we run the regressions using GHG emissions in addition to the specific sustainability variable, we find that some of the significance is not present anymore, meaning either that the impact is already priced via GHG emissions, or that investors do not yet consider other sustainability issues as important for risk management, in addition to

GHG emissions-driven effects. Nonetheless, two main interesting findings emerge in relation to water use and vulnerable employment indicators. For water use, we find positive significance in addition to GHG emissions. Moreover, we find that companies that are located in countries with a high water stress (risk of water scarcity), experience a higher pricing of water use risk. This implies that investors do view water as a pertinent sustainability risk for the profitability of companies. For vulnerable employment, we find that companies in countries with a higher respect for workers' rights, put a higher pricing on vulnerable employment. This would mean that investors expect higher risk for these companies in the future due to possible litigations or actions to protect the vulnerable workers.

Our results show that, even with no standardized, company-level reported data on other sustainability issues than GHG emissions, investors still price in some of the effects, perhaps due to industry-level knowledge on possible material risks developing in the future. Further work exploring the implications of other material risks on returns is needed, and our work stands as a proof that better company-level data on an extended set of sustainability indicators is needed.

6.5 Tables and Figures

Table 6.1: Final sample distribution of companies, by year and by SIC category classification

Total unique company ISINs for the whole time period is of 30,197. There are 29,241 unique company names. There are 167,137 unique company-year observations.

Year	#	# by SIC category name								
	Total	Agriculture, Forestry, & Fishing	Construction	Finance, Insurance, & Real Estate	Manufacturing	Mining	Retail Trade	Services	Transportation & Public Utilities	Wholesale Trade
2012	**3,404**	37	40	192	1,790	263	110	541	333	98
2013	**13,128**	176	287	544	7,410	703	437	1,874	1,188	509
2014	**15,708**	228	382	618	8,890	742	543	2,229	1,419	657
2015	**16,459**	248	385	615	9,475	710	562	2,326	1,448	690
2016	**15,635**	233	354	576	8,900	630	569	2,282	1,459	632
2017	**17,038**	257	399	653	9,762	719	600	2,416	1,540	692
2018	**18,421**	267	418	622	10,712	724	650	2,649	1,640	739
2019	**19,087**	291	425	619	11,190	703	646	2,784	1,666	763
2020	**18,687**	268	404	622	11,076	665	632	2,797	1,480	743
2021	**8,401**	108	169	327	4,926	318	372	1,342	490	349
Total	**145,968**	**2,113**	**3,263**	**5,388**	**84,131**	**6,177**	**5,121**	**21,240**	**12,663**	**5,872**

Table 6.2: Final sample distribution of unique companies, by regional area

The "area" classification is based on FactSet.

Area/Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
Australia and NZ	17	263	416	420	417	460	457	470	480	421	**3,821**
Caribbean	30	61	75	72	70	77	78	83	79	34	**659**
Central America	21	60	72	71	78	66	76	72	70	2	**588**
Central Middle East	74	520	609	671	539	685	720	741	718	278	**5,555**
Eastern Africa		10	21	18	15	15	14	12	11	4	**120**
Eastern EU	2	353	382	408	389	386	429	419	338	44	**3,150**
Eastern Middle East	4	85	105	146	128	145	125	172	175	97	**1,182**
Eastern Non-EU	27	91	91	96	80	96	106	98	76	2	**763**
Far East	662	5,219	6,449	6,914	6,732	7,343	8,508	8,816	8,750	2,998	**62,391**
Indian Region	93	781	1,254	1,261	1,072	1,386	1,230	1,490	1,522	1,015	**11,104**
Northern EU	23	355	343	377	378	404	519	540	543	200	**3,682**
Northern Non-EU	8	80	93	98	87	97	106	106	111	25	**811**
Pacific Islands	89	426	534	523	488	570	499	535	537	164	**4,365**
South America	55	250	313	331	285	330	354	350	329	110	**2,707**
Southern Africa	12	83	115	122	131	140	138	153	134	83	**1,111**
Southern EU	13	122	124	125	116	111	113	101	87	13	**925**
Southern Non-EU		3	5	3	5	7	9	5	4		**41**
US and Canada	1,991	2,553	2,624	2,723	2,596	2,623	2,746	2,724	2,641	2,058	**25,279**
Western Africa		31	51	47	38	44	53	51	60	4	**379**
Western EU	184	1,111	1,182	1,186	1,176	1,200	1,300	1,290	1,222	398	**10,249**
Western Middle East	4	39	62	63	52	66	66	57	39	6	**454**
Western Non-EU	95	632	788	784	763	787	775	802	761	445	**6,632**
Total	**3,404**	**13,128**	**15,708**	**16,459**	**15,635**	**17,038**	**18,421**	**19,087**	**18,687**	**8,401**	**145,968**

Table 6.3: Summary of impact indicators

This table details the impact indicators estimated for this paper. The estimation method is based on input-output life cycle assessment and uses the EXIOBASE database. The environmental impact categories are based on the Environmental Footprint Methodology.

Impact category	Impact category indicator (unit)	Description	Source	Included environmental flows	Realm (Area of protection/ endpoint from LCA[13])
Acidification	Accumulated Exceedance (mol H+ eq)	emissions to air, soil, and water that cause changes in the pH and can lead to impacts on fish and plants (PRé Sustainability, 2021).	EU PEF, Beylot (2019, 2020)	SOx, NH_3	damage to ecosystems
GHG emissions – Climate change, total	GHG emissions, GWP100 ($kgCO_2$ eq)	increase in the global temperature, caused by high concentration of greenhouse gases in the atmosphere.	EU PEF, EXIOBASE, adjusted as per Popescu et al. (2022)	CO_2, CH_4, N_2O	damage to ecosystems / damage to human health
Human toxicity, cancer	Comparative Toxic Unit for humans (CTUh)	impacts are caused by absorbing substances through air, water, and soil. The direct impacts to humans are uncertain and complex (Erhart and Erhart, 2023; E. P. Fantke et al., 2017).	EU PEF, Beylot (2019, 2020)	Benzo(a)pyrene, PCDD_F, HCB, As, Cd, Hg, Ni, Pb	damage to human health
Particulate matter	Impact on human health (Disease incidence)	change in mortality due to emissions of particulate matter. Smaller particles are more dangerous (Fantke et al., 2016).	EU PEF, Beylot (2019, 2020)	PM2.5, CO, SOx, NH_3, TSP	damage to human health
Water use	m3 water eq of deprived water (m3)	real data on water use at international level is scarce; modelled data is used. The accounts comprise data used in agriculture, livestock, manufacturing and electricity (Stadler et al., 2018b)	EU PEF, Beylot (2019, 2020)	Water consumption blue from a set of activities	damage to ecosystems
Vulnerable employment	1,000 persons	workers without employee status as a proxy for vulnerable employment, as defined under International Labor Organisation (ILO) and in EXIOBASE (ILO, 2013; Stadler et al., 2018b)	EXIOBASE	n/a	damage to human health

[13] *As per LCIA methods, the ReCiPe model*

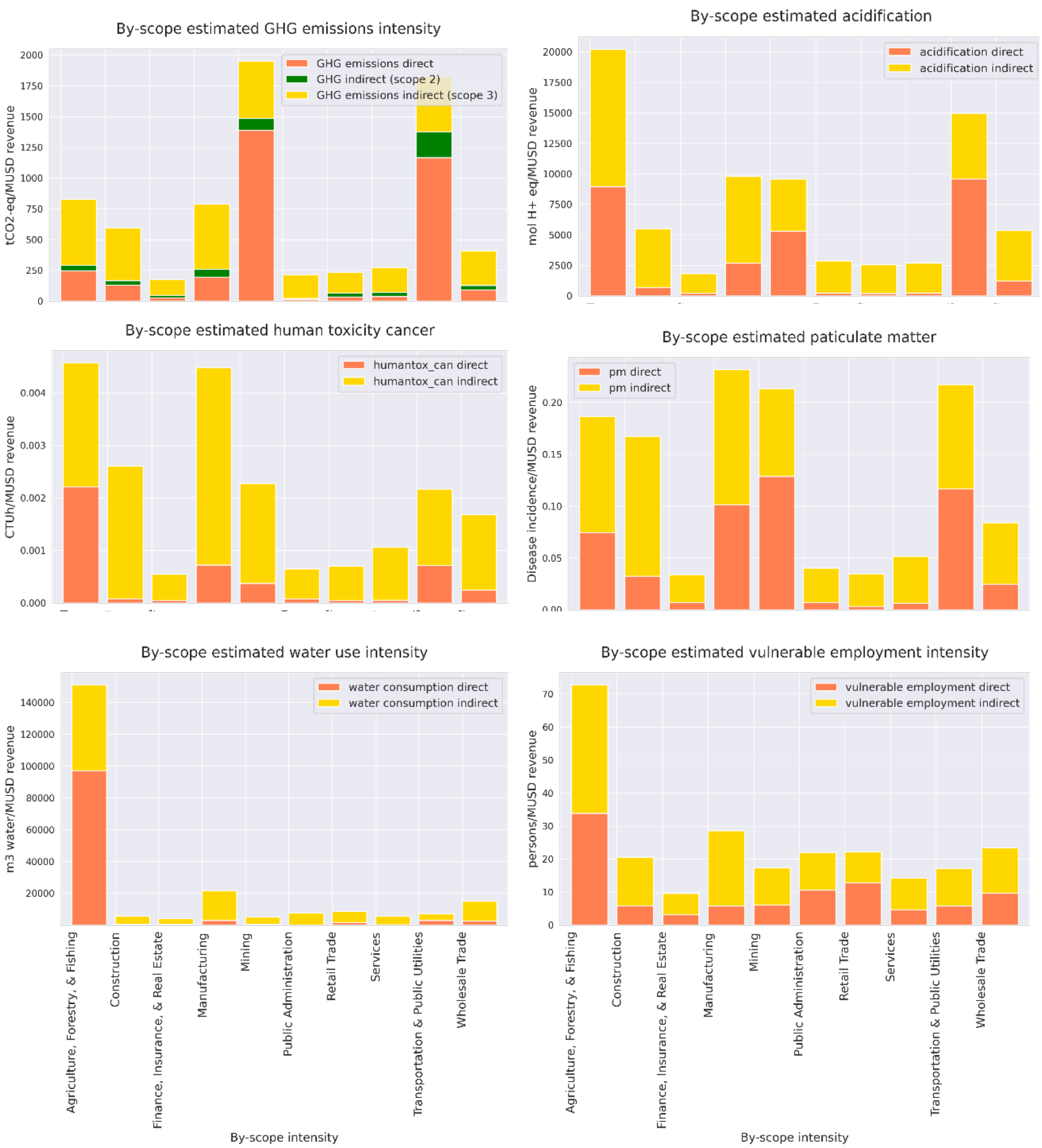


Figure 6.1: Mean impact intensity, per industry.

Direct and indirect intensity illustrated with different colors. For GHG emissions, we split between scope 1 (direct), scope 2 and scope 3 upstream (indirect). We show a separate graph for each indicator. Only observations for year 2019 are shown, to avoid differences between years.

Table 6.4: Top 10 companies by life cycle impact

Company values are for year 2019, listed in separate tables for each impact indicator.

Panel A1: Direct GHG emissions (MtCO2-eq), top 10 companies, year 2019

Name	Ctr	Industry	SIC description	Direct abs	Indirect abs	Sales (MUSD)
China Petroleum & Chemical Corp.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	530	357	394,081
Saudi Arabian Oil Co.	SA	Oil & Gas Extraction	Crude Petroleum and Natural Gas	390	257	329,810
Enel SpA	IT	Transport and Utilities	Electric Services	361	52	86,596
Saudi Electricity Co.	SA	Transport and Utilities	Electric Services	341	5	17,344
PetroChina Co., Ltd.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	304	261	340,352
China National Building Material Co., Ltd.	CN	Manufacturing	Cement, Hydraulic	200	47	36,672
China Shenhua Energy Co., Ltd.	CN	Mining	Coal Mining Services	168	90	35,003
Anhui Conch Cement Co., Ltd.	CN	Manufacturing	Cement, Hydraulic	157	31	22,517
Shell Plc	GB	Oil & Gas Extraction	Crude Petroleum and Natural Gas	154	349	340,832
Iberdrola SA	ES	Transport and Utilities	Electric Services	148	18	40,785

Panel A2: Indirect GHG emissions (MtCO2-eq), top 10 companies, year 2019

Name	Ctr	Industry	SIC description	Direct abs	Indirect abs	Sales (MUSD)
China Petroleum & Chemical Corp.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	530	357	394,081
Shell Plc	GB	Oil & Gas Extraction	Crude Petroleum and Natural Gas	154	349	340,832
BP Plc	GB	Oil & Gas Extraction	Oil and Gas Field Exploration Services	102	280	279,052
PetroChina Co., Ltd.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	304	261	340,352
Saudi Arabian Oil Co.	SA	Oil & Gas Extraction	Crude Petroleum and Natural Gas	390	257	329,810
China State Construction Engineering Corp. Ltd.	CN	Finance, RE and Services	Highway and Street Construction, Except Elevated Highways	3	246	202,942
Exxon Mobil Corp.	US	Oil & Gas Extraction	Crude Petroleum and Natural Gas	95	231	255,997
Oil Co. LUKOIL PJSC	RU	Manufacturing	Petroleum Refining	30	199	114,581
China Railway Group Ltd.	CN	Finance, RE and Services	Heavy Construction, Not Elsewhere Classified	4	170	123,132
China Railway Construction Corp. Ltd.	CN	Finance, RE and Services	Heavy Construction, Not Elsewhere Classified	2	156	119,510

Panel B1: Direct Acidification (million mol H+), top 10 companies, year 2019

Name	**Ctr**	**Industry**	**SIC description**	**Direct abs**	**Indirect abs**	**Sales (MUSD)**
Japfa Ltd.	SG	Manufacturing	Prepared Feed and Feed Ingr. for Animals/Fowls Except Dogs/Cats	3,913	43	3,890
Nippon Yusen KK	JP	Transport and Utilities	Deep Sea Foreign Transportation of Freight	3,298	41	16,786
Saudi Electricity Co.	SA	Transport and Utilities	Electric Services	2,610	73	17,344
Enel SpA	IT	Transport and Utilities	Electric Services	2,327	231	86,596
Neoenergia SA	BR	Transport and Utilities	Electric Services	2,150	43	7,216
Enel Américas SA	CL	Transport and Utilities	Electric Services	1,937	58	13,839
China National Building Material Co., Ltd.	CN	Manufacturing	Cement, Hydraulic	1,825	625	36,672
Iberdrola SA	ES	Transport and Utilities	Electric Services	1,767	90	40,785
CPFL Energia SA	BR	Transport and Utilities	Electric Services	1,710	29	7,589
Centrais Elétricas Brasileiras SA	BR	Transport and Utilities	Electric Services	1,668	28	7,030

Panel B2: Indirect Acidification (million mol H+), top 10 companies, year 2019

Name	**Ctr**	**Industry**	**SIC description**	**Direct abs**	**Indirect abs**	**Sales (MUSD)**
PetroChina Co., Ltd.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	952	3,368	340,352
JBS SA	BR	Manufacturing	Sausages and Other Prepared Meat Products	31	2,646	51,855
China State Construction Engineering Corp. Ltd.	CN	Finance, RE and Services	Highway and Street Construction, Except Elevated Highways	16	2,277	202,942
China Petroleum & Chemical Corp.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	573	2,128	394,081
WH Group Ltd. (HK)	HK	Manufacturing	Sausages and Other Prepared Meat Products	8	1,791	24,102
Tyson Foods, Inc.	US	Manufacturing	Meat Packing Plants	89	1,777	42,428
China Railway Group Ltd.	CN	Finance, RE and Services	Heavy Construction, Not Elsewhere Classified	22	1,535	123,132
Marfrig Global Foods SA	BR	Manufacturing	Sausages and Other Prepared Meat Products	3	1,474	12,363
Nestlé SA	CH	Manufacturing	Food Preparations, Not Elsewhere Classified	40	1,455	93,151
China Railway Construction Corp. Ltd.	CN	Finance, RE and Services	Heavy Construction, Not Elsewhere Classified	10	1,453	119,510

Panel C1: Direct human toxicity, cancer (CTUh), top 10 companies, year 2019

Name	Ctr	Industry	SIC description	Direct abs	Indirect abs	Sales (MUSD)
ArcelorMittal SA	LU	Manufacturing	Steel Works, Blast Furnaces (Incl. Coke Ovens), and Rolling Mills	1,568	580	70,619
Ternium SA	LU	Manufacturing	Steel Works, Blast Furnaces (Incl. Coke Ovens), and Rolling Mills	618	122	10,217
En+ Group International PJSC	RU	Mining	Bituminous Coal and Lignite Surface Mining	607	80	11,752
Eregli Demir ve Çelik Fabrikalari TAS	TR	Manufacturing	Steel Works, Blast Furnaces (Incl. Coke Ovens), and Rolling Mills	579	43	4,835
NIPPON STEEL CORP.	JP	Manufacturing	Steel Works, Blast Furnaces (Incl. Coke Ovens), and Rolling Mills	449	594	56,690
United Co. RUSAL International PJSC	RU	Manufacturing	Primary Production of Aluminium	401	84	9,709
Gerdau SA	BR	Manufacturing	Steel Works, Blast Furnaces (Incl. Coke Ovens), and Rolling Mills	384	147	10,051
Metalúrgica Gerdau SA	BR	Manufacturing	Steel Works, Blast Furnaces (Incl. Coke Ovens), and Rolling Mills	384	147	10,051
Baoshan Iron & Steel Co., Ltd.	CN	Manufacturing	Steel Works, Blast Furnaces (Incl. Coke Ovens), and Rolling Mills	377	1,464	42,074
Tata Steel Ltd.	IN	Manufacturing	Steel Works, Blast Furnaces (Incl. Coke Ovens), and Rolling Mills	361	120	22,387

Panel C2: Indirect human toxicity, cancer (CTUh), top 10 companies, year 2019

Name	Ctr	Industry	SIC description	Direct abs	Indirect abs	Sales (MUSD)
China State Construction Engineering Corp. Ltd.	CN	Finance, RE and Services	Highway and Street Construction, Except Elevated Highways	2	1,476	202,942
Baoshan Iron & Steel Co., Ltd.	CN	Manufacturing	Steel Works, Blast Furnaces (Incl. Coke Ovens), and Rolling Mills	377	1,464	42,074
China Railway Group Ltd.	CN	Finance, RE and Services	Heavy Construction, Not Elsewhere Classified	2	983	123,132
China Railway Construction Corp. Ltd.	CN	Finance, RE and Services	Heavy Construction, Not Elsewhere Classified	1	959	119,510
SAIC Motor Corp. Ltd.	CN	Manufacturing	Motor Vehicles and Passenger Car Bodies	2	908	121,063
Volkswagen AG	DE	Manufacturing	Motor Vehicles and Passenger Car Bodies	4	885	282,773
China Petroleum & Chemical Corp.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	55	838	394,081
Toyota Motor Corp.	JP	Manufacturing	Motor Vehicles and Passenger Car Bodies	4	817	277,346
PetroChina Co., Ltd.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	29	781	340,352
Samsung Electronics Co., Ltd.	KR	Electronics & Telecom	Radio and Television Broadcasting and Communications Equipment	4	753	197,552

Panel D1: Direct particulate matter (Disease incidence), top 10 companies, year 2019

Name	Ctr	Industry	SIC description	Direct abs	Indirect abs	Sales (MUSD)
China National Building Material Co., Ltd.	CN	Manufacturing	Cement, Hydraulic	116,927	20,859	36,672
Anhui Conch Cement Co., Ltd.	CN	Manufacturing	Cement, Hydraulic	91,069	14,739	22,517
ArcelorMittal SA	LU	Manufacturing	Steel Works, Blast Furnaces (Incl. Coke Ovens), and Rolling Mills	70,161	18,568	70,619
Nippon Yusen KK	JP	Transport and Utilities	Deep Sea Foreign Transportation of Freight	55,318	582	16,786
Holcim Ltd.	CH	Manufacturing	Cement, Hydraulic	41,368	6,015	26,890
Saudi Electricity Co.	SA	Transport and Utilities	Electric Services	34,081	1,315	17,344
The Siam Cement Public Co. Ltd.	TH	Manufacturing	Cement, Hydraulic	30,151	2,788	14,109
PetroChina Co., Ltd.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	28,532	49,646	340,352
Enel SpA	IT	Transport and Utilities	Electric Services	27,336	4,216	86,596
Japfa Ltd.	SG	Manufacturing	Prepared Feed and Feed Ingr. for Animals/Fowls Except Dogs/Cats	27,262	446	3,890

Panel D2: Indirect particulate matter (Disease incidence), top 10 companies, year 2019

Name	Ctr	Industry	SIC description	Direct abs	Indirect abs	Sales (MUSD)
China State Construction Engineering Corp. Ltd.	CN	Finance, RE and Services	Highway and Street Construction, Except Elevated Highways	162	73,569	202,942
PetroChina Co., Ltd.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	28,532	49,646	340,352
China Railway Group Ltd.	CN	Finance, RE and Services	Heavy Construction, Not Elsewhere Classified	261	48,895	123,132
China Railway Construction Corp. Ltd.	CN	Finance, RE and Services	Heavy Construction, Not Elsewhere Classified	100	46,721	119,510
China Petroleum & Chemical Corp.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	5,727	34,330	394,081
China Communications Construction Co. Ltd.	CN	Finance, RE and Services	Heavy Construction, Not Elsewhere Classified	92	33,155	79,963
Toyota Motor Corp.	JP	Manufacturing	Motor Vehicles and Passenger Car Bodies	488	27,202	277,346
Volkswagen AG	DE	Manufacturing	Motor Vehicles and Passenger Car Bodies	367	25,712	282,773
Samsung Electronics Co., Ltd.	KR	Electronics & Telecom	Radio and Television Broadcasting and Communications Equipment	515	22,746	197,552
SAIC Motor Corp. Ltd.	CN	Manufacturing	Motor Vehicles and Passenger Car Bodies	174	21,995	121,063

Panel E1: Direct water use (million m3), top 10 companies, year 2019

Name	**Ctr**	**Industry**	**SIC description**	**Direct abs**	**Indirect abs**	**Sales (MUSD)**
Japfa Ltd.	SG	Manufacturing	Prepared Feed and Feed Ingr. for Animals/Fowls Except Dogs/Cats	1,468	129	3,890
Golden Agri-Resources Ltd.	SG	Manufacturing	Vegetable Oil Mills, Except Corn, Cottonseed, and Soybean	1,421	579	6,431
Sime Darby Plantation Bhd.	MY	Agriculture	Crop Planting, Cultivating, and Protecting	1,386	325	2,911
Yara International ASA	NO	Manufacturing	Nitrogenous Fertilizers	1,284	148	12,858
FGV Holdings Bhd.	MY	Manufacturing	Vegetable Oil Mills, Except Corn, Cottonseed, and Soybean	1,227	581	3,200
Shenzhen Cereals Holdings Co., Ltd.	CN	Manufacturing	Bottled and Canned Soft Drinks and Carbonated Waters	727	62	1,598
Batu Kawan Bhd.	MY	Manufacturing	Industrial Inorganic Chemicals, Not Elsewhere Classified	629	205	3,873
Kuala Lumpur Kepong Bhd.	MY	Agriculture	Cash Grains, Not Elsewhere Classified	619	197	3,750
Neoenergia SA	BR	Transport and Utilities	Electric Services	581	17	7,216
Baoshan Iron & Steel Co., Ltd.	CN	Manufacturing	Steel Works, Blast Furnaces (Incl. Coke Ovens), and Rolling Mills	577	519	42,074

Panel E2: Indirect water use (million m3), top 10 companies, year 2019

Name	**Ctr**	**Industry**	**SIC description**	**Direct abs**	**Indirect abs**	**Sales (MUSD)**
Nestlé SA	CH	Manufacturing	Food Preparations, Not Elsewhere Classified	42	7,066	93,151
Archer-Daniels-Midland Co.	US	Manufacturing	Vegetable Oil Mills, Except Corn, Cottonseed, and Soybean	83	6,752	64,691
Wilmar International Ltd.	SG	Agriculture	Crop Planting, Cultivating, and Protecting	68	5,967	42,634
Mitsubishi Corp.	JP	Retail and Trade	Durable Goods, Not Elsewhere Classified	37	4,700	147,772
PepsiCo, Inc.	US	Manufacturing	Bottled and Canned Soft Drinks and Carbonated Waters	11	4,582	67,173
China Petroleum & Chemical Corp.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	60	3,557	394,081
Bunge Ltd.	US	Manufacturing	Vegetable Oil Mills, Except Corn, Cottonseed, and Soybean	88	3,462	41,143
Kweichow Moutai Co., Ltd.	CN	Manufacturing	Wines, Brandy, and Brandy Spirits	1	3,299	11,014
Unilever Plc	GB	Manufacturing	Perfumes, Cosmetics, and Other Toilet Preparations	63	3,250	58,151
Anheuser-Busch InBev SA/NV	BE	Manufacturing	Malt Beverages	7	3,230	52,332

Panel F1: Direct vulnerable employment (1,000 workers), top 10 companies, year 2019

Name	Ctr	Industry	SIC description	Direct abs	Indirect abs	Sales (MUSD)
PetroChina Co., Ltd.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	17,452	9,538	340,352
China Petroleum & Chemical Corp.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	11,745	9,934	394,081
JD.com, Inc.	CN	Retail and Trade	Catalog and Mail-Order Houses	5,870	431	83,486
Glencore Plc	CH	Retail and Trade	Petroleum and Pete. Prods. Whslers., Excp. Bulk Stations/Terms.	4,341	4,215	215,008
China State Construction Engineering Corp. Ltd.	CN	Finance, RE and Services	Highway and Street Construction, Except Elevated Highways	3,402	5,295	202,942
Alibaba Group Holding Ltd.	CN	Retail and Trade	Catalog and Mail-Order Houses	2,944	626	56,197
Wen's Foodstuff Group Co., Ltd.	CN	Agriculture	Animal Specialties, Not Elsewhere Classified	2,772	1,277	10,568
Suning.com Co., Ltd.	CN	Retail and Trade	Household Appliance Stores	2,706	175	38,801
Walmart, Inc.	US	Retail and Trade	Grocery Stores	2,706	568	482,717
China Railway Group Ltd.	CN	Finance, RE and Services	Heavy Construction, Not Elsewhere Classified	2,209	3,521	123,132

Panel F2: Indirect vulnerable employment (1,000 workers), top 10 companies, year 2019

Name	Ctr	Industry	SIC description	Direct abs	Indirect abs	Sales (MUSD)
China Petroleum & Chemical Corp.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	11,745	9,934	394,081
PetroChina Co., Ltd.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	17,452	9,538	340,352
Wilmar International Ltd.	SG	Agriculture	Crop Planting, Cultivating, and Protecting	181	6,052	42,634
China State Construction Engineering Corp. Ltd.	CN	Finance, RE and Services	Highway and Street Construction, Except Elevated Highways	3,402	5,295	202,942
Glencore Plc	CH	Retail and Trade	Petroleum and Pete. Prods. Whslers., Excp. Bulk Stations/Terms.	4,341	4,215	215,008
China Life Insurance Co. Ltd.	CN	Finance, RE and Services	Life Insurance	37	3,856	132,475
China Railway Group Ltd.	CN	Finance, RE and Services	Heavy Construction, Not Elsewhere Classified	2,209	3,521	123,132
Nestlé SA	CH	Manufacturing	Food Preparations, Not Elsewhere Classified	229	3,417	93,151
China Railway Construction Corp. Ltd.	CN	Finance, RE and Services	Heavy Construction, Not Elsewhere Classified	2,155	3,395	119,510
Mitsubishi Corp.	JP	Retail and Trade	Durable Goods, Not Elsewhere Classified	298	3,154	147,772

Table 6.5: Total impacts by year and by impact category

This sample contains all companies for which IOLCA-based sustainability impacts were estimated, before matching with the financial data.

Impact category / Year		2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
GHG emissions (MtCO2)	**direct**	7,548	11,879	13,502	15,352	13,052	13,824	14,596	16,029	13,065	7,299
	indirect	10,867	17,613	19,581	80,580	18,082	19,789	20,445	23,370	20,127	13,027
acidification (million mol H+)	**direct**	51,486	95,348	106,087	105,235	99,872	112,100	120,023	118,847	115,041	76,827
	indirect	90,816	169,427	187,615	838,254	173,878	200,909	202,500	219,766	214,407	134,961
human toxicity cancer (CTUh)	**direct**	25,168	27,813	31,091	29,981	22,248	35,790	26,192	21,606	33,657	12,196
	indirect	46,605	81,874	92,332	470,234	88,248	120,920	113,663	112,514	115,354	68,906
particulate matter (DALYs)	**direct**	1,041,072	2,113,163	2,395,917	2,599,941	2,125,790	2,462,678	2,591,427	2,700,359	2,690,538	1,544,124
	indirect	1,677,852	3,205,416	3,427,188	25,151,011	3,178,135	3,829,364	3,815,097	4,163,628	4,145,589	2,474,834
water use (Mm3)	**direct**	21,923	47,701	57,595	61,274	51,360	56,435	63,420	60,282	59,296	32,822
	indirect	180,628	356,057	412,605	1,100,415	413,756	453,941	459,332	473,314	483,144	325,586
vulnerable employment (1000 workers)	**direct**	60,231	144,425	177,749	673,833	209,896	236,787	256,950	266,769	262,078	138,766
	indirect	171,219	367,547	455,017	2,327,295	476,521	524,115	563,761	594,001	600,990	360,552
sales allocated (bnUSD)		25,022	40,136	45,269	532,804	42,137	46,167	51,145	53,519	49,493	38,595
nb. of unique company ISINs per year		4,319	17,387	20,900	22,103	20,878	22,511	24,468	25,273	25,285	11,869

Table 6.6: Total impacts by main industry and impact category

Data is for year 2019. This sample contains all companies for which IOLCA-based sustainability impacts were estimated, before matching with the financial data.

Impact category and scope / Industry		Agriculture	Electronics & Telecom	Finance and Services	Manufacturing	Mining	Oil & Gas Extraction	Retail and Trade	Transport and Utilities
GHG emissions (MtCO2-eq)	dir	50	134	599	3,651	1,315	3,033	390	6,859
	indir	220	1,911	3,703	9,702	906	2,998	1,239	2,691
	lc	270	2,045	4,302	13,353	2,221	6,031	1,629	9,550
Acidifcation (mil mol H+)	dir	3,181	818	3,191	47,797	7,584	7,398	1,805	47,072
	indir	4,478	20,100	34,282	109,519	7,735	13,520	11,910	18,222
	lc	7,659	20,918	37,473	157,316	15,319	20,918	13,715	65,294
Human toxicity cancer (CTUh)	dir	319	97	566	16,715	1,128	260	473	2,049
	indir	1,047	15,297	15,877	62,376	3,363	6,036	3,842	4,675
	lc	1,366	15,394	16,443	79,091	4,491	6,296	4,315	6,724
Particulate matter (DALY)	dir	24,906	13,847	97,353	1,723,113	148,145	114,369	31,690	546,935
	indir	41,134	456,563	769,620	2,017,346	133,727	240,202	164,385	340,651
	lc	66,040	470,410	866,973	3,740,459	281,872	354,571	196,075	887,586
Water use (Mm3)	dir	8,041	2,259	1,841	35,732	753	351	2,102	9,203
	indir	16,844	28,417	60,783	299,528	7,003	15,884	31,471	13,385
	lc	24,885	30,676	62,624	335,260	7,756	16,235	33,573	22,588
Vulnerable employment (1,000 persons)	dir	9,203	18,455	49,722	68,617	8,821	33,302	69,417	9,233
	indir	17,120	51,909	119,671	284,331	20,237	34,694	36,848	29,192
	lc	26,323	70,364	169,393	352,948	29,058	67,996	106,265	38,425
Sales (MUSD allocated)		204,923	4,933,295	13,671,492	15,347,237	773,561	3,233,424	6,130,248	3,519,798
Nb companies (year 2019)		393	3,659	7,289	10,015	439	448	1,703	1,327

Table 6.7: Summary statistics for variables used in the regression

Panel A shows measures of GHG emissions, natural logarithm absolute emissions (measured in ktCO$_2$-eq), intensity values, measured in tCO$_2$-eq per MUSD and winsorized at 2.5% (_w). Change in emissions is the year-on-year change. Scope 1 denotes direct emissions, Scope 2 emissions from electricity and heat purchased and Scope 3 emissions from the upstream value chain (supply chain) of the company. Panel B shows the summary statistics for all other IOLCA-estimated sustainability variables, as natural logarithm value. ***Water use*** *is in Mm3.* ***Vulnerable employment*** *is in 1,000 persons.* ***Human toxicity cancer effects*** *are in CTUh.* ***Particulate matter formatio****n is in DALY. Acidification is in mol H$^+$. Panel C summarizes the financial controls used in the model.* ***Returns*** *are in percentages.* ***Momentum*** *(mom), expressed by the average of the most recent 12 months returns, up to month t-1. LOGSIZE is the market value of the company, in million USD, here using the natural logarithm. Capex to assets is the capital expenditures (CAPEX) as percent of total assets (capextoassets). BTOM is the book-to-market ratio, computed as the firm's book value (or shareholders' equity) divided by mcap. Leverage (lvrg) is the ratio of Debt to Assets.LOGPPE is the physical capital owned by the company, computed using the firm's value for property, plant & equipment. Volatility (volat) is computed as the standard deviation of returns, considering the returns from the past 12 months. MSCI is the MSCI World Index dummy. HHI is a proxy for the industry concentration – Herfindahl–Hirschman Index (HHI), computed based on a company's EXIOBASE industry breakdown. Panel D and E show the distribution of sustainability variables in original units, not logarithmic: GHG emissions in kgCO2-eq, water use in m3, vulnerable employment in 1,000 persons, human toxicity cancer effects in CTUh * 10-3, particulate matter formation in DALY, and acidification in mol H$^+$ eq. Panel F shows summary statics for GHG emissions, computed with both IOLCA model and from Trucost, for a smaller sample matching the coverage in Trucost.*

Panel A: GHG emissions variables

	Mean	Median	SD	Min	Max	p25	p75
logs1abs ghg	9.465	9.258	2.748	-5.533	20.137	7.612	11.159
logs2abs ghg	9.151	9.149	2.376	-5.437	17.542	7.688	10.654
logs3abs ghg	11.406	11.46	2.232	-3.752	19.681	10.067	12.821
s1int ghg w	226.764	30.168	564.344	4.714	2981.256	14.031	133.619
s2int ghg w	57.192	35.548	68.233	2.675	352.945	19.608	64.933
s3int ghg w	443.561	376.873	313.457	49.225	1295.62	195.846	613.417
s1chg ghg w	.114	.009	0.563	-.706	2.559	-.138	.188
s2chg ghg w	.254	.002	1.086	-.83	5.434	-.225	.294
s3chg ghg w	.088	.013	0.444	-.641	1.816	-.139	.198

Panel B: Other sustainability indicator variables

	Mean	Median	SD	Min	Max	p25	p75
logdirabs wat	10.388	10.915	3.683	0	22.844	8.34	12.834
logindirabs wat	14.371	14.436	2.383	.393	23.136	12.91	15.917
logdirabs vemp	.96	.47	1.200	0	9.74	.1	1.389
logindirabs vemp	1.71	1.353	1.475	0	9.204	.495	2.577
logdirabs htoxcan	2.342	1.757	2.236	0	16.408	.505	3.545
logindirabs htoxcan	6.093	6.152	2.309	0	15.115	4.585	7.629
logdirabs pm	1.33	.555	1.790	0	11.682	.11	1.845
logindirabs pm	3.18	3.057	1.910	0	11.346	1.707	4.426
logdirabs aci	10.988	10.834	3.013	0	22.329	8.979	12.844
logindirabs aci	13.835	13.914	2.283	.312	22.067	12.467	15.3
dirint wat w	1218.412	279.516	2991.244	.027	16278.159	23.169	985.88
indirint wat w	13924.315	6274.62	21217.065	478.889	105622.88	2727.339	14502.18
dirint vemp w	.005	.002	0.007	0	.031	.001	.006
indirint vemp w	.018	.01	0.021	.001	.1	.004	.022
dirint aci w	1682.478	167.249	4723.368	7.396	25393.186	50.828	825.219
indirint aci w	5784.727	4219.382	5143.267	373.272	22953.613	1945.461	8221.084
dirint pm w	.033	.003	0.109	0	.612	.001	.01
indirint pm w	.107	.081	0.094	.006	.396	.034	.151
dirint htoxcan w	.203	.017	0.718	0	4.039	.004	.064
indirint htoxcan w	2.857	1.832	3.016	.107	12.92	.682	3.946

Panel C: Summary Statistics control variables

	Mean	Median	SD	Min	Max	p25	p75
ret	.806	-.03	13.079	-97.201	99.967	-5.766	6.122
logsize unadj	5.735	5.644	2.008	-3.915	13.609	4.289	7.038
btom bk w	.93	.644	0.907	.075	4.456	.339	1.171
lvrg	.467	.467	0.211	.004	1.063	.303	.62
mom w	.008	.004	0.035	-.061	.103	-.014	.026
capextoas w	.043	.029	0.043	.001	.184	.012	.059
hhi exio	.84	.98	0.210	.11	1	.678	1
hhi	6303.622	5847.181	2728.553	351.42	10000	3963.249	9342.263
logppe	4.306	4.334	2.438	-6.795	12.467	2.881	5.845
roe w	3.198	7.299	23.245	-92.4	39.292	1.238	13.71
volat w	.114	.099	0.063	.033	.313	.069	.142
msci	.035	0	0.185	0	1	0	0
salesgr w	.075	.042	0.267	-.458	1.035	-.053	.154
mcap unadj	2.787e+09	2.827e+08	1.419e+10	19940.904	8.134e+11	72918264	1.139e+09
sales	2355.352	255.739	11397.458	0	559131.25	74.561	1014.823

Panel D: GHG emissions variables, original

	Mean	Median	SD	Min	Max	p25	p75
s1abs ghg	738,200,000	10,489,853	6,943,145,410	3.95	556,600,000,000	2,023,121	70,162,016
s2abs ghg	137,500,000	9,402,498	848,688,717	4.35	41,550,000,000	2,182,232	42,356,500
s3abs ghg	943,500,000	94,835,312	6,087,043,437	23.47	352,700,000,000	23,556,264	369,900,000

Panel E: Other sustainability indicator variables, original

	Mean	Median	SD	Min	Max	p25	p75
dirabs wat	3,169,197	54,993	40,623,000	0.00	8,337,000,000	4,188	374,891
indirabs wat	24,233,475	1,859,600	166,114,672	0.48	11,160,000,000	404,407	8,179,824
dirabs vemp	11.70	0.60	122	0.00	16,989	0.11	3.01
indirabs vemp	26.66	2.87	138	0.00	9,934	0.64	12.16
dirabs htoxcan	1,698	4.79	67,188	0.00	13,361,720	0.66	33.66
indirabs htoxcan	5,768	469	36,486	0.00	3,668,782	97.04	2,056
dirabs pm	136	0.74	1,571	0.00	118,439	0.12	5.33
indirabs pm	202	20	1,146	0.00	84,613	4.51	82.58
dirabs aci	5,922,335	50,726	66,638,006	0.00	4,982,000,000	7,937	378,365
indirabs aci	10,691,860	1,103,689	61,119,573	0.37	3,833,000,000	259,713	4,411,228

Panel F: Trucost-matched sample, own IOLCA-estimated GHG emissions and Trucost data

	Mean	Median	SD	Min	Max	p25	p75
s1abs ghg	957,834.73	22,777.73	6,236,391.01	0.166	340,600,000.00	4,859.66	130,427.77
s2abs ghg	180,643.15	22,557.13	803,656.36	0.095	35,528,948.00	5,971.03	84,148.23
s3abs ghg	1,272,187.80	211,036.65	6,273,367.02	0.910	294,300,000.00	58,172.27	733,637.56
lifecycleabs ghg	2,410,665.60	303,077.02	11,012,864.55	1.209	436,400,000.00	80,508.52	1,124,908.30
trucost s1abs ghg	1,024,576.60	16,658.13	7,587,060.27	0.000	323,700,000.00	3,467.49	92,747.86
trucost s2abs ghg	167,193.68	17,188.42	1,377,120.45	0.000	155,800,000.00	4,267.01	69,497.88
trucost s3abs ghg	781,292.90	110,914.91	3,702,929.07	0.390	151,200,000.00	28,379.75	415,342.06
trucost lifecyclea~g	1,973,063.20	181,103.00	10,090,790.43	0.783	424,300,000.00	43,664.49	755,010.50
logs1abs ghg	10.27	10.03	2.53	-1.79	19.65	8.49	11.78
logs2abs ghg	10.01	10.02	2.10	-2.35	17.39	8.70	11.34
logs3abs ghg	12.21	12.26	1.97	-0.09	19.50	10.97	13.51
trucost logs1abs ghg	2.98	2.82	2.73	-9.34	12.69	1.25	4.53
trucost logs2abs ghg	2.82	2.85	2.19	-9.71	11.96	1.45	4.24
trucost logs3abs ghg	4.66	4.71	2.08	-7.85	11.93	3.35	6.03
s1int ghg w	0.21	0.02	0.54	0.004	2.83	0.01	0.11
s2int ghg w	0.05	0.03	0.06	0.002	0.33	0.02	0.06
s3int ghg w	0.38	0.32	0.30	0.038	1.28	0.13	0.53
trucost s1int ghg w	0.19	0.02	0.55	0.001	2.87	0.01	0.06
trucost s2int ghg w	0.04	0.02	0.06	0.001	0.27	0.01	0.04
trucost s3int ghg w	0.20	0.15	0.18	0.024	0.83	0.06	0.27

Table 6.8: Cross-correlations between scopes and metrics, by impact indicator

Panel A: Carbon Emissions Cross-Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) logs1abs_ghg	1.000								
(2) logs2abs_ghg	0.813	1.000							
(3) logs3abs_ghg	0.831	0.916	1.000						
(4) s1int_ghg_w	0.522	0.194	0.140	1.000					
(5) s2int_ghg_w	0.297	0.407	0.190	0.432	1.000				
(6) s3int_ghg_w	0.225	0.223	0.343	0.218	0.462	1.000			
(7) s1chg_ghg_w	0.060	0.002	-0.005	0.081	0.053	0.041	1.000		
(8) s2chg_ghg_w	0.022	0.074	0.005	0.039	0.199	0.094	0.384	1.000	
(9) s3chg_ghg_w	0.011	0.020	0.027	0.026	0.056	0.099	0.547	0.473	1.000

Panel B: Acidification Cross-Correlations

Variables	(1)	(2)	(3)	(4)
(1) logdirabs_aci	1.000			
(2) logindirabs_aci	0.807	1.000		
(3) dirint_aci_w	0.515	0.168	1.000	
(4) indirint_aci_w	0.275	0.368	0.277	1.000

Panel C: Human toxicity cancer Cross-Correlations

Variables	(1)	(2)	(3)	(4)
(1) logdirabs_ htoxcan	1.000			
(2) logindirabs_htoxcan	0.701	1.000		
(3) dirint_htoxcan_w	0.579	0.141	1.000	
(4) indirint_htoxcan_w	0.214	0.450	0.210	1.000

Panel D: Particulate Matter Cross-Correlations

Variables	(1)	(2)	(3)	(4)
(1) logdirabs_pm	1.000			
(2) logindirabs_pm	0.694	1.000		
(3) dirint_pm_w	0.658	0.193	1.000	
(4) indirint_pm_w	0.273	0.405	0.339	1.000

Panel E: Water Use Cross-Correlations

Variables	(1)	(2)	(3)	(4)
(1) logdirabs_wat	1.000			
(2) logindirabs_wat	0.760	1.000		
(3) dirint_wat_w	0.485	0.139	1.000	
(4) indirint_wat_w	0.240	0.443	0.210	1.000

Panel F: Vulnerable employment Cross-Correlations

Variables	(1)	(2)	(3)	(4)
(1) logdirabs_vemp	1.000			
(2) logindirabs_vemp	0.781	1.000		
(3) dirint_vemp_w	0.451	0.151	1.000	
(4) indirint_vemp_w	0.104	0.353	0.392	1.000

Table 6.9: Autocorrelations between impact indicators

Autocorrelations are between ghg emissions at time t and at time t-12. The dependent variables for all regression tables are the logged absolute levels of direct and indirect impacts

Panel A: Autocorrelation log12months vs. current value GHG emissions

VARIABLES	(1) logdirabs_ghg	(2) logindirabs_ghg	(3) logdirabs_ghg	(4) logindirabs_ghg
L12.logdirabs_ghg	0.975***		0.423***	
	(0.002)		(0.056)	
L12.logindirabs_ghg		0.978***		0.426***
		(0.001)		(0.062)
Constant	0.246***	0.265***	5.553***	6.713***
	(0.028)	(0.018)	(0.539)	(0.720)
Observations	99,971	99,971	96,802	96,802
R-squared	0.949	0.952	0.970	0.973
Yr/mo FE	N	N	Y	Y
Company FE	N	N	Y	Y

Panel B: Autocorrelation log12months vs. current value Water Use

VARIABLES	(1) logdirabs_wat	(2) logindirabs_wat	(3) logdirabs_wat	(4) logindirabs_wat
L12.logdirabs_wat	0.962***		0.387***	
	(0.004)		(0.054)	
L12.logindirabs_wat		0.979***		0.443***
		(0.001)		(0.065)
Constant	0.436***	0.334***	6.524***	8.108***
	(0.045)	(0.017)	(0.567)	(0.939)
Observations	99,971	99,971	96,802	96,802
R-squared	0.926	0.955	0.958	0.974
Yr/mo FE	N	N	Y	Y
Company FE	N	N	Y	Y

Panel C: Autocorrelation log12months vs. current value Vulnerable Employment

VARIABLES	(1) logdirabs_vemp	(2) logindirabs_vem p	(3) logdirabs_vemp	(4) logindirabs_vem p
L12.logdirabs_vemp	0.977***		0.449***	
	(0.005)		(0.109)	
L12.logindirabs_vem p		0.991***		0.504***
		(0.002)		(0.088)
Constant	0.036***	0.036***	0.565***	0.904***
	(0.005)	(0.006)	(0.109)	(0.156)
Observations	99,971	99,971	96,802	96,802
R-squared	0.939	0.968	0.963	0.981
Yr/mo FE	N	N	Y	Y
Company FE	N	N	Y	Y

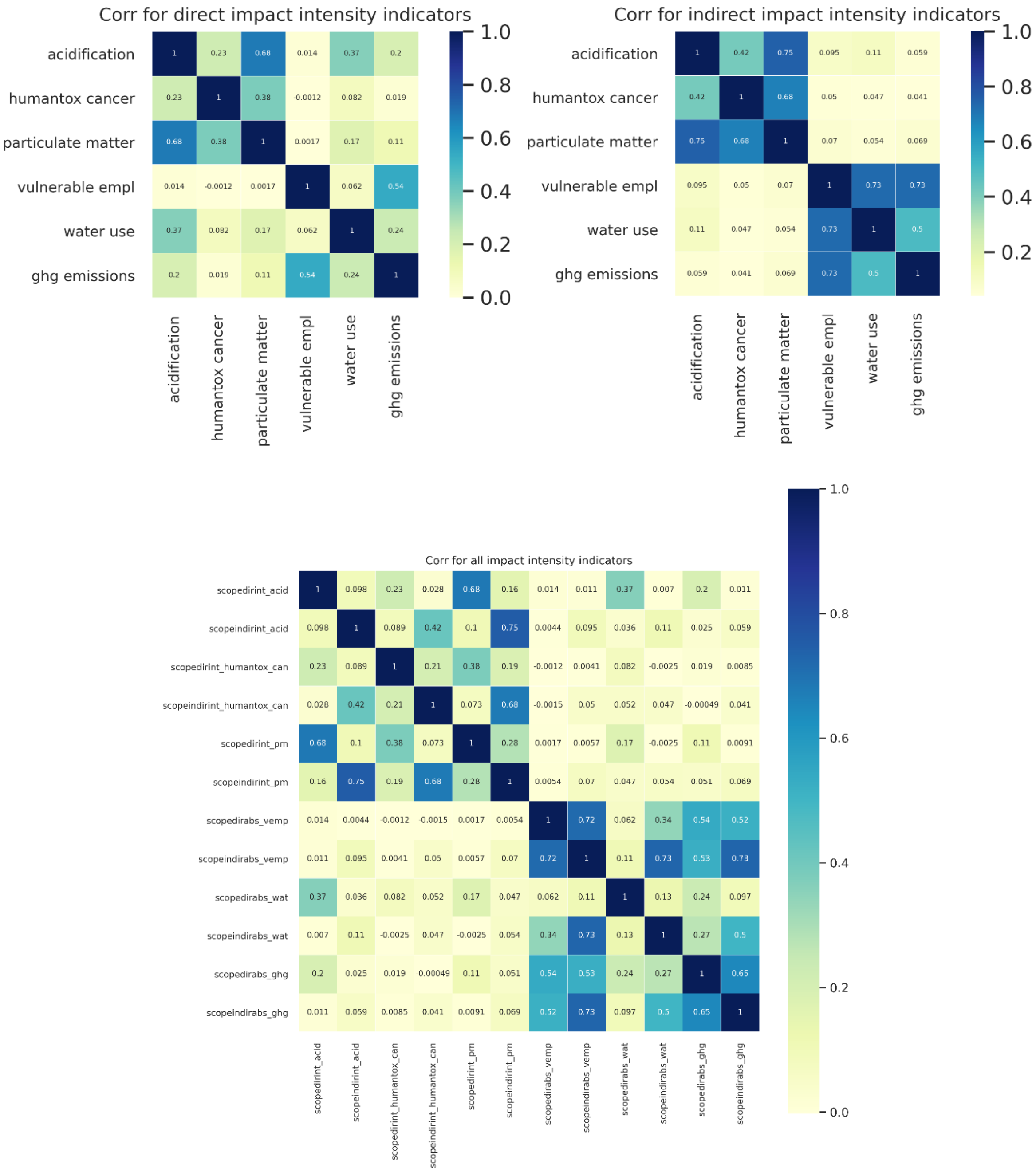


Figure 6.2: Correlation between impact indicators

Correlations are computed for year 2019, all companies in the sample. This figure displays the pairwise correlation between IOLCA-estimated impacts. The correlations are computed for the complete sample of companies for year 2019, 27,896 unique companies where data was available for all indicators. The upper left graph shows the correlation between direct impact intensities, while the upper right graph shows the correlation for the indirect impact intensities. The lower graph shows the correlations between direct and indirect scopes together.

Table 6.10: Correlations between impact indicators

Panel A shows correlations between absolute levels of impact. Panel B absolute levels of impact, but in natural logarithm, while Panel C shows correlations between intensity metrics.

Panel A: Correlations between impacts, absolute values, raw

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) dirabs_ghg	1.000											
(2) indirabs_ghg	**0.541**	1.000										
(3) dirabs_aci	**0.672**	0.299	1.000									
(4) indirabs_aci	0.344	**0.761**	0.223	1.000								
(5) dirabs_htoxcan	0.360	0.178	0.210	0.155	1.000							
(6) indirabs_htoxcan	0.267	**0.688**	0.190	**0.696**	0.165	1.000						
(7) dirabs_pm	**0.591**	0.273	**0.700**	0.231	**0.471**	0.261	1.000					
(8) indirabs_pm	0.351	**0.815**	0.239	**0.851**	0.173	**0.887**	0.313	1.000				
(9) dirabs_wat	0.152	0.100	0.324	0.123	0.046	0.143	0.225	0.120	1.000			
(10) indirabs_wat	0.171	0.444	0.112	**0.651**	0.079	0.452	0.094	0.489	0.183	1.000		
(11) dirabs_vemp	0.310	0.399	0.175	0.381	0.122	0.331	0.139	0.429	0.126	0.226	1.000	
(12) indirabs_vemp	0.359	0.721	0.207	**0.815**	0.154	**0.682**	0.204	**0.787**	0.166	0.729	0.527	1

Panel B: Correlations between impacts, absolute values, natural logarithm

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) logdirabs_ghg	1.000											
(2) logindirabs_ghg	0.839	1.000										
(3) logdirabs_aci	0.947	0.820	1.000									
(4) logindirabs_aci	0.798	0.976	0.807	1.000								
(5) logdirabs_htox~n	0.761	0.708	0.834	0.714	1.000							
(6) logindirabs_ht~n	0.741	0.945	0.755	0.958	0.701	1.000						
(7) logdirabs_pm	0.814	0.658	0.865	0.638	0.876	0.605	1.000					
(8) logindirabs_pm	0.782	0.948	0.791	0.957	0.756	0.969	0.694	1.000				
(9) logdirabs_wat	0.793	0.776	0.870	0.787	0.946	0.760	0.795	0.779	1.000			
(10) logindirabs_wat	0.744	0.951	0.758	0.964	0.689	0.996	0.593	0.957	0.760	1.000		
(11) logdirabs_vemp	0.543	0.648	0.546	0.652	0.611	0.639	0.532	0.694	0.594	0.626	1.000	
(12) logindirabs_v~p	0.707	0.861	0.718	0.890	0.723	0.866	0.650	0.917	0.723	0.850	0.781	1

Panel C: Correlation between impacts, intensity values, winsorized

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) dirint_ghg	1.000											
(2) indirint_ghg	0.059	1.000										
(3) dirint_aci_w	0.197	0.253	1.000									
(4) indirint_aci_w	0.006	0.591	0.277	1.000								
(5) dirint_htoxcan_w	0.094	0.189	0.603	0.223	1.000							
(6) dirint_htoxcan_w	0.094	0.189	0.603	0.223	1.000	1.000						
(7) dirint_pm	0.109	0.175	0.663	0.131	0.421	0.421	1.000					
(8) indirint_pm_w	0.021	0.604	0.312	0.817	0.305	0.305	0.270	1.000				
(9) dirint_wat_w	0.094	0.189	0.603	0.223	1.000	1.000	0.421	0.305	1.000			
(10) indirint_wat_w	-0.016	0.411	0.078	0.585	0.210	0.210	0.055	0.808	0.210	1.000		
(11) dirint_vemp_w	-0.014	0.041	0.149	0.158	0.173	0.173	0.057	0.159	0.173	0.061	1.000	
(12) indirint_vemp_w	-0.023	0.334	0.148	0.718	0.119	0.119	0.061	0.519	0.119	0.347	0.392	1

Panel D: Correlation between Trucost and own IOLCA-estimated GHG emissions, absolute

	(1)	(2)	(3)	(4)	(5)	(6)
(1) logs1abs_ghg	1.00	0.78	0.81	0.79	0.70	0.79
(2) logs2abs_ghg	0.78	1.00	0.89	0.71	0.76	0.82
(3) logs3abs_ghg	0.81	0.89	1.00	0.75	0.77	0.90
(4) trucost_logs1abs_ghg	0.79	0.71	0.75	1.00	0.78	0.81
(5) trucost_logs2abs_ghg	0.70	0.76	0.77	0.78	1.00	0.84
(6) trucost_logs3abs_ghg	0.79	0.82	0.90	0.81	0.84	1.00

Panel E: Correlation between Trucost and own IOLCA-estimated GHG emissions, intensity

	(1)	(2)	(3)	(4)	(5)	(6)
(1) s1int_ghg	1.00	0.48	0.57	0.57	0.31	0.51
(2) s2int_ghg	0.48	1.00	0.63	0.35	0.34	0.40
(3) s3int_ghg	0.57	0.63	1.00	0.47	0.35	0.62
(4) trucost_s1int_ghg	0.57	0.35	0.47	1.00	0.55	0.61
(5) trucost_s2int_ghg	0.31	0.34	0.35	0.55	1.00	0.50
(6) trucost_s3int_ghg	0.51	0.40	0.62	0.61	0.50	1.00

Table 6.11: Drivers of GHG emissions

We run regressions with the ghg variable as dependent variable and financial controls as independent variables.

VARIABLES	(1) L.logdirabs_ghg	(2) L.logindirabs_ghg	(3) L.logdirabs_ghg	(4) L.logindirabs_ghg
L.logsize_unadj	0.359***	0.470***	0.509***	0.556***
	(0.0128)	(0.00935)	(0.0109)	(0.00878)
btom_bk_w	0.218***	0.227***	0.318***	0.325***
	(0.0249)	(0.0186)	(0.0186)	(0.0151)
lvrg_w	1.188***	1.611***	1.822***	1.900***
	(0.0759)	(0.0450)	(0.0527)	(0.0368)
capextoas_w	-0.848**	-3.087***	-2.173***	-2.471***
	(0.346)	(0.215)	(0.188)	(0.139)
hhi_exio	-0.904***	-0.420***	-0.746***	-0.289***
	(0.0452)	(0.0315)	(0.0377)	(0.0287)
logppe	0.599***	0.388***	0.408***	0.329***
	(0.0107)	(0.00742)	(0.00934)	(0.00714)
roe_w	0.00627***	0.0109***	0.00928***	0.0108***
	(0.000545)	(0.000385)	(0.000394)	(0.000398)
Constant	4.847***	6.664***	4.336***	6.067***
	(0.0919)	(0.0728)	(0.0741)	(0.0599)
Observations	1,599,994	1,599,994	1,599,994	1,599,994
R-squared	0.646	0.753	0.751	0.795
Yr/mo FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Industry FE	N	N	Y	Y
Adjusted R-squared	0.646	0.752	0.750	0.795

Table 6.12: Drivers of water use, including GHG emissions

We run regressions with the water use variable as dependent variable and ghg emissions and financial controls as independent variables.

VARIABLES	(1) L.logdirabs_wat	(2) L.logindirabs_wat	(3) L.logdirabs_wat	(4) L.logindirabs_wat	(5) L.logdirabs_wat	(6) L.logindirabs_wat	(7) L.logdirabs_wat	(8) L.logindirabs_wat
L.logdirabs_ghg					0.840***		0.805***	
					(0.0140)		(0.0104)	
L.logindirabs_ghg						0.977***		0.947***
						(0.00509)		(0.00460)
L.logsize_unadj	0.0997***	0.479***	0.498***	0.576***	-0.202***	0.0199***	0.0892***	0.0493***
	(0.0211)	(0.0109)	(0.0162)	(0.00932)	(0.0179)	(0.00545)	(0.0142)	(0.00443)
btom_bk_w	-0.228***	0.165***	0.237***	0.325***	-0.410***	-0.0569***	-0.0189	0.0173***
	(0.0400)	(0.0212)	(0.0254)	(0.0161)	(0.0261)	(0.00719)	(0.0177)	(0.00525)
lvrg_w	-0.847***	1.268***	1.158***	1.800***	-1.846***	-0.305***	-0.308***	-0.000661
	(0.134)	(0.0492)	(0.0871)	(0.0418)	(0.113)	(0.0281)	(0.0771)	(0.0203)
capextoas_w	-5.255***	-3.455***	-2.831***	-2.652***	-4.542***	-0.441*	-1.081***	-0.310**
	(0.632)	(0.341)	(0.315)	(0.168)	(0.643)	(0.196)	(0.278)	(0.102)
hhi_exio	-2.082***	-0.611***	-1.626***	-0.436***	-1.323***	-0.201***	-1.025***	-0.163***
	(0.0841)	(0.0417)	(0.0654)	(0.0350)	(0.0757)	(0.0251)	(0.0543)	(0.0179)
logppe	0.697***	0.369***	0.409***	0.312***	0.194***	-0.00948*	0.0807***	-3.07e-05
	(0.0167)	(0.00901)	(0.0140)	(0.00776)	(0.0146)	(0.00459)	(0.0114)	(0.00353)
roe_w	0.00379***	0.0105***	0.00668***	0.0106***	-0.00148	-6.84e-05	-0.000783	0.000301*
	(0.000767)	(0.000349)	(0.000521)	(0.000356)	(0.000877)	(0.000351)	(0.000432)	(0.000151)
Constant	9.385***	9.914***	6.475***	9.032***	5.313***	3.405***	2.985***	3.284***
	(0.159)	(0.0842)	(0.117)	(0.0657)	(0.142)	(0.0492)	(0.0949)	(0.0397)
Observations	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994
R-squared	0.340	0.668	0.608	0.775	0.479	0.876	0.698	0.936
Yr/mo FE	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	N	Y	Y	N	N	Y	Y
Adjusted R-squared	0.340	0.668	0.607	0.775	0.479	0.876	0.698	0.936

Table 6.13: IOLCA-estimated absolute GHG emissions and stock returns, full sample

*The period considered is 2013 – 2021. In Panel A, GHG emissions are in absolute values (kgCO₂-eq, in log values). Financial controls are lagged by one year and GHG emissions are lagged by one month. Columns (4) to (6) include industry-fixed effects. In Panel B, GHG emissions intensity expressed in tCO2-eq/MEUR of revenue. In Panel C, we show the regression with absolute GHG emissions, split into two samples, before and after 2018. In Panel D we run the same regression as in Panel A but using data on GHG emissions from Trucost. In Panel E we show regression results split by region. Robust standard errors are shown in parentheses and are double clustered at company and year level. ***, ** and * denote significance at 1%; 5% and 10% level.*

Panel A

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret
L.logdirabs_ghg	0.0424			0.114***		
	(0.0294)			(0.0290)		
L.logindirabs_ghg		0.277***			0.298***	
		(0.0329)			(0.0336)	
L.loglifecycleabs_ghg			0.194***			0.254***
			(0.0376)			(0.0381)
L.logsize_unadj	-0.207**	-0.322***	-0.275***	-0.294***	-0.402***	-0.372***
	(0.0665)	(0.0663)	(0.0690)	(0.0648)	(0.0662)	(0.0689)
btom_bk_w	0.180*	0.128	0.148	0.174*	0.115	0.130
	(0.0849)	(0.0845)	(0.0841)	(0.0850)	(0.0837)	(0.0843)
lvrg_w	0.241	-0.162	0.00667	0.0741	-0.292	-0.190
	(0.179)	(0.180)	(0.181)	(0.171)	(0.178)	(0.177)
mom_w	8.108	8.242	8.249	7.953	8.126	8.109
	(4.986)	(4.967)	(4.974)	(4.965)	(4.941)	(4.949)
capextoas_w	-1.980	-1.188	-1.633	-1.201	-0.725	-0.894
	(1.087)	(1.074)	(1.086)	(1.033)	(1.025)	(1.020)
hhi_exio	0.105	0.181**	0.148*	0.180*	0.179*	0.171*
	(0.0793)	(0.0746)	(0.0752)	(0.0863)	(0.0838)	(0.0835)
logppe	-0.000634	-0.0810*	-0.0636*	0.0445	-0.00534	0.00121
	(0.0294)	(0.0366)	(0.0309)	(0.0252)	(0.0266)	(0.0241)
roe_w	0.0142***	0.0116***	0.0126***	0.0133***	0.0113***	0.0118***
	(0.00102)	(0.000990)	(0.00103)	(0.00115)	(0.00115)	(0.00118)
volat_w	-0.669	-0.361	-0.554	-0.420	-0.181	-0.279
	(2.735)	(2.746)	(2.735)	(2.654)	(2.652)	(2.647)
Constant	1.280*	-0.406	0.132	0.867	-0.482	-0.275
	(0.583)	(0.654)	(0.640)	(0.600)	(0.634)	(0.618)
Observations	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994
R-squared	0.115	0.116	0.116	0.116	0.117	0.116
Yr/mo FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y
Adjusted R-squared	0.115	0.116	0.116	0.116	0.116	0.116

Panel B

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret
L.dirint_ghg_w	-0.271***			-0.159**		
	(0.0802)			(0.0626)		
L.indirint_ghg_w		0.199**			0.206***	
		(0.0792)			(0.0333)	
L.lifecycleint_ghg_w			-0.123**			-0.0452
			(0.0500)			(0.0349)
L.logsize_unadj	-0.205***	-0.184**	-0.202***	-0.239***	-0.233***	-0.237***
	(0.0620)	(0.0622)	(0.0617)	(0.0595)	(0.0596)	(0.0593)
btom_bk_w	0.184*	0.196*	0.182*	0.207**	0.212**	0.208**
	(0.0888)	(0.0884)	(0.0891)	(0.0900)	(0.0896)	(0.0898)
lvrg_w	0.243	0.329*	0.247	0.273	0.297	0.280
	(0.171)	(0.172)	(0.171)	(0.171)	(0.169)	(0.170)
mom_w	8.022	8.020	8.066	7.814	7.809	7.820
	(4.989)	(5.014)	(4.999)	(4.987)	(4.987)	(4.990)
capextoas_w	-1.864	-1.999*	-1.948*	-1.433	-1.440	-1.438
	(1.046)	(1.076)	(1.060)	(1.029)	(1.034)	(1.033)
hhi_exio	0.0612	0.0700	0.0617	0.0929	0.0906	0.0957
	(0.0818)	(0.0814)	(0.0813)	(0.0901)	(0.0906)	(0.0903)
logppe	0.0483	0.0150	0.0414	0.0960**	0.0861**	0.0926**
	(0.0372)	(0.0399)	(0.0368)	(0.0302)	(0.0311)	(0.0302)
roe_w	0.0141***	0.0145***	0.0142***	0.0143***	0.0143***	0.0143***
	(0.00102)	(0.00101)	(0.00102)	(0.00110)	(0.00110)	(0.00110)
volat_w	-0.598	-0.696	-0.637	-0.515	-0.540	-0.523
	(2.730)	(2.736)	(2.728)	(2.663)	(2.665)	(2.664)
Constant	1.539**	1.359**	1.591**	1.414**	1.273*	1.411**
	(0.544)	(0.563)	(0.549)	(0.580)	(0.574)	(0.574)
Observations	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994
R-squared	0.116	0.115	0.115	0.116	0.116	0.116
Yr/mo FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y
Adjusted R-squared	0.115	0.115	0.115	0.116	0.116	0.116

Panel C

VARIABLES	(1)	(2) <2018	(3)	(4)	(5) >= 2018	(6)
L.logdirabs_ghg	0.119*			0.100**		
	(0.0512)			(0.0290)		
L.logindirabs_ghg		0.313***			0.288**	
		(0.0454)			(0.0526)	
L.loglifecycleabs_ghg			0.277***			0.229**
			(0.0581)			(0.0469)
L.logsize_unadj	-0.376***	-0.490***	-0.464***	-0.135	-0.245*	-0.208*
	(0.0612)	(0.0586)	(0.0651)	(0.0799)	(0.0866)	(0.0860)
btom_bk_w	0.104	0.0441	0.0582	0.296**	0.233*	0.252*
	(0.123)	(0.123)	(0.122)	(0.0878)	(0.0819)	(0.0860)
lvrg_w	0.0792	-0.301	-0.214	-0.156	-0.538*	-0.405
	(0.201)	(0.214)	(0.222)	(0.205)	(0.182)	(0.176)
mom_w	13.24*	13.30*	13.32*	-3.760	-3.451	-3.522
	(6.110)	(6.120)	(6.122)	(3.808)	(3.736)	(3.764)
capextoas_w	-2.278*	-1.775	-1.936	1.090	1.551	1.355
	(1.057)	(1.023)	(1.039)	(1.516)	(1.590)	(1.549)
hhi_exio	0.0637	0.0700	0.0619	0.315**	0.311**	0.302**
	(0.133)	(0.128)	(0.127)	(0.0898)	(0.0924)	(0.0933)
logppe	0.0647*	0.0125	0.0154	-0.0143	-0.0664	-0.0536
	(0.0255)	(0.0319)	(0.0272)	(0.0331)	(0.0387)	(0.0339)
roe_w	0.0111***	0.00919***	0.00962***	0.0158***	0.0135***	0.0142***
	(0.00126)	(0.00135)	(0.00132)	(0.00116)	(0.00134)	(0.00125)
volat_w	-4.254**	-3.976*	-4.078*	4.231	4.410	4.320
	(1.588)	(1.613)	(1.611)	(4.767)	(4.771)	(4.761)
Constant	1.901*	0.471	0.624	-0.547	-1.864	-1.564
	(0.770)	(0.802)	(0.856)	(0.682)	(0.870)	(0.806)
Observations	920,669	920,669	920,669	679,325	679,325	679,325
R-squared	0.074	0.074	0.074	0.165	0.165	0.165
Yr/mo FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.073	0.074	0.074	0.165	0.165	0.165

Panel D

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret
L.trucost_logdirabs_ghg	0.0452**		0.0810***	
	(0.0193)		(0.0202)	
L.trucost_logindirabs_ghg		0.164**		0.215***
		(0.0576)		(0.0542)
L.logsize_unadj	-0.155*	-0.206**	-0.223**	-0.301***
	(0.0741)	(0.0859)	(0.0732)	(0.0909)
btom_bk_w	0.203**	0.183**	0.262***	0.211**
	(0.0713)	(0.0716)	(0.0724)	(0.0673)
lvrg_w	-0.0672	-0.179	0.0202	-0.246
	(0.245)	(0.256)	(0.167)	(0.163)
mom_w	7.288*	7.515*	6.999*	7.256*
	(3.572)	(3.530)	(3.675)	(3.640)
capextoas_w	0.262	0.682	0.951	1.323
	(1.438)	(1.432)	(1.407)	(1.383)
hhi_exio	0.133	0.190**	0.215*	0.234**
	(0.0905)	(0.0795)	(0.0993)	(0.0931)
logppe	-0.0701	-0.123**	-0.0192	-0.0621*
	(0.0453)	(0.0464)	(0.0386)	(0.0337)
roe_w	0.00863***	0.00729**	0.00849***	0.00710**
	(0.00230)	(0.00233)	(0.00251)	(0.00261)
volat_w	4.431	4.444	4.410	4.576
	(3.562)	(3.572)	(3.404)	(3.408)
Constant	1.533***	1.518***	1.451**	1.542***
	(0.364)	(0.354)	(0.475)	(0.470)
Observations	668,989	669,405	668,989	669,405
R-squared	0.161	0.162	0.163	0.163
Yr/mo FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Industry FE	N	N	Y	Y
Adjusted R-squared	0.161	0.161	0.162	0.163

Panel E

VARIABLES	(1) EU28	(2) EU28	(3) EU28	(4) US	(5) US	(6) US	(7) China	(8) China	(9) China	(10) Rest	(11) Rest	(12) Rest
L.logdirabs_ghg	0.111***			0.185***			0.131***			0.121***		
	(0.0334)			(0.0566)			(0.0371)			(0.0221)		
L.logindirabs_ghg		0.251***			0.383***			0.343***			0.306***	
		(0.0427)			(0.0505)			(0.0322)			(0.0313)	
L.loglifecycleabs_ghg			0.210***			0.329***			0.322***			0.265***
			(0.0409)			(0.0661)			(0.0308)			(0.0358)
L.logsize_unadj	-0.151**	-0.232***	-0.206***	-0.120	-0.225*	-0.191	-0.493**	-0.636***	-0.618***	-0.356***	-0.466***	-0.439***
	(0.0594)	(0.0556)	(0.0581)	(0.122)	(0.121)	(0.127)	(0.187)	(0.189)	(0.188)	(0.0568)	(0.0625)	(0.0626)
btom_bk_w	0.283**	0.258**	0.266**	0.208	0.140	0.152	-0.388	-0.500*	-0.487*	0.242***	0.183**	0.197**
	(0.112)	(0.110)	(0.111)	(0.143)	(0.141)	(0.144)	(0.220)	(0.224)	(0.222)	(0.0697)	(0.0696)	(0.0689)
lvrg_w	-0.157	-0.451*	-0.352	-0.0203	-0.359	-0.261	-0.714*	-1.101**	-1.057**	0.224	-0.177	-0.0720
	(0.229)	(0.221)	(0.223)	(0.303)	(0.327)	(0.325)	(0.351)	(0.393)	(0.371)	(0.156)	(0.159)	(0.161)
mom_w	13.43***	13.73***	13.68***	4.540	4.711	4.612	7.679	7.648	7.644	7.203	7.361	7.343
	(2.904)	(2.906)	(2.905)	(4.000)	(4.002)	(4.007)	(5.390)	(5.362)	(5.365)	(5.299)	(5.238)	(5.256)
capextoas_w	0.207	0.608	0.468	-2.295	-1.277	-1.677	2.051	2.444	2.453	-2.006**	-1.644*	-1.764*
	(1.693)	(1.705)	(1.701)	(2.062)	(2.060)	(2.030)	(1.737)	(1.761)	(1.745)	(0.885)	(0.860)	(0.873)
hhi_exio	0.0586	0.107	0.0846	0.192	0.212	0.180	0.292	0.181	0.196	0.103	0.0906	0.0846
	(0.126)	(0.128)	(0.126)	(0.140)	(0.140)	(0.139)	(0.267)	(0.247)	(0.248)	(0.0925)	(0.0947)	(0.0948)
logppe	-0.0428	-0.0832	-0.0741	-0.0180	-0.0821	-0.0712	0.131***	0.0843	0.0793	0.0283	-0.0185	-0.0134
	(0.0533)	(0.0584)	(0.0559)	(0.0590)	(0.0635)	(0.0553)	(0.0380)	(0.0538)	(0.0494)	(0.0206)	(0.0180)	(0.0195)
roe_w	0.0137***	0.0124***	0.0128***	0.00879***	0.00686***	0.00740***	0.00837***	0.00575***	0.00602***	0.0143***	0.0121***	0.0127***
	(0.00133)	(0.00141)	(0.00138)	(0.00206)	(0.00192)	(0.00197)	(0.00178)	(0.00161)	(0.00160)	(0.00187)	(0.00186)	(0.00186)
volat_w	-0.0283	0.0769	0.0185	-1.118	-0.817	-0.910	-5.979**	-5.678**	-5.732**	0.299	0.527	0.443
	(2.150)	(2.134)	(2.139)	(2.938)	(2.972)	(2.949)	(2.265)	(2.279)	(2.278)	(2.776)	(2.758)	(2.763)
Constant	0.333	-0.715	-0.521	-0.139	-1.626**	-1.396**	3.195	1.652	1.721	0.913	-0.448	-0.266
	(0.587)	(0.684)	(0.668)	(0.562)	(0.594)	(0.551)	(1.784)	(1.746)	(1.779)	(0.552)	(0.587)	(0.594)
Observations	259,393	259,393	259,393	223,951	223,951	223,951	236,712	236,712	236,712	879,938	879,938	879,938
R-squared	0.168	0.168	0.168	0.148	0.148	0.148	0.315	0.316	0.316	0.123	0.124	0.124
Yr/mo FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.167	0.168	0.167	0.147	0.148	0.147	0.315	0.315	0.315	0.123	0.123	0.123

Table 6.14: Water use and stock returns

The period considered is 2013 – 2021. Water use is measured in million m³. In Panel A, water use as a sole impact variable is the independent variable. Financial controls are lagged by one year and impact variables are lagged by one month. Columns (4) to (6) include industry-fixed effects. In Panel B, water use is used in addition to GHG emissions expressed in tCO2-eq. In Panel C, we show the regression with water use, absolute GHG emissions, by region/country of incorporation. In Panel D, we run the regression with water use and water use interacted with water stress dummy. The water stress dummy is described in **Figure 6.3**. *In Panel E, we show the regression tables for the specification using water use, ghg emissions and interaction term water use and water stress. Robust standard errors are shown in parentheses and are double clustered at company and year level. ***, ** and * denote significance at 1%; 5% and 10% level.*

Panel A

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret
L.logdirabs_wat	0.0439***			0.0535***		
	(0.0104)			(0.00870)		
L.logindirabs_wat		0.198***			0.245***	
		(0.0182)			(0.0227)	
L.loglifecycleabs_wat			0.185***			0.229***
			(0.0186)			(0.0230)
L.logsize_unadj	-0.196**	-0.286***	-0.275***	-0.263***	-0.377***	-0.365***
	(0.0622)	(0.0654)	(0.0654)	(0.0607)	(0.0646)	(0.0651)
btom_bk_w	0.199*	0.158	0.162*	0.197*	0.132	0.137
	(0.0887)	(0.0880)	(0.0879)	(0.0888)	(0.0867)	(0.0866)
lvrg_w	0.329*	0.0341	0.0691	0.223	-0.163	-0.122
	(0.172)	(0.174)	(0.174)	(0.165)	(0.168)	(0.166)
mom_w	8.067	8.179	8.152	7.916	8.114	8.100
	(5.003)	(4.978)	(4.983)	(4.979)	(4.946)	(4.951)
capextoas_w	-1.786	-1.357	-1.382	-1.292	-0.806	-0.861
	(1.081)	(1.022)	(1.028)	(1.035)	(1.016)	(1.020)
hhi_exio	0.158*	0.186**	0.185**	0.182*	0.200**	0.197**
	(0.0779)	(0.0723)	(0.0719)	(0.0884)	(0.0833)	(0.0832)
logppe	-0.00595	-0.0469	-0.0472	0.0686**	0.0159	0.0173
	(0.0400)	(0.0390)	(0.0382)	(0.0293)	(0.0273)	(0.0264)
roe_w	0.0143***	0.0125***	0.0127***	0.0140***	0.0119***	0.0121***
	(0.000998)	(0.00104)	(0.00104)	(0.00111)	(0.00114)	(0.00113)
volat_w	-0.667	-0.388	-0.397	-0.514	-0.297	-0.317
	(2.739)	(2.729)	(2.735)	(2.661)	(2.644)	(2.648)
Constant	1.074	-0.519	-0.426	1.028	-0.867	-0.751
	(0.594)	(0.561)	(0.574)	(0.597)	(0.621)	(0.628)
Observations	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994
R-squared	0.116	0.116	0.116	0.116	0.117	0.116
Yr/mo FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y
Adjusted R-squared	0.115	0.116	0.116	0.116	0.116	0.116

Panel B

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret
L.logdirabs_wat	0.0422**			0.0272**		
	(0.0146)			(0.00909)		
L.logdirabs_ghg	0.00694			0.0923**		
	(0.0368)			(0.0324)		
L.logindirabs_wat		0.0559			0.0686**	
		(0.0405)			(0.0226)	
L.logindirabs_ghg		0.223***			0.233***	
		(0.0642)			(0.0487)	
L.loglifecycleabs_wat			0.144***			0.128***
			(0.0417)			(0.0301)
L.loglifecycleabs_ghg			0.0703			0.141**
			(0.0664)			(0.0584)
L.logsize_unadj	-0.198**	-0.323***	-0.287***	-0.296***	-0.405***	-0.384***
	(0.0671)	(0.0663)	(0.0685)	(0.0646)	(0.0662)	(0.0685)
btom_bk_w	0.197**	0.131	0.153*	0.174*	0.114	0.125
	(0.0842)	(0.0829)	(0.0832)	(0.0850)	(0.0840)	(0.0847)
lvrg_w	0.319	-0.145	0.0148	0.0827	-0.292	-0.205
	(0.188)	(0.181)	(0.180)	(0.173)	(0.178)	(0.175)
mom_w	8.075	8.240	8.201	7.977	8.142	8.136
	(4.984)	(4.963)	(4.960)	(4.965)	(4.942)	(4.945)
capextoas_w	-1.789	-1.165	-1.383	-1.170	-0.703	-0.815
	(1.080)	(1.057)	(1.033)	(1.034)	(1.020)	(1.018)
hhi_exio	0.160*	0.192**	0.188**	0.208**	0.190**	0.194**
	(0.0768)	(0.0717)	(0.0715)	(0.0867)	(0.0835)	(0.0834)
logppe	-0.00886	-0.0804*	-0.0634*	0.0423	-0.00535	0.000320
	(0.0301)	(0.0366)	(0.0308)	(0.0251)	(0.0265)	(0.0239)
roe_w	0.0142***	0.0116***	0.0124***	0.0133***	0.0113***	0.0117***
	(0.00105)	(0.001000)	(0.00106)	(0.00115)	(0.00115)	(0.00118)
volat_w	-0.666	-0.342	-0.414	-0.433	-0.192	-0.273
	(2.739)	(2.739)	(2.734)	(2.654)	(2.651)	(2.644)
Constant	1.056	-0.599	-0.496	0.787	-0.706	-0.725
	(0.600)	(0.570)	(0.589)	(0.604)	(0.599)	(0.623)
Observations	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994
R-squared	0.116	0.116	0.116	0.116	0.117	0.117
Yr/mo FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y
Adjusted R-squared	0.115	0.116	0.116	0.116	0.116	0.116

Panel C

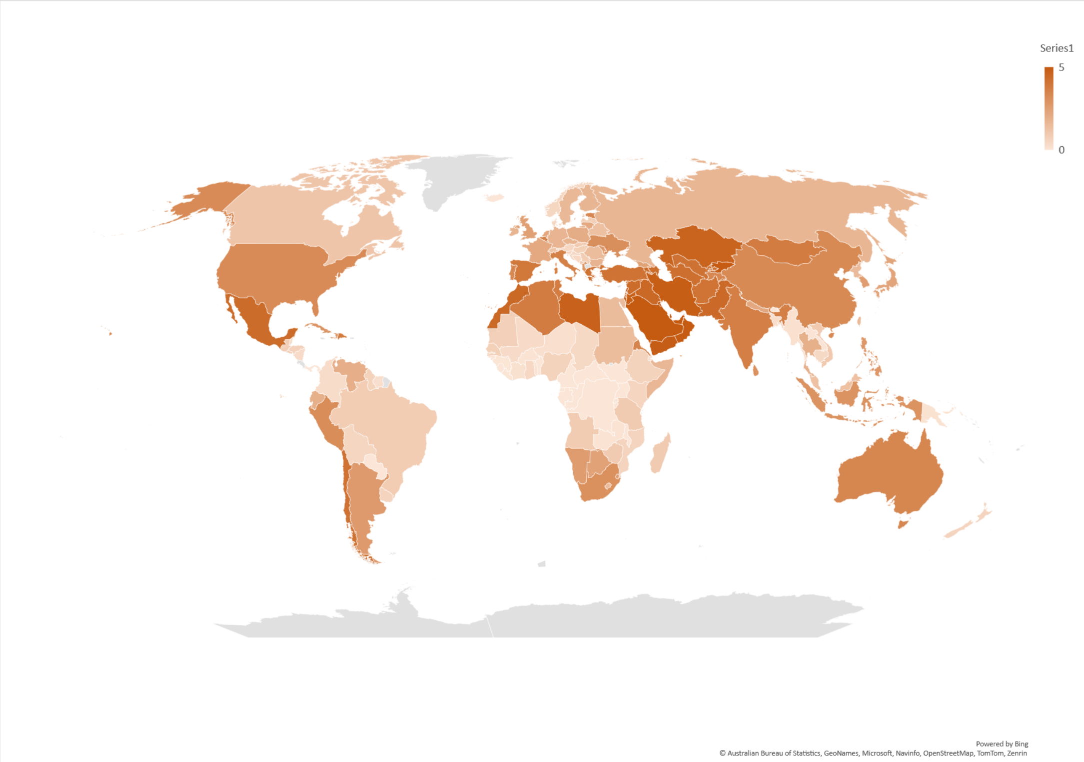
VARIABLES	(1) EU28	(2) EU28	(3) EU28	(4) US	(5) US	(6) US	(7) China	(8) China	(9) China	(10) Rest	(11) Rest	(12) Rest
L.logdirabs_wat	0.0297			0.0105			0.0317**			0.0205*		
	(0.0242)			(0.0125)			(0.0135)			(0.00916)		
L.logdirabs_ghg	0.0829*			0.175**			0.114**			0.105***		
	(0.0403)			(0.0602)			(0.0380)			(0.0238)		
L.logindirabs_wat		0.0382			-0.0822			0.217***			0.0586	
		(0.0702)			(0.0533)			(0.0656)			(0.0344)	
L.logindirabs_ghg		0.213*			0.466***			0.178***			0.250***	
		(0.0990)			(0.0839)			(0.0504)			(0.0505)	
L.loglifecycleabs_wat			0.165*			0.145			0.176***			0.0956***
			(0.0779)			(0.0910)			(0.0480)			(0.0234)
L.loglifecycleabs_ghg			0.0507			0.189			0.199***			0.180***
			(0.0966)			(0.137)			(0.0322)			(0.0461)
Constant	0.261	-0.815	-0.961	-0.145	-1.403**	-1.813**	3.006	0.629	0.814	0.851	-0.639	-0.610
	(0.599)	(0.579)	(0.653)	(0.560)	(0.520)	(0.571)	(1.802)	(1.995)	(1.976)	(0.555)	(0.552)	(0.577)
Observations	259,393	259,393	259,393	223,951	223,951	223,951	236,712	236,712	236,712	879,938	879,938	879,938
R-squared	0.168	0.168	0.168	0.148	0.148	0.148	0.315	0.316	0.316	0.123	0.124	0.124
Yr/mo FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.167	0.168	0.168	0.147	0.148	0.147	0.315	0.315	0.315	0.123	0.123	0.123

Panel D

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret	(7) ret	(8) ret	(9) ret
waterstress_interaction_dir	0.0177	0.0145	0.00641						
	(0.0234)	(0.0227)	(0.0110)						
L.logdirabs_wat	0.0361*	0.0398**	0.0499***						
	(0.0160)	(0.0157)	(0.00946)						
waterstress_interaction_indir				0.00892	0.00678	0.0403*			
				(0.0176)	(0.0172)	(0.0211)			
L.logindirabs_wat				0.189***	0.229***	0.217***			
				(0.0503)	(0.0499)	(0.0251)			
waterstress_interaction_lc							0.00992	0.00785	0.0401*
							(0.0176)	(0.0173)	(0.0213)
L.loglifecycleabs_wat							0.175***	0.214***	0.201***
							(0.0489)	(0.0480)	(0.0246)
Observations	1,549,002	1,549,002	1,549,002	1,549,002	1,549,002	1,549,002	1,549,002	1,549,002	1,549,002
R-squared	0.116	0.117	0.117	0.116	0.117	0.118	0.116	0.117	0.118
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Yr/mo FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	N	N	Y	N	N	Y	N	N	Y
Industry FE	N	Y	Y	N	Y	Y	N	Y	Y
Adjusted R-squared	0.116	0.117	0.117	0.116	0.117	0.118	0.116	0.117	0.118

Panel E

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret	(7) ret	(8) ret	(9) ret
waterstress_interaction_dir	0.0177			0.0140			0.00941		
	(0.0234)			(0.0228)			(0.0115)		
L.logdirabs_wat	0.0367*			0.0151			0.0214		
	(0.0195)			(0.0170)			(0.0128)		
L.logdirabs_ghg	-0.00289			0.0922*			0.0935**		
	(0.0496)			(0.0454)			(0.0317)		
waterstress_interaction_indir		0.00946			0.00719			0.0411*	
		(0.0174)			(0.0171)			(0.0211)	
L.logindirabs_wat		0.0740			0.130			0.0419	
		(0.0827)			(0.107)			(0.0334)	
L.logindirabs_ghg		0.186**			0.141			0.231***	
		(0.0682)			(0.0890)			(0.0465)	
waterstress_interaction_lc			0.0102			0.00803			0.0394*
			(0.0174)			(0.0172)			(0.0212)
L.loglifecycleabs_wat			0.143			0.153			0.102**
			(0.0836)			(0.100)			(0.0337)
L.loglifecycleabs_ghg			0.0566			0.0914			0.140**
			(0.0792)			(0.0940)			(0.0561)
Constant	0.713	-1.023*	-0.863	0.390	-1.236**	-1.175*	0.759	-0.753	-0.772
	(0.557)	(0.508)	(0.498)	(0.564)	(0.540)	(0.528)	(0.593)	(0.585)	(0.611)
Observations	1,549,002	1,549,002	1,549,002	1,549,002	1,549,002	1,549,002	1,549,002	1,549,002	1,549,002
R-squared	0.116	0.116	0.116	0.117	0.117	0.117	0.118	0.118	0.118
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Yr/mo FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	N	N	N	N	N	N	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.116	0.116	0.116	0.117	0.117	0.117	0.117	0.118	0.118



APPENDIX: COUNTRY AND RIVER BASIN RANKINGS (BASELINE WATER STRESS)

Baseline water stress measures total annual water withdrawals expressed as a percentage of the total annual available blue water. Higher values indicate more competition among users.

[4–5]: Extremely high stress (>80%)

[3–4): High stress (40–80%)

[2–3): Medium-high stress (20–40%)

[1–2): Low-medium stress (10–20%)

[0–1): Low stress (<10%)

Figure 6.3: Water Stress Indicator – ranking of countries

The figure is build using data from the WRI dataset. The data represent values for water stress 2030 BAU scenario. Additionally, we show the ranking used by WRI, from 0-1: Low stress to 4-5: Extremely high stress. Data is sourced from Aqueduct WRI water stress document

Table 6.15: Vulnerable employment and stock returns

*The period considered is 2013 – 2021. Vulnerable employment is measured in thousand persons. In Panel A, vulnerable employment is used as a sole impact variable is the independent variable. Financial controls are lagged by one year and impact variables are lagged by one month. Columns (4) to (6) include industry-fixed effects. In Panel B, we show the same regression as Panel A, with country-level split. In Panel C, vulnerable employment is used in addition to GHG emissions expressed in tCO2-eq. In Panel D, we show the regression with vulnerable employment, absolute GHG emissions, by region/country of incorporation. In Panel E, we run the regression with vulnerable employment interacted with human rights dummy. The human rights dummy is described in section 3.2.5. In Panel F, we show the regression tables for the specification using vulnerable employment and interaction term vulnerable employment and World Values Survey dummy on environmental protection and human rights. In panel G, we run the same regression as Panel F, but additionally consider ghg emissions. Robust standard errors are shown in parentheses and are double clustered at company and year level. ***, ** and * denote significance at 1%; 5% and 10% level.*

Panel A

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret
L.logdirabs_vemp	0.141***			0.149***		
	(0.0335)			(0.0365)		
L.logindirabs_vemp		0.252***			0.258***	
		(0.0402)			(0.0435)	
L.loglifecycleabs_vemp			0.240***			0.250***
			(0.0434)			(0.0459)
L.logsize_unadj	-0.244***	-0.299***	-0.304***	-0.291***	-0.357***	-0.363***
	(0.0638)	(0.0670)	(0.0675)	(0.0603)	(0.0645)	(0.0648)
btom_bk_w	0.159*	0.135	0.132	0.175*	0.138	0.134
	(0.0830)	(0.0838)	(0.0826)	(0.0832)	(0.0812)	(0.0800)
lvrg_w	0.137	0.0374	-0.00485	0.135	-0.0319	-0.0618
	(0.165)	(0.164)	(0.169)	(0.154)	(0.148)	(0.147)
mom_w	8.262	8.356	8.406	8.008	8.194	8.216
	(4.979)	(4.984)	(4.972)	(4.964)	(4.960)	(4.948)
capextoas_w	-1.859	-1.577	-1.563	-1.307	-1.070	-1.058
	(1.088)	(1.074)	(1.085)	(1.049)	(1.047)	(1.056)
hhi_exio	0.109	0.147*	0.136	0.143	0.156	0.153
	(0.0804)	(0.0774)	(0.0779)	(0.0915)	(0.0884)	(0.0889)
logppe	0.0193	-0.0127	-0.00949	0.0822**	0.0595*	0.0594*
	(0.0403)	(0.0385)	(0.0389)	(0.0308)	(0.0293)	(0.0296)
roe_w	0.0144***	0.0143***	0.0142***	0.0145***	0.0142***	0.0141***
	(0.000995)	(0.000994)	(0.000993)	(0.00109)	(0.00107)	(0.00107)
volat_w	-0.698	-0.646	-0.633	-0.547	-0.528	-0.514
	(2.732)	(2.750)	(2.746)	(2.664)	(2.672)	(2.669)
Constant	1.731***	1.908***	1.923***	1.640**	1.912***	1.920***
	(0.514)	(0.516)	(0.508)	(0.551)	(0.551)	(0.542)
Observations	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994
R-squared	0.115	0.116	0.116	0.116	0.116	0.116
Yr/mo FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y
Adjusted R-squared	0.115	0.116	0.116	0.116	0.116	0.116

Panel B

VARIABLES	(1) EU28	(2) EU28	(3) EU28	(4) US	(5) US	(6) US	(7) China	(8) China	(9) China	(10) Rest	(11) Rest	(12) Rest
L.logdirabs_vemp	0.126***			0.0174			0.172***			0.255***		
	(0.0354)			(0.0480)			(0.0464)			(0.0398)		
L.logindirabs_vemp		0.200***			0.0413			0.427***			0.391***	
		(0.0322)			(0.0544)			(0.0648)			(0.0511)	
L.loglifecycleabs_vemp			0.207***			0.0591			0.364***			0.376***
			(0.0417)			(0.0537)			(0.0682)			(0.0499)
L.logsize_unadj	-0.131**	-0.177**	-0.187***	-0.0488	-0.0589	-0.0674	-0.514**	-0.692***	-0.664***	-0.386***	-0.484***	-0.491***
	(0.0533)	(0.0581)	(0.0549)	(0.108)	(0.112)	(0.113)	(0.200)	(0.193)	(0.194)	(0.0611)	(0.0725)	(0.0721)
btom_bk_w	0.288**	0.272**	0.269**	0.285*	0.278*	0.273*	-0.419*	-0.552**	-0.534**	0.233***	0.178**	0.173**
	(0.113)	(0.112)	(0.112)	(0.140)	(0.141)	(0.141)	(0.216)	(0.204)	(0.197)	(0.0692)	(0.0705)	(0.0691)
lvrg_w	-0.0502	-0.132	-0.162	0.297	0.269	0.250	-0.769*	-1.148**	-1.154**	0.200	-0.0665	-0.109
	(0.216)	(0.215)	(0.216)	(0.321)	(0.324)	(0.326)	(0.392)	(0.409)	(0.417)	(0.153)	(0.160)	(0.158)
mom_w	13.31***	13.59***	13.67***	4.539	4.596	4.647	7.791	7.772	7.807	7.400	7.574	7.587
	(2.917)	(2.908)	(2.880)	(4.031)	(4.031)	(4.019)	(5.397)	(5.347)	(5.356)	(5.293)	(5.277)	(5.268)
capextoas_w	-0.00395	0.182	0.204	-3.001	-2.879	-2.806	1.921	2.560	2.454	-2.004**	-1.795*	-1.760*
	(1.688)	(1.670)	(1.688)	(2.074)	(2.018)	(2.023)	(1.742)	(1.736)	(1.739)	(0.879)	(0.859)	(0.862)
hhi_exio	-0.00580	0.0265	0.0297	0.0657	0.0755	0.0806	0.277	0.204	0.216	0.105	0.108	0.106
	(0.126)	(0.123)	(0.127)	(0.154)	(0.152)	(0.151)	(0.256)	(0.246)	(0.250)	(0.0901)	(0.0906)	(0.0910)
logppe	-0.00961	-0.0236	-0.0271	0.0597	0.0546	0.0510	0.186***	0.117*	0.134**	0.0600**	0.0275	0.0296
	(0.0551)	(0.0543)	(0.0556)	(0.0772)	(0.0753)	(0.0748)	(0.0528)	(0.0547)	(0.0540)	(0.0191)	(0.0177)	(0.0177)
roe_w	0.0148***	0.0148***	0.0147***	0.0105***	0.0104***	0.0104***	0.00872***	0.00646***	0.00667***	0.0157***	0.0152***	0.0152***
	(0.00128)	(0.00129)	(0.00129)	(0.00192)	(0.00190)	(0.00190)	(0.00197)	(0.00182)	(0.00196)	(0.00194)	(0.00192)	(0.00192)
volat_w	-0.0803	-0.173	-0.198	-1.411	-1.408	-1.417	-5.998**	-5.619**	-5.636**	0.133	0.140	0.184
	(2.150)	(2.155)	(2.136)	(2.969)	(2.970)	(2.970)	(2.242)	(2.279)	(2.260)	(2.780)	(2.778)	(2.774)
Constant	0.997*	1.173*	1.207**	0.815	0.863	0.903	4.211**	5.102**	4.893**	1.865***	2.285***	2.279***
	(0.512)	(0.522)	(0.499)	(0.713)	(0.728)	(0.725)	(1.691)	(1.648)	(1.648)	(0.528)	(0.575)	(0.562)
Observations	259,393	259,393	259,393	223,951	223,951	223,951	236,712	236,712	236,712	879,938	879,938	879,938
R-squared	0.168	0.168	0.168	0.148	0.148	0.148	0.315	0.316	0.316	0.123	0.124	0.124
Yr/mo FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.167	0.167	0.167	0.147	0.147	0.147	0.315	0.315	0.315	0.123	0.123	0.123

Panel C

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret
L.logdirabs_vemp	0.135***			0.118***		
	(0.0313)			(0.0329)		
L.logdirabs_ghg	0.0362			0.103***		
	(0.0289)			(0.0279)		
L.logindirabs_vemp		0.0385			0.0362	
		(0.0400)			(0.0488)	
L.logindirabs_ghg		0.259***			0.282***	
		(0.0346)			(0.0382)	
L.loglifecycleabs_vemp			0.151***			0.110*
			(0.0454)			(0.0488)
L.loglifecycleabs_ghg			0.138***			0.211***
			(0.0406)			(0.0417)
L.logsize_unadj	-0.255***	-0.330***	-0.322***	-0.331***	-0.410***	-0.405***
	(0.0679)	(0.0673)	(0.0695)	(0.0653)	(0.0661)	(0.0684)
btom_bk_w	0.153*	0.124	0.124	0.150*	0.110	0.110
	(0.0807)	(0.0836)	(0.0821)	(0.0803)	(0.0804)	(0.0793)
lvrg_w	0.100	-0.171	-0.0981	-0.0242	-0.306	-0.263
	(0.175)	(0.177)	(0.176)	(0.162)	(0.168)	(0.163)
mom_w	8.296	8.275	8.414	8.089	8.162	8.235
	(4.964)	(4.965)	(4.966)	(4.946)	(4.932)	(4.933)
capextoas_w	-1.836	-1.176	-1.458	-1.118	-0.712	-0.817
	(1.095)	(1.076)	(1.090)	(1.045)	(1.033)	(1.038)
hhi_exio	0.139	0.186**	0.168*	0.209**	0.183*	0.184*
	(0.0796)	(0.0752)	(0.0749)	(0.0885)	(0.0858)	(0.0850)
logppe	-0.00205	-0.0797*	-0.0596*	0.0428	-0.00444	0.00268
	(0.0294)	(0.0367)	(0.0307)	(0.0252)	(0.0267)	(0.0240)
roe_w	0.0142***	0.0118***	0.0130***	0.0136***	0.0114***	0.0122***
	(0.00102)	(0.000986)	(0.00105)	(0.00114)	(0.00116)	(0.00120)
volat_w	-0.688	-0.377	-0.561	-0.445	-0.200	-0.315
	(2.733)	(2.744)	(2.740)	(2.655)	(2.649)	(2.645)
Constant	1.543**	-0.216	0.799	1.126*	-0.305	0.243
	(0.544)	(0.618)	(0.584)	(0.555)	(0.570)	(0.520)
Observations	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994	1,599,994
R-squared	0.116	0.116	0.116	0.116	0.117	0.117
Yr/mo FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y
Adjusted R-squared	0.115	0.116	0.116	0.116	0.116	0.116

Panel D

VARIABLES	(1) EU28	(2) EU28	(3) EU28	(4) US	(5) US	(6) US	(7) China	(8) China	(9) China	(10) Rest	(11) Rest	(12) Rest
L.logdirabs_vemp	0.0915**			0.00208			0.140**			0.220***		
	(0.0349)			(0.0482)			(0.0477)			(0.0363)		
L.logdirabs_ghg	0.102**			0.185***			0.116**			0.0994***		
	(0.0336)			(0.0565)			(0.0380)			(0.0202)		
L.logindirabs_vemp		-0.00346			-0.303***			0.253*			0.224***	
		(0.0498)			(0.0696)			(0.134)			(0.0526)	
L.logindirabs_ghg		0.252***			0.501***			0.195*			0.204***	
		(0.0549)			(0.0625)			(0.0905)			(0.0277)	
L.loglifecycleabs_vemp			0.0680			-0.145*			0.199*			0.263***
			(0.0457)			(0.0659)			(0.103)			(0.0453)
L.loglifecycleabs_ghg			0.187***			0.377***			0.226***			0.163***
			(0.0464)			(0.0758)			(0.0611)			(0.0313)
Constant	0.495	-0.729	-0.247	-0.136	-2.925***	-1.994**	3.661*	3.364	2.961	1.387**	0.671	0.985
	(0.561)	(0.771)	(0.661)	(0.594)	(0.725)	(0.663)	(1.820)	(1.970)	(1.885)	(0.538)	(0.695)	(0.628)
Observations	259,393	259,393	259,393	223,951	223,951	223,951	236,712	236,712	236,712	879,938	879,938	879,938
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.168	0.168	0.168	0.148	0.149	0.148	0.315	0.316	0.316	0.123	0.124	0.124
Yr/mo FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.167	0.168	0.168	0.147	0.148	0.148	0.315	0.315	0.315	0.123	0.123	0.123

Panel E

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret	(7) ret	(8) ret	(9) ret
rights_h_median_vemp_inter_dir	-0.0182			-0.0260			0.156*		
	(0.158)			(0.150)			(0.0756)		
L.logdirabs_vemp	0.125			0.122			0.0223		
	(0.132)			(0.130)			(0.0661)		
L.logdirabs_ghg	0.0290			0.0929**			0.0986***		
	(0.0402)			(0.0380)			(0.0294)		
rights_h_median_vemp_inter_indir		-0.0226			-0.0303			0.103	
		(0.122)			(0.121)			(0.0863)	
L.logindirabs_vemp		0.0647			0.0788			-0.0379	
		(0.164)			(0.162)			(0.0849)	
L.logindirabs_ghg		0.235***			0.235***			0.275***	
		(0.0501)			(0.0560)			(0.0388)	
rights_h_median_vemp_inter_lc			-0.0132			-0.0220			0.114
			(0.115)			(0.114)			(0.0762)
L.loglifecycleabs_vemp			0.145			0.120			0.0319
			(0.153)			(0.147)			(0.0805)
L.loglifecycleabs_ghg			0.128**			0.182***			0.202***
			(0.0457)			(0.0527)			(0.0425)
Constant	1.184	-0.503	0.400	0.687	-0.479	-0.0828	1.179*	-0.257	0.328
	(0.689)	(0.725)	(0.741)	(0.640)	(0.735)	(0.704)	(0.587)	(0.633)	(0.559)
Observations	1,440,430	1,440,430	1,440,430	1,440,430	1,440,430	1,440,430	1,440,430	1,440,430	1,440,430
R-squared	0.115	0.115	0.115	0.116	0.116	0.116	0.116	0.117	0.117
Yr/mo FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	N	N	N	N	N	N	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.115	0.115	0.115	0.115	0.116	0.116	0.116	0.117	0.116

Panel F

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret	(7) ret	(8) ret	(9) ret
wvs_envprot_hr_vemp_dir_inter	0.249*			0.201			-0.119*		
	(0.134)			(0.126)			(0.0572)		
L.logdirabs_vemp	-0.132			-0.0766			0.251***		
	(0.109)			(0.108)			(0.0699)		
wvs_envprot_hr_vemp_indir_inter		0.236*			0.199*			-0.0802	
		(0.111)			(0.106)			(0.0519)	
L.logindirabs_vemp		-0.0109			0.0225			0.334***	
		(0.0612)			(0.0583)			(0.0590)	
wvs_envprot_hr_vemp_lc_inter			0.214*			0.180			-0.0991*
			(0.104)			(0.0986)			(0.0456)
L.loglifecycleabs_vemp			-0.0127			0.0272			0.342***
			(0.0531)			(0.0510)			(0.0662)
Constant	1.361**	1.480**	1.474**	1.197**	1.404**	1.397**	1.618**	1.934***	1.938***
	(0.528)	(0.587)	(0.583)	(0.508)	(0.579)	(0.573)	(0.499)	(0.492)	(0.481)
Observations	1,374,550	1,374,550	1,374,550	1,374,550	1,374,550	1,374,550	1,374,550	1,374,550	1,374,550
R-squared	0.116	0.117	0.117	0.117	0.117	0.117	0.118	0.118	0.118
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Yr/mo FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	N	N	N	N	N	N	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.116	0.117	0.117	0.117	0.117	0.117	0.118	0.118	0.118

Panel G

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret	(7) ret	(8) ret	(9) ret
wvs_envprot_hr_vemp_dir_inter	0.249*			0.199			-0.127*		
	(0.133)			(0.127)			(0.0581)		
L.logdirabs_vemp	-0.137			-0.104			0.227***		
	(0.105)			(0.102)			(0.0682)		
L.logdirabs_ghg	0.0264			0.104**			0.108***		
	(0.0330)			(0.0352)			(0.0288)		
wvs_envprot_hr_vemp_indir_inter		0.235*			0.209*			-0.0436	
		(0.111)			(0.106)			(0.0505)	
L.logindirabs_vemp		-0.231**			-0.197**			0.0726	
		(0.0835)			(0.0759)			(0.0532)	
L.logindirabs_ghg		0.275***			0.281***			0.293***	
		(0.0417)			(0.0426)			(0.0366)	
wvs_envprot_hr_vemp_lc_inter			0.211*			0.180			-0.0961*
			(0.104)			(0.0984)			(0.0458)
L.loglifecycleabs_vemp			-0.103			-0.106*			0.196**
			(0.0584)			(0.0562)			(0.0644)
L.loglifecycleabs_ghg			0.157***			0.221***			0.224***
			(0.0398)			(0.0450)			(0.0438)
Constant	1.236*	-0.778	0.217	0.707	-0.775	-0.313	1.100*	-0.350	0.187
	(0.597)	(0.579)	(0.650)	(0.562)	(0.530)	(0.581)	(0.499)	(0.456)	(0.428)
Observations	1,374,550	1,374,550	1,374,550	1,374,550	1,374,550	1,374,550	1,374,550	1,374,550	1,374,550
R-squared	0.116	0.117	0.117	0.117	0.118	0.118	0.118	0.118	0.118
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Yr/mo FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	N	N	N	N	N	N	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.116	0.117	0.117	0.117	0.117	0.117	0.118	0.118	0.118

7 Contributions summary and Conclusion

In this thesis, the application of the input-output life cycle assessment (IOLCA) methodology to estimate impacts of investment funds has been improved, achieving more detail at the level of company representation, extending the indicators studied to a large spectrum of environmental indicators and, for the first time, to a large suite of social indicators.

In the following sub-sections, we will answer the overarching research question set in the Introduction and highlight the main contributions to academic research, but also to policy and to the financial industry. Then, we will summarize the key limitations of this research. To conclude, the outlook foreseen as a result of this work will be presented.

7.1 Main contributions to academia

7.1.1 A critical review of state-of-the-art frameworks for sustainability assessment of investment funds

In **Chapter 2**, a comprehensive critical review of 37 state-of-the-art methods and frameworks from academia and practice was conducted to motivate the need to develop more science-based assessment tools for the investment funds industry. The critical review identified key criteria that state-of-the-art methods and frameworks should concomitantly address: the consideration of a full value chain perspective, the integration of impact categories beyond climate change and a quantitative rather than qualitative approach to impact measurements, focusing on the real contribution to impact of the financial product. These criteria supported the development of an IOLCA-based model to assess sustainability of investment funds, detailed in **Chapter 3**.

7.1.2 A step forward in the adoption of IOLCA-based models to estimate the sustainability of investment funds

IOLCA models can be used to assign responsibility based on an investment perspective – allocating real impacts to the holders of capital that make those impacts possible. IOLCA models have already been employed in literature and practice to estimate impacts at investment fund level, albeit infrequently and for small samples. Our model is more detailed than previous iterations of IOLCA-based estimation methods that solely use a one-region input-output table (Koellner et al., 2007), by employing a 49-region differentiation of impacts across regions, thus resulting in more variation in estimated impacts. Compared to previous iterations of similar models, our model is applied to a larger sample of companies. For example, in Koellner et al. (2007), 3,500 companies are assessed, while Trucost offers data for around 15,000 companies (Trucost, 2019a). In our most extensive model iteration, impacts are estimated for a sample of over 25,000 companies. We employ detailed revenue information at company level for assigning the corresponding share of impact by sector, using FactSet RBICS and GeoRev by-sector and by-country revenue share databases (FactSet, 2021). We also apply the model to a larger sample of funds: Koellner et al. (2007) study 26 funds, while we look, in a first case study, at over 1,340 funds. Compared to advances in the commercial data providers space (PCAF, 2019; Trucost, 2019b), our model's methodology is transparent and estimated values rely solely on science-based impact factors. Moreover, compared to company self-reported data, we achive a coverage of 95% of all listed companies compared to 17% coverage in CDP company self-reported data (as of 2021, with company-level data for year 2018).

7.1.3 A quantification of the carbon footprint of equity investment funds domiciled in Europe

Our research advanced the understanding of the drivers of impact differences at fund level as our developed model helps answering the question whether sustainable funds are greener than conventional funds. The honest answer is – as with many questions in the finance but also in the life cycle assessment field – *it depends*. In Koellner et al. (2007), the authors find a slightly lower footprint than conventional funds, while there is only weak statistical difference between the two for the metric of environmental impact relative to risk-adjusted financial return.

First and foremost, the answer to the question depends on the type of sustainable fund that we analyse. For example, sustainable funds self-labelled Article 9 under the SFDR regulation –funds that aim to bring a social or environmental impact – and also funds that have an "*Environmentally Friendly*" categorization tend to have lower GHG emissions impacts on a life cycle basis (**Chapter 3 Table 3.5**). Another surprising finding was that 38% of the SRI funds sampled had a carbon intensity that was higher than the MSCI World ETF. This is due to the MSCI World ETF being exposed to some sectors that are already low in carbon, like Finance or Tech, that drive its average impact down and make it appear better than some more manufacturing- or energy-intensive funds. Another reason for self-labelled SRI funds being more carbon intensive than conventional peers is the use of ESG ratings as basis for selecting more sustainable portfolios. ESG indices could be designed based on choosing stocks with a good ESG rating, which does not necessarily mean a good carbon footprint, but rather a better disclosure than peers in terms of ESG matters (Berg et al., 2019). Especially in the case of climate change, the level of GHG emissions is quite persistent at industry level, and thus impact is driven by industry allocation rather than by qualitative traits of the company's management practices, as often measured via ESG ratings.

This finding prompted a more in-depth look at the holdings of different funds. In fact, some funds may invest in companies that help with the green transition, but have a high carbon footprint, while other funds may invest in service-oriented companies, that do not have per se a high carbon footprint, but neither help towards decarbonization. Some SRI funds seem to decrease their footprint, not by investing in greener companies, but by decreasing their holding in polluting companies, while investing more in already decarbonized companies, without therefore bringing a change.

Another interesting finding was that funds may rank differently depending on the scope of impact that is assessed. For example, SRI funds had a lower mean weighted average carbon intensity (WACI) in terms of scope 1 GHG emissions (161 vs. 174 tCO_2-eq/MEUR revenue), but a higher mean WACI on scope 3 upstream GHG emissions (271 vs. 265 tCO_2-eq/MEUR revenue). The inclusion of scope 3 upstream impacts in the analysis uncovers the hidden impacts in the supply chains of companies invested in, with a contribution of more than 50% of the total associated impacts, meaning that the exposure to negative impacts is much larger than accounted for via the more widely used direct impact metrics.

Generally, we reached the conclusion that **funds self-labelled as SRI are not consistently less carbon intensive than conventional peers**, thus debunking the myth that an SRI investment is always better in terms of environmental performance, when compared with any other conventional fund. A priori to our main paper on comparing SRI funds to conventional funds, there was little evidence on the differences between these types of funds when it comes to sustainability assessment, despite the abundance on papers about the financial performance of SRI versus conventional funds (Friede et al., 2015).

7.1.4 A framework to consistently estimate an extended set of IOLCA-based environmental and social impact indicators for investment funds

In **Chapter 4** the model prototype is extended to cover 13 environmental and 13 social indicators and additional case studies are performed. The indicators are all based on IOLCA, albeit two different databases are used, one for environmental and one for social categories. Importantly, for social impacts, the MRIO database PSILCA has been linked for the first time with financial revenue data to derive company and fund-level estimates. PSILCA (Maister et al., 2020) offers impact information for social impact categories, such as *exposure to forced labor* or *presence of sufficient safety measures for workers*. While the greater coverage in impact indicators has been achieved, this came with greater uncertainty in results. There are less tools for measurements of impacts beyond GHG emissions, thus making it cumbersome to validate our estimated results.

7.1.5 A global study of the pricing of IOLCA-based sustainability indicators for companies in the cross-section of stock returns, with potentially new implications for water use indicator

In **Chapter 6** we tested whether sustainability characteristics of companies, measured via quantitative indicators, are priced in the cross section of stock returns. In line with previous research, we found that GHG emissions, as absolute metric, are positively associated with stock returns. As a novelty, we tested via a pooled OLS regression whether other impact categories are similarly priced by investors. Specifically, measures of water use, vulnerable employment, or human toxicity have not been previously employed in relation to stock returns. We found that, in addition to GHG emissions, water use, and vulnerable employment seem to have positive correlation with stock returns. This implies that investors acknowledge social issues and water use issues as material for investors. Importantly, we have also observed differences depending on the region or country of domicile of the companies. Especially for companies domiciled in China and in general countries outside EU and the US there is stronger positive significance for absolute sustainability of impacts, which could signal that investors perceive more risk exposure from these countries. This could be due for example to companies being exposed to less stringent environmental and social regulations now, but that could change in the future.

Interestingly, we also found that other impact categories, such as human toxicity, are relevant for investors, but only for companies domiciled in specific jurisdictions and for a certain scope of impact. Specifically, companies domiciled outside of the EU, US, and China positively price in acidification life cycle impacts, in addition to stock returns. This could imply that for companies in the EU, US, and China, GHG emissions are already seen as a good proxy of acidification impacts as well, while in rest of the world countries, in general, acidification is priced in addition to the effect of GHG emissions – possibly because of less stringent regulations in terms of acidification-related emissions. Another interesting finding was that human toxicity cancer effects are negatively priced in the US, for both direct and indirect impact scopes and when running the regressions with GHG emissions as control. This translates into companies with high GHG emissions but also high human toxicity having a lower premium in the cross-section of stock returns.

7.2 Implications for policy

7.2.1 Ready-to-use IOLCA-based indicators to inform reporting requirements under the EU Sustainable Finance Disclosure Regulation

Recently, the EU has adopted regulations on non-financial reporting for companies (CSRD) and for financial products (SFDR). Different impact categories are mandatory for companies and/or financial products to report on. However, it is unclear which specific indicators should be adopted by companies and investment funds, given that companies seldomly report on such data. We proposed a set of indicators based on the life cycle assessment field, that have a clear framework and would allow for applying the same methodology across a sample of financial products. Our study could serve as a **template for developing a standardised set of indicators to be required in reporting for both companies and financial institutions**. This standardisation is needed in order to decrease the burden of companies and financial product providers in developing methods for comparing between different indicators that would be used for the same impact category, in the absence of guidance on what indicators to use. The proposed indicators and the linking have been performed in **Chapter 4**. Often what the regulators ask is burdensome for the companies that need to report, and they do not have the resources to develop and test different tools and indicators. Using standardised measures, such as indicators based on the Environmental Footprint Methods for environmental impacts would ensure that reporting is trustworthy, structured, and clear for the respective entity and trustworthy for the verifies and investors.

7.2.2 Highlighting the responsibility of investment funds in terms of driving impacts, to inform policy of the role that FIs have in the sustainability transition

Our prototype model stands as proof that investors and companies have the tools necessary to estimate their sustainability footprint, where reported data is lacking. Estimation tools, while not able to precisely predict impact, are useful for the **identification of hotspots of impact**. This can be helpful for regulators and other stakeholders in identifying greenwashing, as one would understand the magnitude of impact that the financial product is exposed to, depending on the indicator, as well as driving countries and sector of impact, especially for the indirect phase.

This thesis provided a **quantification of the role that investment funds' shareholdings play in the global economy that can serve as motivation to policy makers to drive better regulations for the financial industry**. Investors manage trillions of euros on the global markets and can indeed have a huge influence on the companies that they invest in. We have showed in our case studies that the impacts associated with fund-level investments are comparable to the impacts of whole economies, especially when accounting for the life cycle impacts, with the funds' impacts being equivalent to the impacts of up to 28.2 million EU citizens, depending on the impact category. More than 50% of the impact of the funds' sample can be traced back to a small number of companies, meaning that funds can put together efforts to engage with companies that have highest impacts. Moreover, investment funds have holdings from all over the world, while investors are usually located in more wealthy countries. Investors could thus have an influence on company-level practices abroad and lead to improvements of their practices. This would be most impactful when referring to social impacts, as these are often influenced by the standard practice in the country or culture where the company is located in. If an investment fund manager would estimate, for example, its exposure to forced labor and would like to decrease it, it could engage with the company and incentivize engagement with companies down the supply chain. This could drive improvement in working conditions for that specific country, even if societal wide interventions from the government of that country would not be taking place.

7.3 Implications for the financial industry

7.3.1 A practical prototype for estimating impacts at investment fund level and its application to relevant case studies

One key contribution of this thesis that can serve financial industry participants is the **design and implementation of a prototype model to estimate sustainability indicators for investment funds**. The model's methodology for GHG emissions, introduced in the open-access paper (Popescu et al., 2023) of **Chapter 3** and extended in **Chapter 4** and **Chapter 5** to additional social and environmental indicators has been applied to four case studies, three in academic papers and one in a market report (LSFI and PwC, 2022). We proved thus how investors and other stakeholders would benefit from a ready-to-use tool that can estimate, in a consistent manner, and using the same data sources, the environmental and social footprint of an investment fund. While some funds already report on their environmental performance, there is not yet a standardized methodology to do so, making comparability between funds cumbersome. With our method, we ensure that funds can be compared on the same indicators. Moreover, investors would benefit from the ability to compare a fund's performance on different indicators, as there are trade-offs that could be important – such as achieving a decrease in environmental damage while negatively impacting workers.

Being able to estimate a large suite of impacts means portfolio managers can identify the best investment opportunities that would target specific environmental and social objectives, while understanding the negative effects they could trigger for other impact categories. In **Chapter 5** we took an in-depth look at the trade-offs between GHG emissions and vulnerable employment and identified industries which expose a fund to larger trade-offs. For example, investing in Retail companies from different regions in the world may reduce the environmental burden of the fund, while increasing the percentage of vulnerable employment that the fund is exposed to.

7.3.2 Translation of the life cycle perspective for financial market players

An important contribution of this thesis is bridging the gap between **environmental and social impact indicators from the IOLCA field and financial products**. In the sustainable finance space, the question of sustainability-related competences is often discussed, along the need to train financial professionals into the science of sustainability and identification of material risks. In Chapter 4, we describe the environmental and social indicators that are recommended in LCA literature and make the link between these and EU-wide sustainability reporting regulations. Using life-cycle-based indicators, which are based on scientific measures for aggregation of impact at indicator level, entire investment portfolios can be mapped, with identification of industries and companies contributing to the larger share of impacts, as done in the case studies of **Chapter 2**, **Chapter 3** and **Chapter 4**. This type of analysis helps investors better integrate information about the impacts of their investments and understand the far-reaching implications of their associated direct and indirect impacts. Personally, I find this contribution to be the most significant one, as it bridges two distinct fields of academia and practice – sustainability and finance – which, in our times, need to walk together.

7.4 Summary of limitations

Throughout the chapters, we highlighted the benefits of calculating sustainability footprints of investments using an IOLCA-based model, while always being aware of the inherent uncertainties. In the following, we summarize the main limitations of our tool.

An important caveat is that **indicators represent an estimation and not the actual impact**. Approximations of impact are needed in order to aid decision-making processes by offering a simplified representation of real impact. We have conducted a validation of estimated GHG emissions using CDP company reported data in Chapter 3. Future research should be undertaken to validate other impact categories' estimates as more company data becomes available. If one would aim to estimate the footprint of a company more precisely, a hybrid process-based LCA and input-output approach may be used (Alvarez et al., 2019). The main advantage of a hybrid approach is achieving precision in the direct impacts associated with the company (Agez et al., 2020). During the PhD, the option to develop a hybrid model was explored. However, this path was not extensively researched, given that it is not yet suitable to be applied in the context of a very large sample of companies due to the lack of structured data to feed a process-based model.

Second, **uncertainties from input-output databases are inherited by the IOLCA-based estimates of impacts**. One main source of uncertainty in the IO databases, relates to the variation in impact factors for the same industry, across countries: country-sector combinations with small outputs can have outliers in terms of impact factors attributed, leading to increased deviation from the exact impact factor to be allocated at country-sector level. Moreover, while year-on-year differences in impact factors derived using IO should reflect technological changes in the economy, these could be influenced by assumptions made in the allocation decisions of the IO tables. Therefore, year-on-year impact factors may not always depict real changes at sectoral level. These uncertainties are inherent to the construction of IO tables and cannot be fully eliminated. Estimates should once again not be considered as the representation of actual impact. In the future, uncertainties could be captured in sensitivity analysis.

Third, **the level of sectorial and regional aggregation drives uncertainty in estimates**. In input-output models, a simplification of the world economy is depicted. This procedure implies aggregation of countries to regions and aggregation of sub-industries to industries. Depending on the IO database of choice, aggregation is done based on different criteria. In EXIOBASE, all EU28 countries are covered separately. At the same time, there are only 44 countries in total, and 5 rest-of-the-world regions, meaning that for some countries only the regional average can be used. When it comes to sectorial split, the EXIOBASE database is detailed, covering 163 sectors, and homogenous, with the same sectorial split across all countries and regions. Nonetheless, some sectors are highly aggregated, such as *Chemicals* sector, which led to higher deviation from the company-reported results in the validation exercise conducted in Chapter 3. Other sectors, for example in Agriculture, *Cultivation of rice*, are very detailed. In adjacent analysis, we have tested the use of an alternative database, EORA, but variations compared to reported data were even higher. Avenues for research would be the development of more detailed EXIOBASE sectorial classification and the harmonization of social input-output databases with the same sectorial classification across all regions.

Finally, **given the high degree of complexity in social impact, assessment results should be analysed with care**. In social LCA, impact is attributed through proxies, such as *worker hours*. Raw units used for social impacts – for example impacts measured in *% of people*, are more difficult to streamline from direct to indirect impacts (Sala et al., 2015). These issues prevail in the application of SLCA to input-output assessment, where more caution needs to be taken when interpreting the estimated results for the social indicators. The main driver of uncertainty is the qualitative nature of social impacts and the heterogeneity of impacts for companies in the same industry, unlike for environmental impacts, where similar impacts can be assumed for all companies that have the same technical processes. SLCA is better used solely for the identification of social hotspots for a company. Given the use of proxies, it can best identify which companies are likely to be associated with a negative social impact (there is a probability, but not a certitude). Thus, social impact assessment at this stage should be used to estimate possible impacts, and to prompt further investigation to confirm or invalidate the findings (Sala et al., 2015).

An additional limitation arises from the linking with financial revenue data: the linking to life-cycle-based databases for environmental and social assessment is as good as the description of the company/holding revenue is. As we have performed a global study, using different classification systems worldwide has proved a challenge in the linking process. Some companies offer good precision in terms of revenue reporting, some less satisfying. For example, two companies may have revenue from production of solar energy, but in one case the sector may be simply nominated as "Wholesale electricity Europe", while for the other as "Alternative electricity production". In the first case, the company will be penalized with a higher impact factor for GHG emissions for example. In the future, breakdown of company revenue should take account of the relevance of the classification in allocating environmental and social impacts.

Finally, the **pricing strategy at company level drives uncertainty in results**. Monetary-based impact factors introduce uncertainty in impacts, as two companies with different levels of pricing but same physical production would end up having different estimates of impact, while they should have the same value. For example, in our model, a company with lower pricing would have a lower total footprint, while having the same impact intensity. Presenting results both in terms of absolute and intensity metrics, as done for some of this paper's case studies, ensures comparability between companies. Nonetheless, the uncertainty in pricing stemming from the IO tables is still present.

7.5 Outlook

After four years of research for the present thesis, the streamlined coupling of life-cycle-based indicators and sustainable investments has been achieved. Nonetheless, this has been only a first attempt, and more work can be undertaken to further develop the application of IOLCA to sustainable finance field until maturity. In the present research, a lot of work has been spent on the analysis of suitability of IOLCA models for sustainable finance, exploration of sources of uncertainty, determining the accuracy of the estimation model and the linking to financial products. To continue enriching this line of work, two main future pathways for research are proposed below.

First, the model of this thesis had as a goal to cover all sectors of the economy using a homogenous approach, in order to simplify the estimation process and allow comparability between companies and investment products. While this has been achieved and rapidity in generation of results has been indeed an advantage, the desire to cover all economic sectors with the same approach led to imprecise estimates for certain companies and perhaps too general conclusions for an assessment at investment portfolio level. One possible direction would be to develop more detailed databases of impact factors on an industry-by-industry basis, thus capturing fine traits of disaggregated industries. For example, the FINEPRINT project (Fineprint, 2022) developed a database of mining output linked to companies, based on many public datasets, and for which harmonization and correction exercises were conducted (Jasansky et al., 2023). Due to its public availability, this dataset and hopefully similar future ones for different industries, will be quintessential to achieving transparency and accuracy in impact calculations for different key industries.

Another relevant development would be prioritising impact assessment based on a classification differentiating between *sectors that contribute to high negative impacts* – while taking into account the fact that this list may be different depending on the impact category considered – and sectors that would, in contrast, *contribute to the achievement of the sustainability transition* – a classification that would vary depending on the impact indicator that is assessed. For the first category, one example would be the classification of companies into climate-policy-relevant sectors (CPRS), introduced by Battiston et al. (2017) that has been explored tangentially in Chapter 3. In our case studies, many funds that invested in solutions for the future have ranked worse than funds simply investing in the market index, solely because the market index would be by default more invested in already low-carbon companies, like the ones from Tech or Finance sectors. I believe that classifying fund holdings between the proposed types would solve the issue of penalizing companies that actually develop solutions for the future, but have high impacts on one indicator, like being carbon-intensive, for example. Moreover, an improvement of the precision of the model could be envisioned from a consequential life cycle assessment perspective, by focusing on the contribution that a company/investment has on the achievement of the low-carbon and sustainability transition. Databases with consequential life cycle impact factors are seldomly available, and therefore a research plan in this direction would be highly useful.

Second, to make sustainability information at investment product level even more insightful for investors, policy makers and other stakeholders, methodological developments could be envisioned that translate the value of impact into prices. Investors make decisions based on risk and profitability: the translation of impacts to speak on these two variables could be more successful in driving action in capital markets. Already implemented by some companies, for example in the case of internal carbon pricing (Addicott et al., 2019), such a unit would allow to understand the degree to which a company or investment would be unprofitable if it continues to generate the estimated negative impact that was associated with it. While pricing of carbon has been the most popular so far and companies worldwide have integrated it in their day-to-day decision-making processes, other impact categories would benefit from such a measure. There have been proposals to introduce a cap-and-trade pricing system for water, in order to better manage scarce water resources (Nugent, 2022). The *Environmental Pricing Handbook* developed by researchers CE Delft and applied in the Netherlands (De Bruyn et al., 2018) could serve as a starting point in this direction, while other monetary valuation methods in LCA are also being developed (Amadei et al., 2021) and could be further linked to investment valuation methods in the finance industry. For example, the *Oiconomy* pricing method has been piloted on a few companies and assigns a monetary value to all environmental and social externalities associated with the company's products (Vermeulen et al., 2023).

Another outlook for the financial industry and associated research would be the mapping of the influence that investment funds can reach. While a lot of the research discourse is centred around the responsibility of countries for worsening the climate crisis, it is equally companies and therefore their owners that should bear the responsibility, given that they are the profit makers. This thesis has already mapped the responsibility of a large sample of funds, but a study of the aggregate responsibility of capital holders is missing, as well as a clear identification of responsibility by type of asset owner, for example pension funds, insurance companies and retail investors.

In terms of type of investments addressed, the scope of the assessment could be significantly widened. This thesis has focused largely on listed companies, given that only for these companies there was enough public information on economic activities that they activate in. Small and medium enterprises (SMEs) represent the biggest share of an economy, and especially so in developing countries, while their sustainability performance remains largely unknown due to lack of capabilities to measure non-financial information and also a lack of regulation mandating these to report. Nonetheless, financial institutions, especially banks but also impact funds and development finance institutions are largely exposed to investments in SMEs and will have to report on the sustainability performance of these investments as well.

Therefore, FIs will need to incentivize and support SMEs to better estimate and report on sustainability performance indicators. Estimation methods based on LCA and EEMRIO analysis would be helpful in providing such estimates, while a minimum set of data points would be required from the firm side.

7.6 Concluding words

Data reliability remains one of the main hurdles in assessing the sustainability of financial products, fuelling greenwashing risk as an obstacle to efficiently deploying capital towards truly sustainable projects and companies. Objective and quantitative measures of sustainability applicable to financial products need to be streamlined across asset classes and geographies. There is no need to reinvent the wheel – robust but still evolving sustainability impact assessment methods from the life cycle assessment field can be adopted in the financial industry. The research undertaken in the current thesis showed that a simple and homogenous IOLCA-based method to assess investment funds as financial products can be proposed and applied in order to achieve estimates of sustainability performance. More interdisciplinary research is needed, as well as advancements from the LCA and the finance and corporate field, to increase adaptability of tools, and the availability of relevant data points. Concomitant with the development of robust sustainability assessment tools, stringent regulations are vital to enforcing the needed sustainability criteria onto financial product providers.

Appendix

A. Appendix to “A critical review of methods and frameworks for measuring the sustainability of investment funds”

Table A.1. List of criteria supported by arguments from internationally reputed institutions, active in sustainable finance

Criteria	OECD	UN / UNPRI / UNEP FI	EU Action Plan on SF	TCFD	NZA and IIGCC
Double Materiality	"we see enterprises and investors **re-labelling as “impact” investments and activities that have little to do with the development of a more sustainable world. To counter the danger of “impact washing”**, public authorities […] have the capacity to regulate the market by establishing and promoting integrity standards" (OECD, 2020a)	“achieving the SDGs will require a **shift towards long-term investment horizons** and **sustainability as a central concern of investment decisions**. This demands […] better measuring the impacts on sustainability” (UN, 2019) "Does your fiduciary duty extend beyond strictly financial benefits for stakeholders? Is positive real-world impact an explicit part of your primary objective for investment results?" (UN PRI, 2018)	“The use of the **EU taxonomy** for (financial) product standards and labels would improve environmental integrity of green investments within as well as outside the EU […] As such, it would help to **minimize the risk of greenwashing and avoid the negative environmental impacts from investing in assets that are not in line with the EU sustainability goals**” (EC, 2019c)		

Criteria	OECD	UN / UNPRI / UNEP FI	EU Action Plan on SF	TCFD	NZA and IIGCC
Reliability	***comparability of impact measurements*** *is key to enable correct assessment of investment achievements on sustainability* (OECD, 2020b) **Comparable, standardized and transparent data is needed to streamline the allocation of funds to sustainable activities**, according to a recent report by the OECD. The report acknowledges that the progress made has not yet reached a satisfactory level and more transparency of data will allow to understand what is efficient and what not. (OECD, 2019a)	"To understand the impact of investment on sustainable development there needs to be **more of a consensus around principles and norms to measure impact**, not just at the corporate level, but also at the security and portfolio levels" (UN, 2019)	*The EU Regulation on Sustainability Disclosures for Financial Institutions* ***mentions that standards for the content, methodologies and presentation of the sustainability information are to be developed by end of 2020 for environmental impacts and by the end of 2021 for social impacts.*** (EU, 2019)	"**The lack of robust and cost-effective tools to quantify the potential impact of climate-related risks** and opportunities at the asset and project level **makes aggregation across an organization's activities or investment portfolios problematic and costly**" (TCFD, 2017b) "Improve data quality and further develop standardized metrics for the financial sector" (TCFD, 2017b) "The methodology should be made available, where not apparent" (TCFD, 2017a)	*robust frameworks would help asset managers align their portfolio with a zero emissions target by 2050* (IIGCC, 2020; Net-Zero Alliance, 2020)
Life-cycle consideration	"Carry out a broad scoping exercise to identify all areas of the business, across its operations and relationships, **including in its supply chains, where RBC risks are most likely to be present and most significant**." (OECD, 2019b)		*In order to assess whether the environmental performance of an* ***activity is consistent with environmental goals, clear and common measurement metrics are needed. These metrics should incorporate life-cycle impacts.*** (EC, 2019c)	"Organizations should provide their Scope 1 and Scope 2 GHG emissions and, if appropriate, Scope 3 GHG emissions and the related risks" (TCFD2017b)	
Comprehensiveness of impact categories	*"SDG-washing"* ***is defined as reporting positive impact on one SDG, while ignoring negative impact caused on others or using SDGs as an image to report on impact without quantifying the real impact.*** (OECD, 2020a)	"deliver **a positive contribution to one or more of the three pillars of sustainable development**, **once any potential negative impacts to any of the pillars have been duly identified and mitigated**" (UNEP FI, 2017)	"An economic activity shall be considered to contribute substantially to one or more of the environmental objectives set out in Article 5 […] and where that activity **does not lead to a lock-in in assets that undermine long-term environmental goals, considering the economic lifetime of those assets**;" (EC, 2019c)	*Does not consider impact beyond climate change, but it* ***recommends that organizations disclose climate risks that are associated with water, land use, waste*** (TCFD 2017b)	

Criteria	OECD	UN / UNPRI / UNEP FI	EU Action Plan on SF	TCFD	NZA and IIGCC
Compatibility with science-based targets (SBTs) for sustainable development	*"SDG-washing"* ***is defined as reporting positive impact on one SDG, while ignoring negative impact caused on others or using SDGs as an image to report on impact without quantifying the real impact.*** (OECD, 2020a)		"Paris alignment disclosures: from 31 December 2021, inclusion in the benchmark statement of information on the **degree of alignment with the target of carbon emission reductions or attainment of the long-term global warming target of the Paris Agreement**" (EC TEG on Sustainable Finance, 2019)	"Further **develop applicable 2°C or lower transition scenarios and supporting outputs, tools, and user interfaces.** Develop broadly accepted methodologies, datasets, and tools for scenario-based evaluation of physical risk by organizations." (TCFD 2017a)	*Encourage the* ***use of science-based transition pathways for identifying and reporting on the alignment of underlying assets,*** *both on current and on forward-looking emissions* (IIGCC, 2020; Net-Zero Alliance, 2020)
Prospectiveness		"Indicate whether the organization **carries out scenario analysis and/or modelling, and if it does, provide a description of the scenario analysis** (by asset class, sector, etc.)" SG13.1 Reporting Framework (UN PRI, 2019)		*Mentions that emissions should be* ***disclosed for more periods, to allow for a trend analysis*** (TCFD 2017b)	*Encourage the use of science-based transition pathways for identifying and reporting on the alignment of underlying assets,* ***both on current and on forward-looking emissions*** (IIGCC, 2020)
Investor's additionality		**"i.e. business and finance solutions that help address an unmet or underserved sustainable development need and hence constitute a significant step forward for the attainment of the SDGs"** (UNEP FI, 2017) "Do you **actively engage with your invested companies**?" (UN PRI, 2018)		*asset owners should* ***disclose engagement with investee companies*** (TCFD 2017b)	*Alliances convened by key actors of the investment management sector aim to lever their influence in driving decarbonization and direct funds to investments that bring a positive impact on the climate* (IIGCC, 2020; Net-Zero Alliance, 2020)

Table A.2. Evaluation of measurement methods against the set of sustainability criteria: " + " represents a positive point, " - " a negative point, " ~ " a neutral point

Method	Double Materiality	Reliability	Life-cycle consideration	Comprehensiveness of impact categories	Compatibility with SBTs	Prospectiveness	Investor's additionality
ESG ratings and scores	- identify risk, not sustainability - based on disclosed policies and strategy, rather than actions	~ hundreds of points + widely available + easy to use - subjective assessments - lack of transparency	- no life-cycle view	+ over hundreds of social and environmental data points - mostly qualitative	~ some address link to goals	- past performance ~ESG risk may be forward looking	- not addressed
Free-to-search ratings	- risk perspective + a few assess sustainability impact	+ transparent methodology + freely available ~ third-party data for emissions and company assessments for other ESG factors	~ report on life-cycle emissions, not for the final metric (yourSRI)	~ some assess impacts beyond carbon (e.g. Climetrics - water and deforestation)	- no link to scientific goals	~ some assess commitments to reach climate targets	~ some assess investor impact: engagement (Climetrics)
Sustainability labels	- assess the policy and strategy of the fund + a few (aligned with the Taxonomy), do mention positive sustainable impact	- rely on fund reporting + some consider quantitative indicators + easy to use - false assurance of sustainability	- no life-cycle view	~ some assess broader environmental and social issues	~some consider alignment of electricity utilities investments to below 2°C scenarios (Febelfin)	~some assess the transition preparedness of companies in a fund's portfolio	~ some assess investor impact through engagement
Carbon Footprint based on reported and estimated data	- no consideration of double materiality + report on quantitative level of emissions	- lack of comparable data, company reporting + some have stronger methodologies (PCAF) - carbon efficiency not accounted for - low comparability + easy to scale	- no life-cycle view	N/A	- no link to scientific goals	- historical snapshot + recommends analysis of historical trend	N/A
Trucost Carbon Scorecard	+ carbon footprint, exposure to fossil fuels, stranded assets, renewable energy, energy mix	~ S&P and scientific sources - low disclosure on methodology - fee-based	+ first-tier suppliers only	- social impact not considered + other environmental issues	~ some assess alignment with the 2 degrees warming scenario	+ exposure metrics based on forecast	N/A

Method	Double Materiality	Reliability	Life-cycle consideration	Comprehensiveness of impact categories	Compatibility with SBTs	Prospectiveness	Investor's additionality
	alignment with 2°C scenarios						
IO-based Carbon Footprint	- no consideration of double materiality + report on quantitative level of emissions	+ reliable, external database for emissions + scalable + enables comparisons - data updated with lag (5 y)	+ life-cycle data incorporated systematically	N/A	- no link to scientific goals	- historical snapshot	N/A
Weighted Average Carbon Intensity based on reported and estimated data	- no consideration of double materiality + report on quantitative level of emissions	+ accounts for carbon efficiency - lack of comparable data + stronger methodologies (PCAF) - low comparability + easy to scale	- no life-cycle view	N/A	- no link to scientific goals	- historical snapshot + recommends analysis of historical trend	N/A
Inrate Climate Impact	~ consideration of impact for portfolio comparison with benchmark; focused on improvement of portfolio construction	+ company level and estimated data + uses physical data for electricity - does not adjust double counting - not open-source	+ covers full life-cycle (supply chain and use phase)	N/A	N/A	N/A	N/A
Carbon Impact Analytics (Carbone4)	+ measures the contribution to low-carbon economy	- no clear data sources + quantitative and qualitative method	~ life-cycle emissions, not complete	N/A	+ qualitative link to warming scenarios ~ includes solely electricity sector	+ accounts for company climate targets - not forward-looking	N/A

Method	Double Materiality	Reliability	Life-cycle consideration	Comprehensiveness of impact categories	Compatibility with SBTs	Prospectiveness	Investor's additionality
PACTA	- portfolio exposure to sectors misaligned with the climate transition + incorporates long-term approach	+ diverse scientific databases + allows for comparison + open-source methodology - data uncertainty	- no life-cycle view	N/A	+ alignment with climate scenarios developed by the IEA	+ using investment and production projections, following a 5-year trend	~ addresses investor's action to drive sustainability
CISL Impact Framework	+ long-term view + focuses on actions	+ open-source methodology ~ scalable ~ metrics from institutions / computed metrics	- no life-cycle view	+ six broad teams, based on the SDGs	+ link to the SDGs	+ carbon budget to compute alignment with the global warming scenarios	N/A
Portfolio Impact Footprint	- risk perspective + map impact on SDGs	+ easy to use and fast - data and method not fully transparent	- no life-cycle view	+ 16 indicators (e.g. "Avoiding env impact", "Tax gap")	+ linking impact to the SDGs	- not forward-looking	N/A
Biodiversity Footprinting	+ measuring the impact of portfolios on biodiversity factors	+ uses scientific environmental databases + open-source methodology ~ complex methodology	+ based on life-cycle assessment	N/A	+ biodiversity loss	- historical data	N/A
Net Environm. Contribution	+ measuring performance on environmental issues	+ data based on external, environmental data sources + differentiated method per sector + transparent methodology + open-source methodology ~ complex methodology	+ based on life-cycle assessment	+ more environmental indicators (biodiversity, waste, water and air)	+impact in terms of contribution to the climate transition	- historical data	N/A

B. Appendix to "An input-output life cycle assessment of investment funds with a case study on carbon emissions of SRI funds"

B.1. Input – Output Methodology

Input-Output Analysis (IOA) is widely used in economic analysis to account for inter-industry trade flows. These can be represented product-by-product or industry-by-industry (Miller and Blair, 2009). Here we use the industry-by-industry format, as it is more suitable for linking to company-level reported data. In addition, multi-regional IO (MRIO) tables capture the relations between countries. In sustainability assessment, environmental extensions (satellite accounts) are added to the IO tables, representing the direct emissions from all industries (EEMRIO analysis) (Wood et al., 2015). The pymrio python package is used to navigate efficiently through the EEMRIO analysis (Stadler, 2021).

The input-output matrix can be described as the inter-industry transaction matrix divided by the output per industry. Thus, matrix A gives the direct requirements or "production recipe" per million EUR of sectorial output, for all sectors in the economy.

$$A = Zx^{-1}$$

By considering the production recipes of all industries, we follow an iterative process of accounting for the intermediate flows production tier after production tier, by successively multiplying the next tier's output by A. The infinite sum of powers of A converges to the Leontief inverse, a life cycle requirement matrix.

$$L = (I - A)^{-1}$$

Thus, the output of the industries can be obtained from each needed final demand y from the following equation.

$$x = (I - A)^{-1} y = L\,y$$

The F matrix contains the direct factors of production and the environmental stressors arising from production. EXIOBASE contains more than 1,000 stressors (e.g., different greenhouse gases – GHGs, chemical substances, land, or water use). These represent environmental stressors associated with the processes under every sector. From the F matrix, one can derive the factors per unit of production, by normalizing them to the industry output. The S matrix thus represents the direct stressors **(direct impact factors)** per unit of industry impact.

$$S = Fx^{-1}$$

So-called multipliers **(life cycle impact factors)** – representing total life cycle requirement factors for production for each sector – can be derived by multiplying the direct stressors with the Leontief inverse.

$$M = S\,L$$

B.2. Adjusting the EIO-LCA factors

To ensure that all emission factors used are reasonable, we perform a manual check for all values above 10 tCO_2-eq/EUR, industry by industry. To determine whether to use the median or the 75th percentile for the adjustment of outlier emission factors, we used scope 1 emission factors published by Eurostat for EU-average emission factors (Eurostat, 2020). We perform the adjustment for scope 1 factors, and then use the new set of emission factors for computing scope 2 and scope 3 emission factors. In total, 16% of the country-industry factors were adjusted. 5% of the country-industry emission factors were capped at the median of the industry and 11% were capped at the value of the 75th percentile. For example, for sector "Mining of iron ores", Portugal, with a recorded industry output of less than 10 EUR in 2018, scope 1 intensity amounts to an unlikely factor of 123 $ktCO_2$-eq/EUR, while the global median is at 2.18 $kgCO_2$-eq/EUR. Therefore, to make sure that this outlier will not affect the results, we assume the emission factor for the respective sector in Portugal is the same as the median.

B.3. Differences between RCF and WACI

The Relative Carbon Footprint (RCF) allocates a holding's emissions based on share ownership. Therefore, it is a way to divide responsibility between different shareholders. It also allows for aggregation of total impact over more funds held by one asset manager, for example. On the other hand, the Weighted Average Carbon Intensity (WACI) is a measure of climate risk exposure of a fund. Companies with a high carbon intensity are more exposed to regulatory and transition risk, which translates to risks for the investment portfolio as well (Kepler Cheuvreux et al., 2015b; MSCI, 2015). WACI is more versatile than RCF, as it allows comparison between different classes as it is not constrained by market valuation. On the other hand, it is also sensitive to outliers.

In the equation below, we express the RCF of fund f, due to only one of the companies it invests into, say company i:

$$RCF_{fi} = sh_{if} \times \frac{R_i}{M_i} \times \frac{E_i}{R_i}$$

where E_i are the emissions of the company, in tCO2-eq, R_i is the revenue of the company, in MEUR, M_i is the market value of the company, in MUSD, and sh_{if} is the share, in MEUR, held by the fund in the company. From the equation, it results that companies with high Price to Sales ratio (or conversely a low Sales to Price ratio), will appear to be less important in terms of carbon emissions contribution to an investment portfolio. When one removes the information regarding Market Value, only the Emissions intensity counts. As such, for RCF, if the sales figure increases and the carbon intensity decreases, the total emissions appear unchanged, even if the company may have improved, while WACI can capture changes in the carbon efficiency of a portfolio.

B.4. Selecting a sustainability classification for funds

As sustainable investment funds are not yet regulated in the market, it is hard to find a clear classification by investment theme. For example, the European Fund and Asset Management Association (EFAMA) classifies funds by using self-reported information from financial market participants, grouping by sustainable investment strategy, such as "Impact Investing", "Engagement and Voting", or "ESG Integration", with the biggest category being "Exclusion" (Eurosif, 2018). Classifications from data providers are also scarce. We have tested MSCI and Bloomberg. MSCI offers a simple ESG/non-ESG flag, without providing more detail for ESG funds, based on fund prospectus. Similarly, Bloomberg uses funds' prospects to identify and classify funds into more detailed categories, under the Bloomberg Fund Classification System (BFCS). The following sustainability-related themes are under the "Thematic", "General Attribute" class: "Clean Energy", "Climate Change", "ESG", "Environmentally Friendly", "Islamic", "Religiously Responsible" and "Socially Responsible" (Bloomberg, 2013).

Morningstar, among other providers, offers ESG scores for funds. It is not in the scope of this study to compare our Emission Measures with ESG fund ratings, their evolution over time and, most importantly, their role in investors' decision in the selection of funds: we are planning to explore these issues in the near future.

B.5. Holdings sample curation

The total number of fund holdings, after running our model, was of 12,900 unique holdings (*Table B.1*). Out of these, 384 represented fund units or fixed income instruments that were removed from our sample. As such, the total number of available equity holdings was of 12,516 company stocks. Out of these, 708 had limited or no revenue information in FactSet, that impeded our estimation exercise. Therefore, the estimation rate was of 94.3% of the total sample, or 11,808 stocks. Furthermore, duplicates in company name can exist because companies have different types of shares listed, which give to the owner different voting and dividends rights but are issued by the same company. In this case, for the fund-level calculation, we kept all listings, and for the holdings-level analysis, we compiled a sample of 11,275 unique companies, keeping only one ISIN for one company.

Table B.1.: Defining the final sample of valid holdings from the funds' sample. The column "pct" illustrates the percentage covered from the total number of companies.

Holdings in sample (number of entities)	*number of companies*	*pct*
	12,900	
Holdings without IOLCA estimated data	1,092	8.5%
fixed income or fund units	*384*	*3.0%*
no FactSet Revenue breakdown	*708*	*5.5%*
Total available equity holdings	12,516	
Total sample holdings with IOLCA estimates	11,808	94.3%
Unique holdings	11,275	

B.6. Validation against CDP data

Comparison based on 400-company CDP self-reported life cycle emissions. To validate our results, we checked our data against CDP data – scope 1 and scope 3 upstream (covering at least Category 1 – Purchased Goods and Services – PGS, of the 15 scope 3 categories of the GHG Protocol), for year 2018 (GHG Protocol, 2015). The CDP data was sourced from the Bloomberg terminal. Out of 11,275 unique companies for which we derived an IOLCA-based carbon footprint life cycle estimate, there were valid self-reported values for 1,865 (16.5%) companies on scope 1 and 1,250 (11.1%) on scope 3 PGS in our CDP self-reporting data, see Table 1. We reached a final validation sample of 400 companies in the CDP data, after checking for outliers and selecting only those that report on more than two scope 3 GHG Protocol categories (Purchased Goods and Services, Capital Goods and Fuel- and energy-related activities).

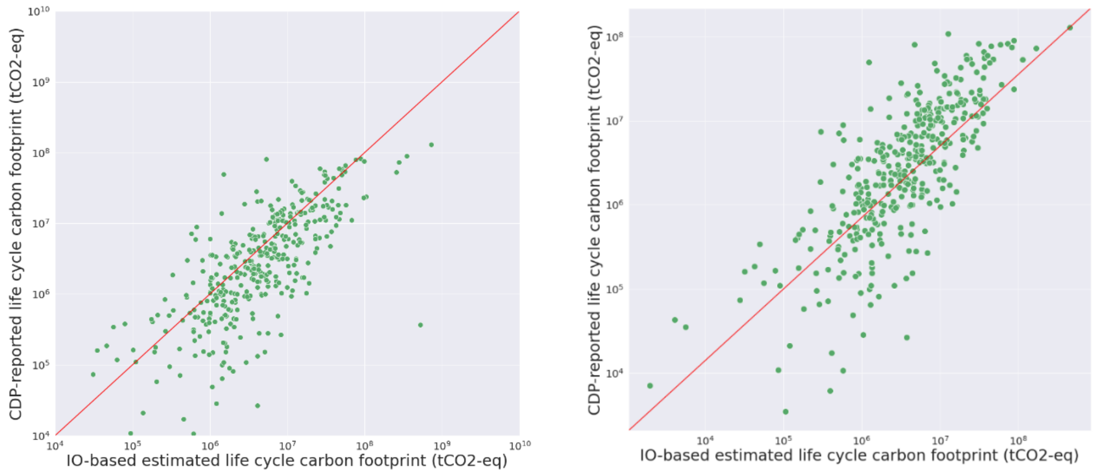


Figure B.1: Scatter plot comparing CDP self-reported company GHG emissions with IOLCA-estimates based on unadjusted EXIOASE emission factors (left side) and adjusted EXIOBASE factors (right side). The sample contains 400 companies that report to CDP in year 2018, on scope 1, scope 2 and selected scope 3 categories (Purchased goods and services, Capital goods and Fuel- and energy-related activities).

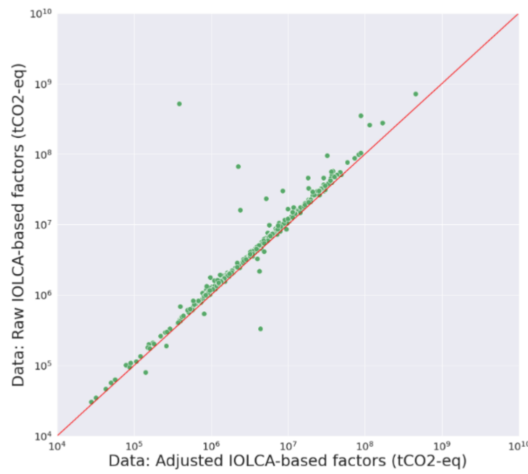


Figure B.2.: Comparing GHG emissions at company level obtained from IOLCA estimation model, using unadjusted and adjusted factors. The sample contains 400 companies, based on the sample of companies reporting to CDP in year 2018, on scope 1, scope 2 and selected scope 3 categories.

For this validation sample, we have compared direct and life cycle emissions for a set of companies reporting completely on scope 1 and 2 and incompletely on scope 3 (1,024 companies). We found that total EXIOBASE emissions for scope 1 and 2 were 5% higher than CDP, while scope 3 emissions were 36% higher. This points towards the large gap in underreported scope 3 emissions that our model helps estimate.

We have also checked our data against REFINITIV data, but here scope 3 are reported in aggregate. Therefore, one cannot distinguish between scope 3 upstream and downstream, which makes the comparison of life cycle data impossible.

For the 400-company sample used for validation we show how results compare when using the raw, unadjusted EXIOBASE factors as extracted directly from the environmental extension of EXIOBASE IO table and adjusted factors. We plot the logarithmic values, as it allows us to visualise both small and large values (Figure B.1). Using adjusted factor gives a better correlation with self-reported emissions. As mentioned above, there are still a few outliers, especially for lower-emitting companies. In the first case, using the raw EXIOBASE factors produces higher compared to self-reported CDP data. Moreover, as observed from the comparison between the two IOLCA-based computations (Figure B.2), the modification of emissions affects a few outlier companies the most.

Extrapolation of CDP company self-reported emissions to the full company sample. In *Figure B.3*, we extrapolate the 400-company sample of CDP self-reported life cycle emissions to the 11,276-company sample. Across most industries, CDP estimates become significantly higher than the IOLCA-estimated emissions. For other sectors, like Oil&Gas Extraction and Mining, the two samples show higher overlap. This indicates that considering non-reporting companies as high emitters is a valid assumption and can work as an incentive for these companies to disclose, or even to improve their practices.

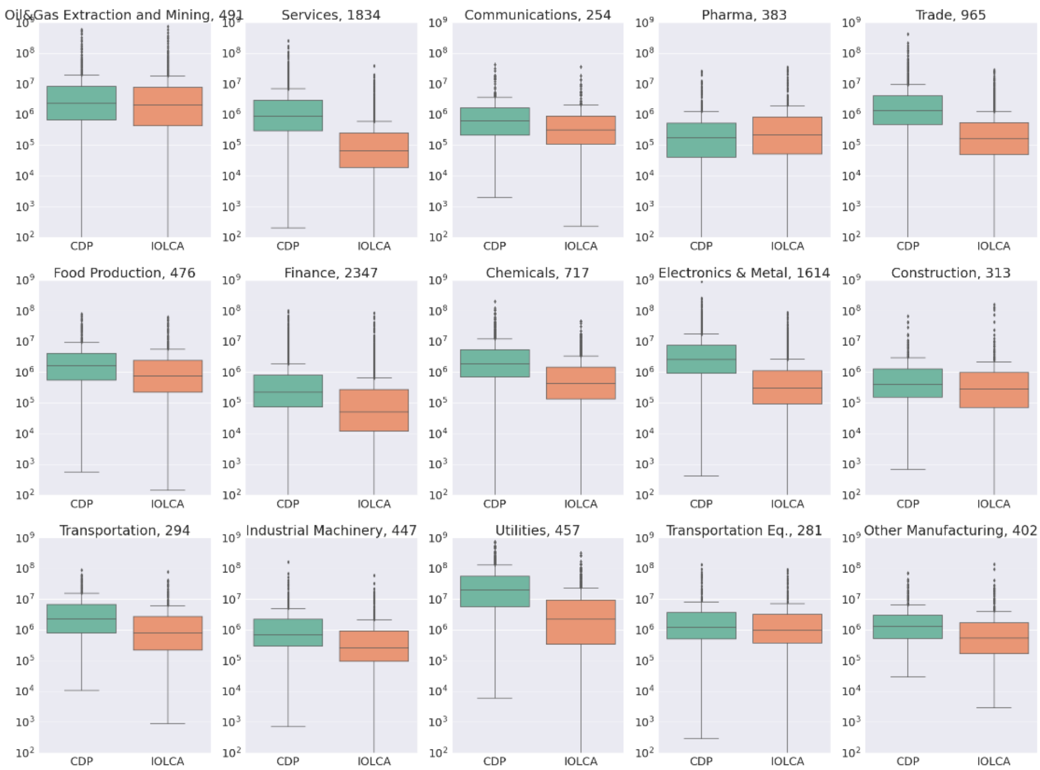


Figure B.3.: Boxplot comparing IOLCA-estimated life cycle GHG emissions for the full sample of companies, compared to CDP-extrapolated values

Using this sample of CDP-extrapolated GHG emissions estimates, we have recomputed results at fund-level (*Table B.2*). On RCF life cycle, SRI and conventional funds seem to perform similarly, while for WACI life cycle, SRI funds have a higher emissions intensity than conventional funds. This could mainly be explained by heavier investment in finance and tech stocks by conventional funds, leading to a lower carbon intensity by default.

Table B.2: Mean life cycle WACI and RCF for conventional and SRI funds, when using CDP-extrapolated data as estimates for non-reporting companies

	WACI (tCO_2-eq/MEUR revenue)	RCF (tCO_2-eq/MUSD invested)
conv	1,654.96	1,128.07
SRI	1,893.91	1,125.21

At the same time, using the CDP-extrapolated data leads to very high RCF and WACI on average. In the CDP-extrapolated sample, all Services companies will have a life cycle intensity of more than 2,000 tCO2-eq/MEUR revenue, due to the high value reported by the "most carbon-intensive" company reporting in Services sector.

B.7. GHG emissions estimates for holdings sample

In *Table B.3*, we present the distribution of absolute emissions of companies, per SIC category. The highest mean intensity for scope 1 is for Mining companies, followed by Transportation & Public Utilities. The highest scope 3 is for Agriculture, Forestry & Fishing, Mining and Manufacturing. Variations between companies are high, especially for Transportation & Public Utilities. The variation is driven by the regional and industrial profile of companies.

Table B.3: Company level WACI, measured in tCO2-eq/MEUR of revenue. Companies are grouped by main industry group (SIC category, from the SIC classification). S1, S2 and S2 refer to scope 1, scope 2 and scope 3, respectively. The column "count" shows the number of companies under each category. 25%, 50% and 75% represent the values at the respective percentile.

SIC category	metric	count	mean	25%	50%	75%	std
Agriculture, Forestry, & Fishing	GHG Intensity S1	87	418	55	137	553	634
	GHG Intensity S2	87	32	15	28	40	26
	GHG Intensity S3	87	529	238	382	595	627
Construction	GHG Intensity S1	313	97	10	18	33	418
	GHG Intensity S2	313	31	9	13	26	117
	GHG Intensity S3	313	291	146	230	317	281
Finance, Insurance, & Real Estate	GHG Intensity S1	2,375	27	6	8	17	104
	GHG Intensity S2	2,375	18	5	9	28	39
	GHG Intensity S3	2,375	96	41	53	121	106
Manufacturing	GHG Intensity S1	4,292	168	20	47	142	467
	GHG Intensity S2	4,292	53	23	36	56	87
	GHG Intensity S3	4,292	437	257	368	544	291
Mining	GHG Intensity S1	419	1,233	405	887	1,520	1,200
	GHG Intensity S2	419	132	18	49	98	372
	GHG Intensity S3	419	446	134	246	568	531
Retail Trade	GHG Intensity S1	630	35	6	10	21	100
	GHG Intensity S2	630	29	4	16	41	176
	GHG Intensity S3	630	114	44	60	124	224
Services	GHG Intensity S1	1,701	29	7	11	19	124
	GHG Intensity S2	1,701	26	9	17	28	80
	GHG Intensity S3	1,701	156	73	96	187	166
Transportation & Public Utilities	GHG Intensity S1	1,090	784	12	62	914	1,426
	GHG Intensity S2	1,090	172	8	23	56	589
	GHG Intensity S3	1,090	379	104	196	362	657
Wholesale Trade	GHG Intensity S1	368	98	7	16	51	335
	GHG Intensity S2	368	28	4	14	41	57
	GHG Intensity S3	368	190	39	93	283	257

B.8. Paired t-test for SRI vs conventional funds

We performed a two-sided paired t-test to verify whether SRI and conventional funds are similar in terms of GHG emissions measurements (*Table B.4*). This table complements the results of the Wilcoxon test. The null hypothesis (H0) of equal mean carbon footprints of SRI and conventional funds was rejected with p-values of <0.02 for RCF scope 1, scope 3 and life cycle, while for WACI, across all scopes and life cycle, and for RCF scope 2, the difference in means is not significant.

Table B.4: Results of paired t-test for the funds sample, performed for WACI and RCF. The t-test is performed for the complete sample of 1,340 SRI and conventional (conv, in the table column title) funds.

Measure	Variance (conv)	Variance (SRI)	Mean (conv)	Mean (SRI)	t-stat	p-value
RCF life cycle	**134,144**	**130,141**	**408**	**346**	**3.16**	**0.002**
RCF scope 1	27,383	19,490	151	116	4.20	0.000
RCF scope 2	1,132	3,480	30	32	-0.63	0.531
RCF scope 3	38,583	45,718	227	198	2.57	0.010
WACI life cycle	**51,675**	**46,929**	**479**	**475**	**0.27**	**0.785**
WACI scope 1	25,060	21,454	174	161	1.58	0.115
WACI scope 2	798	1,843	40	44	-1.71	0.088
WACI scope 3	9,963	8,671	265	271	-1.18	0.240

In *Table B.5*, we perform a t-test on the sample of Article 8/Article 9 funds. As the sample of Article 9 funds is very small, it is hard to make a general conclusion about this type of funds, but generally seems that the two samples do not have a statistically different mean.

Table B.5: Results of paired t-test for the Article 8 and Article 9 funds' sample, performed for WACI and RCF. The t-test is performed for the sample of SFDR self-classified funds (139 art. 8 and 20 art. 9).

Measure	Variance (art 8)	Variance (art 9)	Median (art 8)	Median (art 9)	Mean (art 8)	Mean (art 9)	t-stat	p-value
RCF lc	253,752	30,054	281	235	405	274	1.1440	0.2540
RCF s1	42,028	3,576	95	63	147	84	1.3540	0.1780
RCF s2	2,735	1,821	19	18	34	31	0.2310	0.8180
RCF s3	75,299	8,384	148	131	224	159	1.0460	0.2970
WACI lc	64,053	45,932	463	448	506	501	0.0880	0.9300
WACI s1	21,441	21,250	157	133	178	176	0.0630	0.9500
WACI s2	1,893	920	33	38	47	46	0.0330	0.9730
WACI s3	14,075	6,740	264	262	282	279	0.0970	0.9220

Figure B.4 below depicts graphs that are an extension of Figure 3.3. These show the density distribution plots for computed scope 1, scope 2 and scope 3 RCF and WACI. In the figures, we show SRI and conventional funds separately and study the difference between the two samples' distributions. It is interesting to observe, in addition to the t-stat Table 3.4, that the funds have similar distributions for the WACI variables across all scopes, but especially so for the scope 3 WACI.

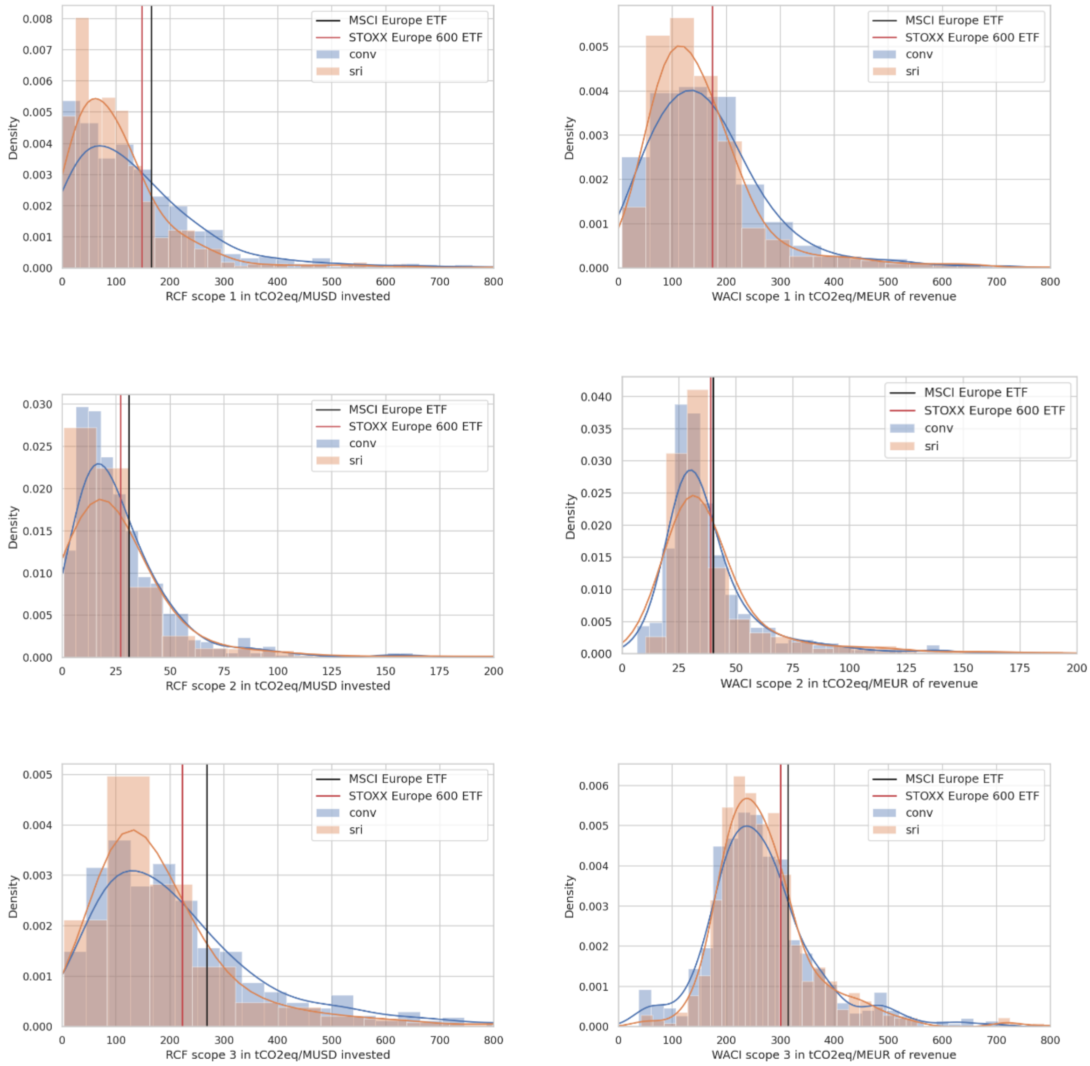


Figure B.4.: Density plots comparing scope 1 (up), scope 2 (middle) and scope 3 (down) RCF and WACI of conventional and SRI funds. With vertical lines, we plotted the values for each scope for two ETFs representing conventional market indices MSCI Europe and STOXX 600.

B.9. Comparing SRI and conventional funds by specific theme, on mean WACI and RCF

Table B.6.: Comparing SRI and conventional funds by specific theme, on mean WACI (tCO2-eq/MEUR revenue) and RCF (tCO2-eq/MUSD invested). The funds in each theme are selected by name, due to the lack of a different classification source (i.e., if the fund contains the specific theme in its name, it is included under the theme).

sri/ conv	number of funds	theme	WACI s1	WACI s2	WACI s3	WACI life cycle	RCF s1	RCF s2	RCF s3	RCF life cycle
conv	670		174	40	265	479	151	30	227	408
sri	670	*Bloomberg SRI Flag*	161	44	271	475	116	32	198	346
conv	*1155*		*172*	*42*	*268*	*482*	*141*	*32*	*219*	*392*
sri	*185*	*FactSet MSCI SRI flag*	*138*	*43*	*264*	*445*	*87*	*27*	*169*	*283*
conv	9	MSCI World	155	34	226	415	114	20	124	257
sri	7	MSCI World	175	32	216	423	84	14	104	201
index		**ETF - MSCI World**	**206**	**34**	**226**	**466**	**113**	**17**	**133**	**263**
conv	2	MSCI USA	205	25	201	431	92	10	110	212
sri	8	MSCI USA	190	26	189	405	72	8	68	147
index		**ETF - MSCI USA**	**123**	**32**	**217**	**372**	**111**	**29**	**204**	**344**
index		**ETF - S&P 500**	**216**	**26**	**195**	**436**	**86**	**9**	**77**	**172**
index		**ETF - Dow Jones Industrial Average**	**69**	**26**	**221**	**317**	**29**	**10**	**90**	**128**
conv	5	MSCI Europe	297	56	243	595	287	50	201	539
sri	9	MSCI Europe	139	33	281	453	100	20	168	287
index		**ETF - MSCI Europe**	**174**	**40**	**314**	**528**	**165**	**31**	**268**	**463**
conv	1	Impact	62	19	193	275	103	23	305	431
sri	13	Impact	102	49	274	424	52	38	157	247
conv	25	Emerging Markets	182	54	336	572	237	62	387	686
sri	42	Emerging Markets	167	67	380	615	195	60	374	629
conv	13	China	100	101	524	725	276	114	687	1,078
sri	7	China	158	92	486	736	380	120	554	1,054
conv	4	Tech	50	26	204	280	30	12	88	130
sri	4	Tech	102	48	299	449	43	23	141	207
conv	2	Energy	298	32	406	735	265	30	523	819
sri	13	Energy	420	144	411	975	235	181	454	870
conv	2	Resource	725	181	587	1,493	653	142	554	1,349
sri	2	Resource	299	85	415	800	212	61	411	684
sri	*203*	*Socially Responsible*	*142*	*37*	*252*	*431*	*92*	*24*	*165*	*281*
sri	*211*	*Env. Friendly*	*144*	*41*	*260*	*445*	*91*	*26*	*167*	*284*
sri	*641*	*ESG*	*169*	*47*	*279*	*495*	*127*	*35*	*212*	*374*
sri	*23*	*Climate Change*	*185*	*64*	*326*	*575*	*138*	*58*	*235*	*431*
sri	*29*	*Clean Energy*	*244*	*127*	*395*	*766*	*149*	*134*	*479*	*762*

An analysis comparing SRI and conventional funds from the same thematic universe (by industry) is desirable because it would allow us to compare peers (*Table B.6*). However, we do not have enough information to classify the funds as such. Instead, we have used the fund title to explore the environmental profile by investment focus: we compare SRI and conventional funds with different investment objectives, such as "Emerging Markets", "Tech", or tracking the same index, e.g., MSCI Europe. We notice that, for "Emerging Markets" funds, WACI scope 3 is higher for SRI funds than for conventional funds. While this finding cannot be generalized due to the small funds sample, it could suggest that SRI funds are choosing companies based on scope 1 intensity, while their industries are more intense in terms of scope 3 emissions. This could be due to having many companies from Manufacturing industries, which have a larger scope 3 intensity. On the other hand, it is reassuring for SRI investors to see that sustainability-screened funds tracking MSCI Europe (7 ETFs and 2 SRI OEFs) or MSCI World (15 ETFs and 1 SRI OEFs – index fund) do have a smaller intensity than the respective benchmarks, both on direct and indirect emissions.

SFDR-labelled funds. The EU Sustainable Finance Disclosure Regulation (EC, 2019a) came into force in March 2021. Asset managers must disclose whether their managed funds are classified as Article 8 (taking into account ESG criteria) or Article 9 funds (having an environmental or social objective). To study whether Article 9 funds perform better than Article 8 funds, we extracted a total sample of more than 1,200 Article 8 and Article 9 investment funds listed on the Luxembourg Stock Exchange. We retrieved fund-level information for the latest reporting date in 2019, for 1,049 of these. After removing fixed-income funds, fund duplicates due to a fund having more classes and funds that hold less than 90% in stocks and cash we had a final sample of 159 funds (20 art. 9 and 139 art. 8).

Table B.7: Mean life cycle RCF and WACI for SFDR-labelled Article 8 and Article 9 funds

fund type	mean WACI life cycle	mean RCF life cycle
article 8 across funds	506	405
article 9 across funds	501	274
article 8 pool of holdings	454	237
article 9 pool of holdings	506	202

The samples of Article 8 and Article 9 funds group funds with different investment objectives, and thus formulating a general conclusion is inadequate. Alternatively, we pooled together the investee companies of the two fund samples. Article 8 funds hold together 4,684 unique stocks, while Article 9 funds hold 1,514 funds. Interestingly, only 2.6% (40 companies) of the Article 9 fund holdings are not invested in by Article 8 funds.

We have applied the RCF and WACI to the Article 8 and Article 9 pools of holdings, accounting also for the respective held amount. If we average results at fund level, Article 9 funds perform better in terms of RCF, while for WACI the two types of funds are similar. However, if we weight all fund holdings proportionally, the WACI of the pooled sample of impact funds is higher than the one of ESG promoting funds, while, for RCF, Article 8 funds still perform better (*Table B.7*). To better understand the source of carbon emissions attributable to a fund, we ran an analysis using the climate-policy-relevant sectors (CPRS) classification introduced by Battiston et al. (2017). *Figure B.5* presents the results for two funds, in a pie chart visualisation, that could be useful for future EU SFDR reporting requirements, as stipulated in the Regulatory Technical Standards (ESAs, 2021). This figure is an extension to Figure 3.6.

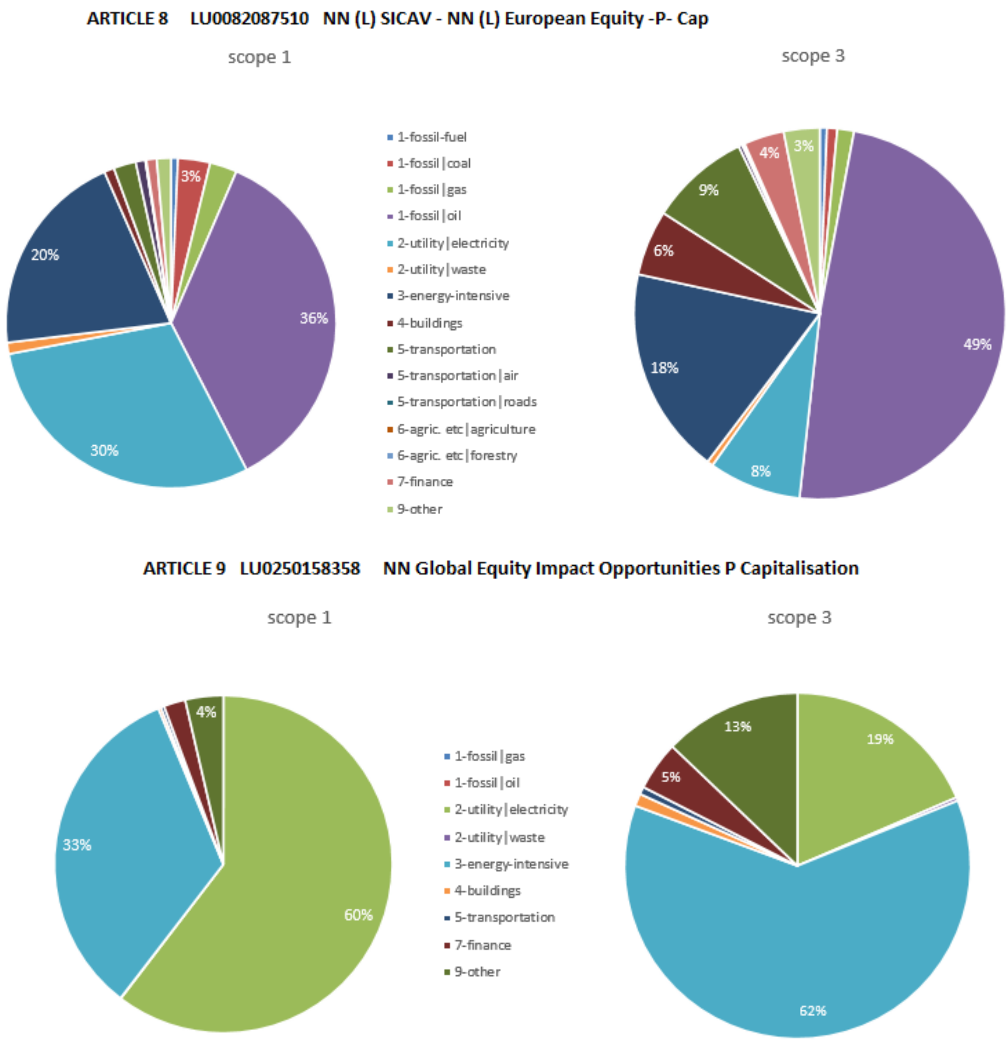


Figure B.5: Comparing the exposure to CPRS sectors of two selected Article 8 (up) and Article 9 funds (down). Percentages are based on the relative carbon footprint due to the specific sector. The results are represented only for scope 1 and scope 3, in order to emphasize the different sectorial distribution of the emissions.

Sectorial ownership breakdown for selected market indices

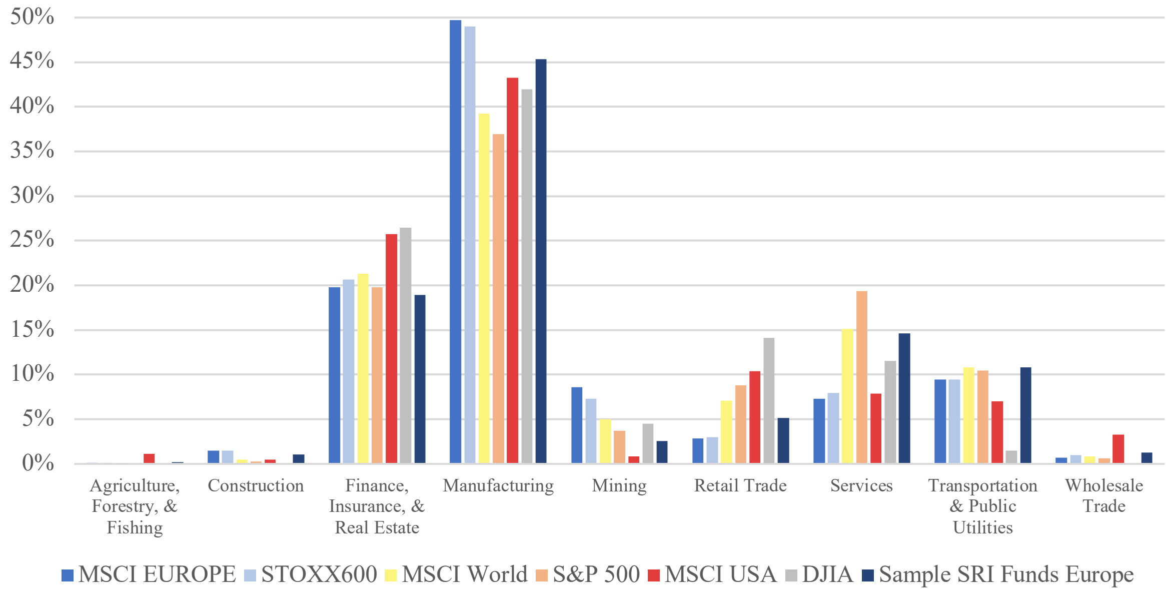


Figure B.6: Sectorial ownership breakdown by market value weight, grouped by SIC category.

C. Appendix to "Input-output life cycle assessment extended to additional environmental and social indicators with identification of trade-offs between impact categories"

C.1. Assessment of the EU sustainable finance regulatory background.

In the European Union, under the EU Sustainable Finance Action Plan, three pieces of regulation have been developed with the aim to standardize sustainability reporting: 1) the EU Taxonomy for sustainable activities (EC, 2020, 2019c), with data to be reported at economic activity level (e.g., manufacture of low carbon technologies; afforestation), 2) the EU Corporate Sustainability Reporting Directive (CSRD) (EC, 2022), with reporting at firm level (e.g., carbon footprint of company's operations); and 3) the Sustainable Finance Disclosure Regulation (SFDR) (EC, 2019a) at financial product level (e.g., investments in companies with supplier code of conduct), with its associated template for Principle Adverse Impacts (PAIs) that financial institutions should report on. These pieces of regulations are reviewed in *Table C.1*.

Table C.1: Summary of European Union legislative package on Sustainable Finance

	EU TAXONOMY Regulation & Environmental Objectives Delegated Acts (DA)	EU Corporate Sustainability Reporting Directive (CSRD)	EU Sustainable Finance Disclosure Regulation (SFDR)
Level of disclosure / target entity	economic activity / companies covered by the CSRD & financial product providers under the SFDR	firm / 50,000 companies in the EU	financial product / firms selling investment products
Aim	Disclosure of alignment thresholds defining economic activities that are sustainable	Companies to report reliable and comparable sustainability information, to support stakeholders, such as investors	Provide sustainability-related information for financial products, to better inform investors
Reporting required	Company-level OPEX, CAPEX, & Turnover Taxonomy aligned	Sector-agnostic Sector specific standards	All mandatory PAIs & one additional PAI
Environmental and social impact indicators	6 environmental objectives & 3 topics for minimum social safeguards	5 topical environmental standards & 4 topical social standards	25 environmental indicators (9 mandatory and 7 additional) & 23 social indicators (5 mandatory and 17 additional)
Adoption	12th July 2020	21st April 2021	27th Nov 2019 & 6th Apr 2022
Entry into force	Application Date Climate DA: - 1st Jan 2022: eligibility - 1st Jan 2024: alignment	Application date: - Gradual roll-out: 2025 – 2030	PAIs reporting: - 30th June 2023
Reporting standards/ guidelines	Technical Screening Criteria (TSC) by objective & Do No Significant Harm (DNSH)	European Sustainability Reporting Standards (ESRS)	Draft Regulatory Technical Standard (RTS), Principle Adverse Impacts (PAIs)
Life-cycle assessment	Mandatory for all categories	Only if impact in the value chain is material	Only mentioned for GHG emissions indicator
Scope of indicators	Impact indicators	Impact and inventory indicators	System characteristics indicators Inventory indicators Impact indicators

The EU Taxonomy defines sustainable economic activities under six environmental objectives (BNP Paribas, 2019; EC, 2020): climate change mitigation, climate change adaptation, sustainable use and protection of water and marine resources, transition to a circular economy, waste prevention and recycling, pollution prevention and control and the protection and restoration of biodiversity and ecosystems. Using the criteria set under the environmental objectives, one can decide which investments achieve sustainability thresholds, based on scientific criteria (EC, 2020), and life cycle assessments must be conducted before deeming an economic activity aligned to one of the six environmental objectives. Minimum Social Safeguards must be adhered too, for an investment to be aligned (such as respect of human rights) (EU Platform on Sustainable Finance, 2022).

In the same vein, the EU CSRD will require large companies to disclose non-financial information relating to different environmental (E) and social (S) issues. The reporting requirements will be organized by topic, under the European Sustainability Reporting Standards (ESRS). For environmental topics the standards for indicators are grouped into climate change, pollution, water and marine resources, resource use and circular economy, and biodiversity and ecosystems. For social impacts, the standards are referring to: own workforce, workers in the value chain, affected communities, and consumers and end-users.

Finally, the EU SFDR mandates financial market participants to report on sustainability indicators regarding their financial products (such as equity investment funds, insurance products or alternative investment funds). Under the SFDR's Regulatory Technical Standards (RTS) ("Final Report on draft Regulatory Technical Standards with regard to the content, methodologies and presentation of disclosures pursuant to," 2021), a first template for reporting on Principal Adverse Impact (PAIs) indicators has been compiled by mandated EU institutions, known as the European Supervisory Authorities (ESAs). The template contains a list of mandatory and optional sustainability indicators (both E and S), mainly addressing investments in investee companies – Table I, Annex I, of the Commission Delegated Regulation (EU) 2022/1288 of 6 April 2022 (EC, 2019a): 14 mandatory indicators (9 environmental and 5 social) and 33 additional indicators (16 environmental and 17 social).

We critically analyzed the sustainability reporting requirements under the SFDR. The SFDR reporting regulation may be the hardest to follow, as financial institutions have to aggregate data from underlying investments and deal with a lot of uncertainty in data, if available, or missing data. We identify four potential issues in the design of the EU SFDR, related to (1) reduced coverage of sustainability indicators, (2) lack of a life cycle perspective, (3) inconsistency in level of indicator aggregation and (4) lack of operability of indicators – not ready-to-use. We specifically look at the principle adverse impact (PAI) indicators proposed under the SFDR RTS for equity investment funds (funds investing in shares of publicly listed companies), as these address financial product providers.

First, the proposed mandatory PAI indicators mainly focus only on climate change; six out of nine mandatory environment indicators are climate change related. From the perspective of the triple planetary crisis[54] that we are facing, biodiversity and pollution are two other key sustainability issues besides climate change which are not extensively covered. Other environmental and social problems should as well be included in a sustainability assessment. Otherwise, there is a risk of pursuing reduction of climate change impacts, at the expense of increases in other negative impacts (Castellani et al., 2019). Moreover, there are no guidelines regarding the choice of data or methodology for quantifying the indicators, thus making comparison between different investment products cumbersome. The CSRD directive, via its European Sustainability Reporting Standards (ESRS), refers to science-based measurement methods and standards, such as ISO:14046-1:2018, on greenhouse gases (ISO, 2018) or the Environmental Footprint methods (Manfredi et al., 2012). While the EU CSRD does offer satisfactory guidance in terms of impact indicators assessment and underlying methodologies to be used, this is to come into force only after the EU SFDR. For the latter, clear methodologies for assessment are lacking, making comparison between different financial products cumbersome.

Second, the indicators should encompass the complete life cycle of the economic activities invested in by the financial products, in order to avoid impact stage shifting which would undermine the overall performance of the instruments (EC, 2020). The EU Taxonomy embeds a life cycle perspective on all levels, as sustainability must be proved at any point of the value chain. The CSRD mentions that impact should be measured over the value chain, when deemed material (and is not mandatory in the first three years of reporting) (EC, 2022), while the SFDR only mandates scope 3 (upstream and downstream value chain) measurements for GHG emissions.

Third, indicators proposed are not of the same type. For example, "average amount of water consumed by investee companies" is a quantitative indicator, while "share of investments in companies without water management policies" is rather qualitative. For the latter indicator, and in general, for qualitative indicators, it is not clear how the result can be linked to an impact – as a company can have a policy in place but still cause high environmental harm. Indicators should seek to be quantitative and, in the best-case scenario, linkable to specific targets or limits for absolute or relative levels of emissions.

Finally, the major challenge in the operability of the SFDR reporting framework is that it does not go further than proposing impact categories, i.e., not proposing impact assessment methods. This leaves the choice of measurement at the financial product provider, not only making it more cumbersome, but also giving way to greenwashing actions. Taking the example of the PEF, designing a set of indicators for impact assessment should come together with a set of best-available methods for measurement.

Established data vendors have joined the race for PAIs data offering. For example, FactSet and ISS offer data points for over 7,000 companies (FactSet, 2023; ISS, 2023). However, for some indicators there is poor data quality or no data. In its Principle Adverse Impact Statement, Robeco Institutional Asset Management details how it will cover the needed PAIs (Robeco, 2022). For the mandatory indicators, it lists seven different providers of data, which raises concerns over methodologies and data reliability.

C.2. Impact indicators

In previous literature(Steinmann et al., 2017b), a set of nine indicators has been proposed, that can be produced with EXIOBASE in order to cover environmental impacts embedded in international products. Four of these indicators refer to Carbon, Water, Land and Material Footprint, while other five are needed to be supplemented, in order to cover the variation in EXIOBASE (marine ecotoxicity, terrestrial ecotoxicity, photochemical oxidant formation, terrestrial acidification, eutrophication). Interestingly, indicators like

"Particulate Matter formation" can be proxied via other indicators, namely the Carbon Footprint.

The Environmental Footprint represents the state-of-the-art of environmental impact indicators used for product life cycle assessment in the European Union(PEF, 2021). 16 indicators are proposed, and for each characterization factors on respective environmental flows are provided, based on best practice methods by impact indicator. In this paper, we are using the Environmental Footprint version 3.1.

We estimate the set of environmental indicators using the methods mainly described in Beylot et al. (2019)(Beylot et al., 2020, 2019). The authors of the aforementioned papers link EF indicators to available EXIOBASE flows to build the impact indicators. Some indicators cannot be computed as there is less coverage in terms of elementary flows in the EXIOBASE database. Moreover, indicators "Ionizing radiation" and "Ozone depletion" cannot be covered by EXIOBASE, while for other indicators, such as "Human toxicity", impact will be underestimated when using EXIOBASE, due to certain elementary flows missing in the EXIOBASE extensions (e.g., emissions of zinc and chromium to soil or emissions of pesticides).

For toxicity, IO analysis only considers emissions of metals to air, while in process LCA, one could also account for emissions of metals to water and pesticides, which are not available in EXIOBASE(Beylot et al., 2020). Generally, toxicity-related indicators are less represented in environmentally extended input-output databases(Persson et al., 2019), despite their importance in impact and public regulations (e.g., pesticides). One can use additional data from external sources and attribute emissions to each country-sector category in an input-output database, in order to derive life cycle impact factors. For example, Persson et al. (2019)(Persson et al., 2019) propose the extension to pesticides and other chemicals in the case of Sweden.

For *Eutrophication freshwater*, in EXIOBASE we only have data on Phosphorus from agriculture processes and there are not enough sectors characterized, producing a smaller sample in terms of company-level impact, when compared to other impact indicators.

C.3. Characterization factors

Characterization is a way of reducing the number of parameters resulting from the environmental assessment. It is used to group more parameters (environmental flows) that are contributing to the same impact category, by accounting for their importance. For example, a widely used characterised impact indicator is greenhouse gas (GHG) emissions, expressed in carbon dioxide equivalents: all emissions of other gases than CO_2 are multiplied by their respective characterization factor, as a weighting of their contribution to the total impact. The latest IPCC report gives a characterization factor of 28 for CH_4 emissions over 100 years (GWP100 values), meaning that, over 100 years, 1 ton of CH_4 is 28 times more potent than 1 ton of CO_2 (IPCC, 2021).

We obtained the characterization factors for all linked EXIOBASE-flows to EF-based impact categories. We have the values for EF3.0 and EF3.1. Some stressors are not accounted for in the construction of impact indicators in the EF framework (as seen in the EF 3.0 file) – for example HFCs, PFCs and SF_6 are not considered for GHG emissions. This was further adapted in EF3.1. Where more characterization factors were available –

e.g., copper, the first characterization factor was used. These were then uploaded in matrix format in a *python jupyter notebook*, where the impact factors were built. The factors were adjusted by giving the countries with industry output (*indout*) smaller than 1, the factor that corresponds to the country with the maximum output (assuming that this would be the most reliable impact factor). Afterwards, we have applied winsorization at 5% to correct for remaining outliers. The impact factors derived based on the EF 3.1. and EXIOBASE country-industry combinations, were then translated to RBICS industry classification. These will be used to compute impact for the chosen environmental indicators.

C.4. Inventory vs. impact indicators

We have performed a selection of SFDR indicators for both environmental and social indicators, only keeping impact-driven indicators. SFDR PAI indicators lack consistency, as these are measured at different levels of aggregation – system level indicators (drivers), inventory indicators or impact indicators (*Figure C.1* and *Figure C.2*).

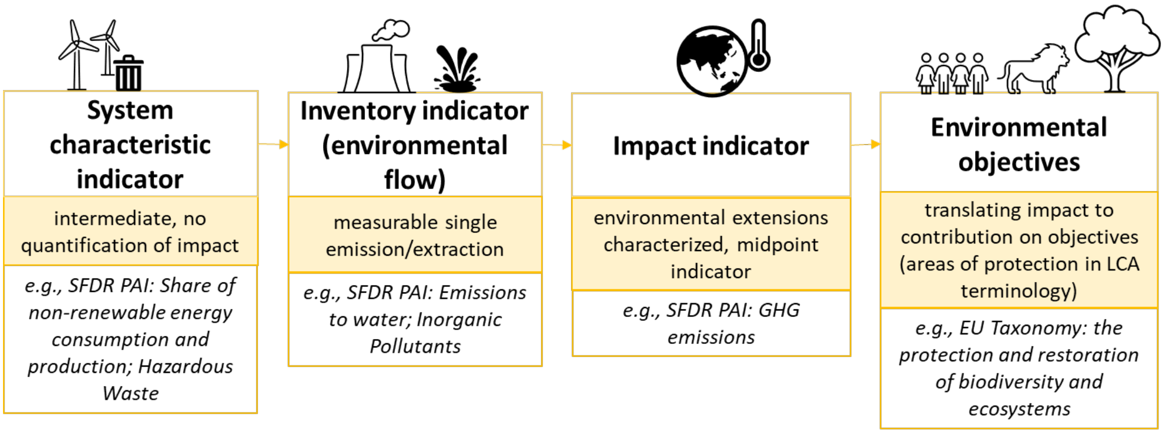


Figure C.1: Schematic representation of development of indicator types, from less to more aggregated and inventory level to impact level. Inspired from the Driver-Pressure-State-Impact-Response (DPSIR) framework

We propose to only use impact indicators, to ensure consistency between the different disclosure requirements and with life cycle assessment. Measuring impact at inventory level would be cumbersome in terms of reporting, as certain categories, such as emissions of organic pollutants or toxic substances, may contain hundreds of substances to be reported on. Measurement at impact indicator level allows to understand the severity of the inventory indicators, as these are weighted based on their importance. We show the process for selecting only impact-related indicators from the SFDR, to present in the matching figures.

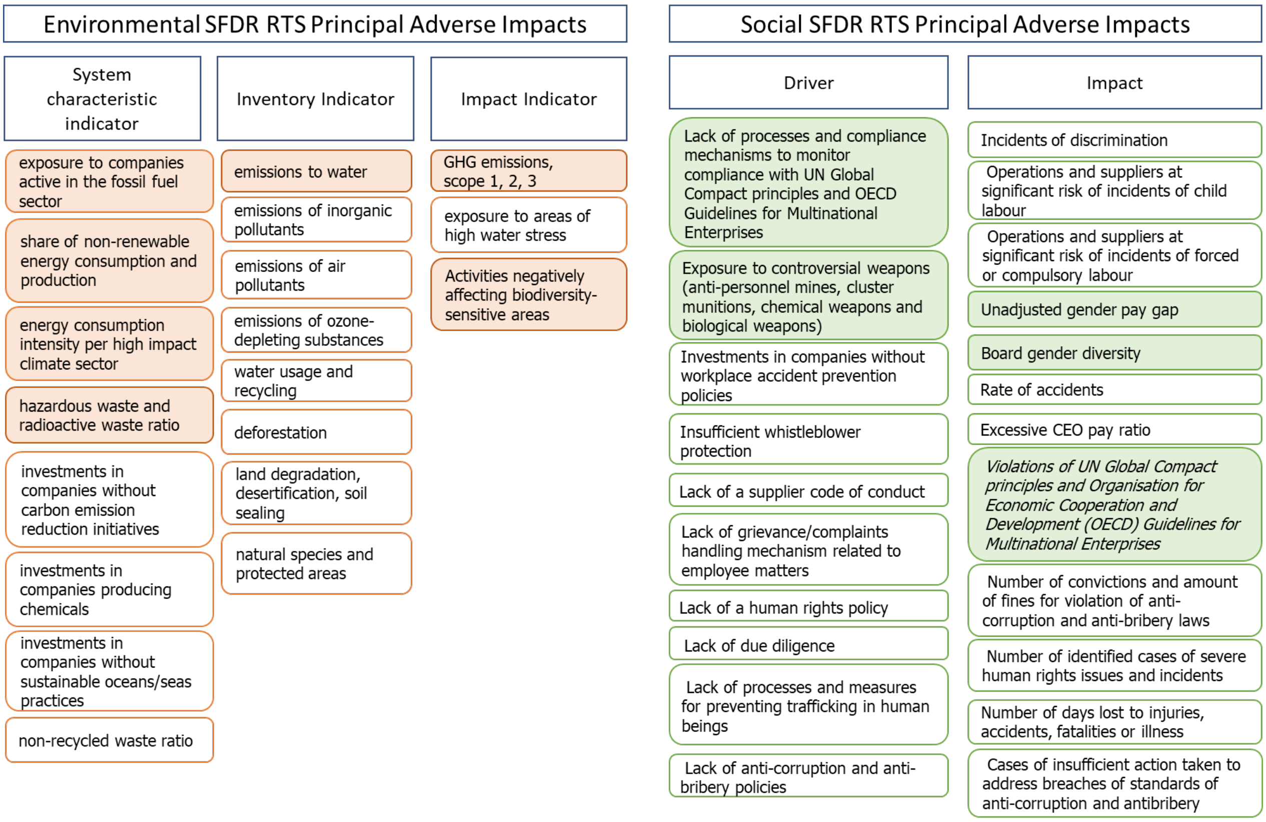


Figure C.2: Classification of environmental and social indicators into "system characteristic", "inventory" and "impact" indicators. The color-filled boxes represent mandatory indicators

The indicators suggested under the SFDR RTS Template are not always clearly defined, and best practice life cycle assessment methodologies can be helpful in offering a clear set of indicators and grouping of different environmental and social issues. For example, as stated in the SFDR document, "*emissions to water* means direct emissions of priority substances as defined in Article 2(30) of Directive 2000/60/EC of the European Parliament and of the Council(6) and direct emissions of nitrates, phosphates, and pesticides". The list of priority substances contains 45 different substances, such as: nickel, lead, dichloromethane, and other chemical substances. For pesticides, the EU is now setting a target for concentration of pesticides in groundwater: "a precautionary quality standard of 0.1μg/L is set for pesticides according to the Groundwater Directive"[14]. In LCA, emissions are grouped by different impacts they have to different water bodies – freshwater and marine eutrophication, and ecotoxicity. However, in EXIOBASE one has data only on heavy metal emissions (Castellani et al., 2019), meaning that currently not all substances listed under the EU can be estimated with our proposed model.

For indicator of inorganic pollutants, the SFDR does not give very clear guidance, mentioning that the emissions of inorganic pollutants that are within or lower than the limit values set in the EU directive must be disclosed. In EF 3.1., indicators related to inorganic pollutants are consistently grouped by effect on different environmental issues – toxicity or particulate matter.

[14] https://www.eea.europa.eu/ims/pesticides-in-rivers-lakes-and

For biodiversity-related impacts, the indicator of "land-use related biodiversity loss" (Cabernard et al., 2019), with the corresponding unit being PDF km^3 year (potentially disappeared species) is used. We started from the indicator dataset provided upon request by the authors of Cabernard et al. (2019). The data contains regionalized impact indicators for 189 x 163 country-industry combinations. We have aggregated the dataset to 49 x 163 region-industry combinations, using the median to derive the value for the "rest of the world" (ROW) regions, that group countries from the EORA 189-country classification to the EXIOBASE 49-region classification. EXIOBASE has a regional classification of 44 individual countries and 5 ROW regions. The values are very small, between 0 and 1. We will change, when computing fund impact, in PDF m^3 year (multiply by 10^9), to have easier to interpret values. For "biodiversity-related land-use change" the unit is in PDF km^3 year. The values are very small, between 0 and 1. We will change, when computing fund impact, in m^3 (multiply by 10^9), to have easier to interpret values. To assess the biodiversity footprint of investments, ENCORE or IBAT have been used in literature and practice. The Biodiversity Footprint for Financial Institutions (BFFI) tool uses EXIOBASE just like we use it, but biodiversity is used as end point, grouping other midpoint indicators (European Comission, 2021). Another tool is the GLOBIO model that uses as measurement mean species abundance (MSA).

Drivers of impact across categories. For toxicity indicators, like human toxicity cancer and non-cancer effects and freshwater ecotoxicity, it is mainly releases of heavy metals that is accounted for and the main holdings driving the impact are in the manufacturing field.

For water stress, similar to biodiversity, and freshwater eutrophication, almost 90% of the attributable fund impact happens in the upstream supply chain. It is rather because areas with high water stress and biodiversity-sensitivity are located mainly at sites where publicly listed companies have their suppliers. In addition, these environmental issues are more present at the extractive, raw materials production stages of the value chain. For example, for biodiversity loss, it is companies in forestry and paper production that have the highest negative impacts.

For freshwater eutrophication, the EXIOBASE database records only agriculture-related phosphorous emissions, and hence we find that indirect freshwater eutrophication is much larger in the upstream supply chain than for the direct operations of holdings. For marine and terrestrial eutrophication, impact is driven by emissions of ammonia, nitrogen, and nitrogen oxides. There are significant direct emissions as well.

For the material footprint indicator, the direct impact is driven by holdings in the mining industry, as these involve extraction of depletable minerals and metals. In terms of indirect impacts, holdings from the manufacturing sector play the largest role, due to their processing operations with require a large stock of materials.

C.5. Relative footprint metric: mean results and standard deviation

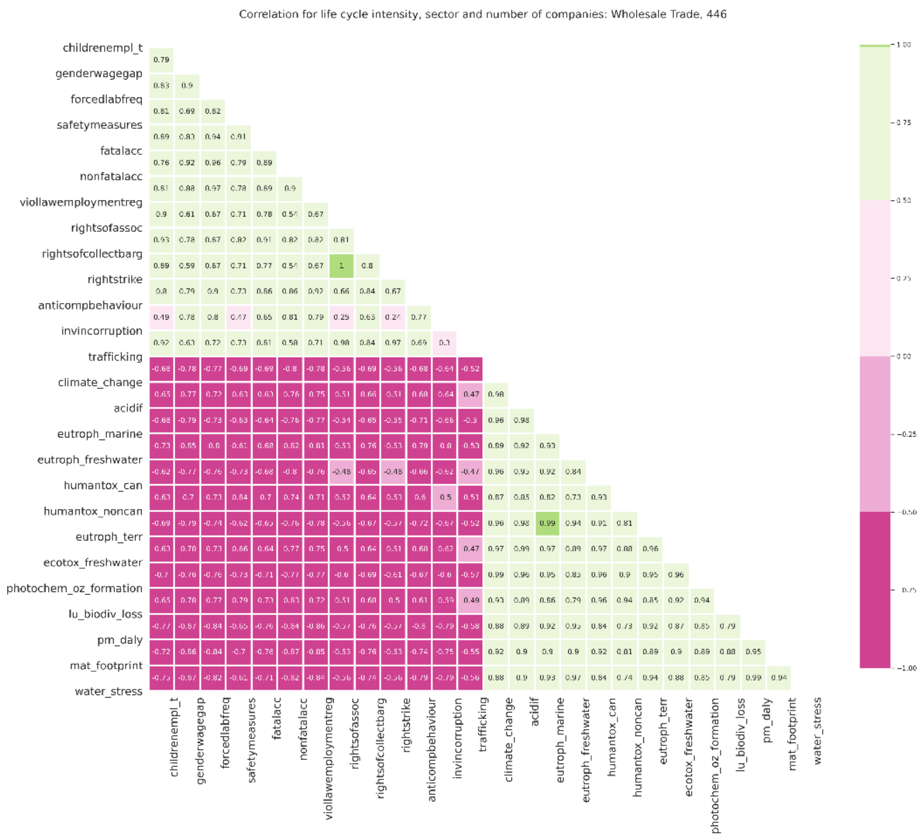
We display the distribution of impact indicators across the funds sample. It can be observed that impacts vary widely between funds, driven by the heterogeneity in companies invested in, and the differences in industry allocation (*Table C.2*).

Table C.2: Mean relative footprint across the set of impact indicators, measured in unit per million USD invested in the funds sample. In parentheses we show the standard deviation for the funds sample.

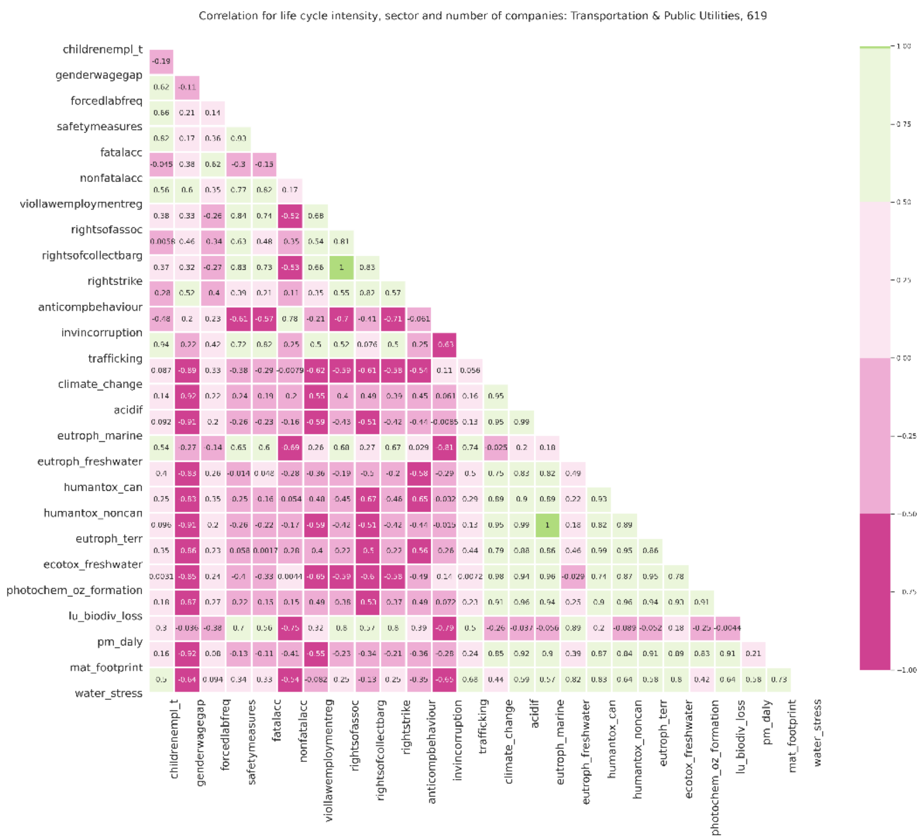
E/S	impact indicator	unit	Relative footprint (impact/MUSD invested)	
			direct	indirect
E	Acidification	mol H^+ eq	968.21 (1732.97)	2188.52 (2526.71)
E	Climate change, total	kg CO_2 eq	245177.44 (481277.95)	248201.63 (308827.14)
E	Ecotoxicity, freshwater	CTUe	19275.06 (43214.63)	93356.51 (97492.77)
E	Eutrophication, freshwater	kg P eq	1.4 (7.29)	124.19 (144.24)
E	Eutrophication, marine	kg N eq	208.97 (353.32)	413.65 (456.46)
E	Eutrophication, terrestrial	mol N eq	2430.56 (4219.04)	6417.63 (7286.3)
E	Human toxicity, cancer	CTUh * 10^{-3}	0.14 (0.31)	1.12 (1.32)
E	Human toxicity, non-cancer	CTUh	0.01 (0.01)	0.02 (0.02)
E	Land-use related biodiversity loss	global km^2 year PDF	0.00001 (0.00008)	0.00038 (0.00045)
E	Material footprint	kt	0.08 (0.19)	0.46 (0.56)
E	Photochemical ozone formation, human health	kg NMVOC eq	846.43 (1196.36)	821.98 (927.87)
E	PM health impacts	DALYs	0.25 (0.54)	0.24 (0.26)
E	Water stress	Mm^3 H_2O-eq	0.0028 (0.004)	0.0972 (0.0938)
S	Presence of anti-competitive behaviour or violation of anti-trust and monopoly legislation	worker hours	0.02 (0.04)	0.14 (0.17)
S	Children in employment, total	worker hours	0.08 (0.2)	0.5 (0.85)
S	Rate of fatal accidents at workplace	worker hours	0.001 (0.0022)	0.0068 (0.0106)
S	Frequency of forced labour	worker hours	0.0004 (0.0007)	0.0283 (0.0559)
S	Gender wage gap	worker hours	0.05 (0.09)	0.22 (0.33)
S	Active involvement of enterprises in corruption and bribery	worker hours	0.02 (0.02)	0.17 (0.24)
S	Rate of non-fatal accidents at workplace	worker hours	0.0035 (0.0045)	0.1705 (0.3167)
S	Right of Association	worker hours	0.06 (0.17)	0.07 (0.12)
S	Right of Collective bargaining	worker hours	0.0019 (0.0043)	0.0056 (0.0084)
S	Right to Strike	worker hours	0.61 (1.7)	0.7 (1.24)
S	Presence of sufficient safety measures	worker hours	0.04 (0.15)	0.26 (0.36)
S	Trafficking in persons	worker hours	0.71 (1.92)	1.07 (1.53)
S	Evidence of violations of laws and employment regulations	worker hours	(0.05)	6.16 (0.28)

C.6. Correlations between impact indicators at company level

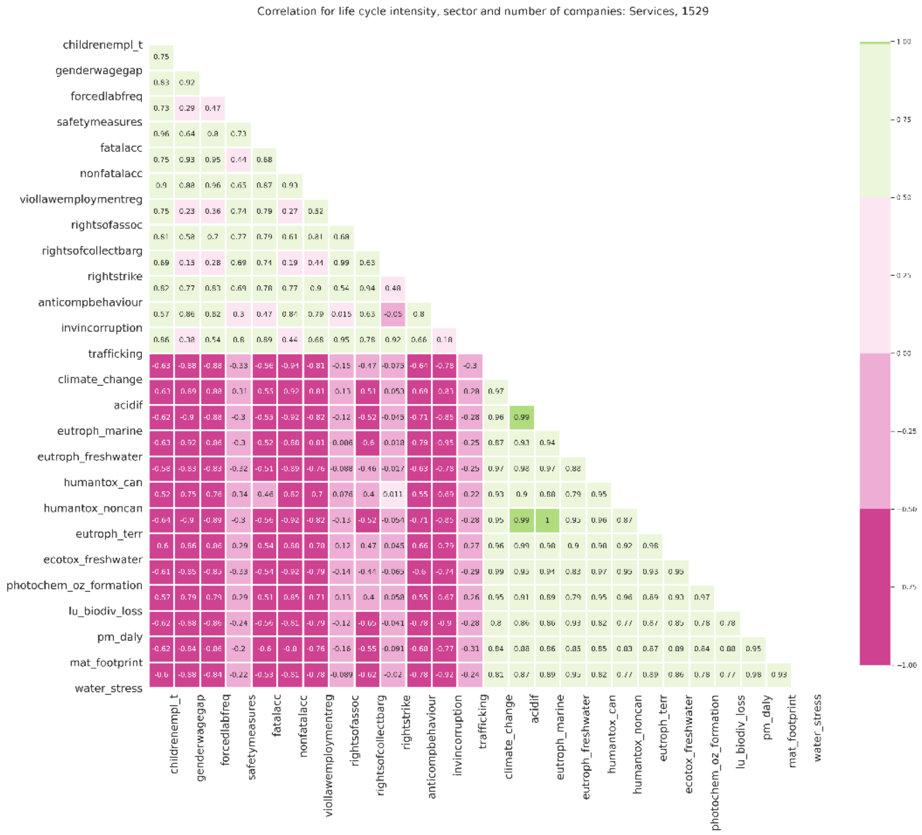
Panel A: Wholesale Trade industry



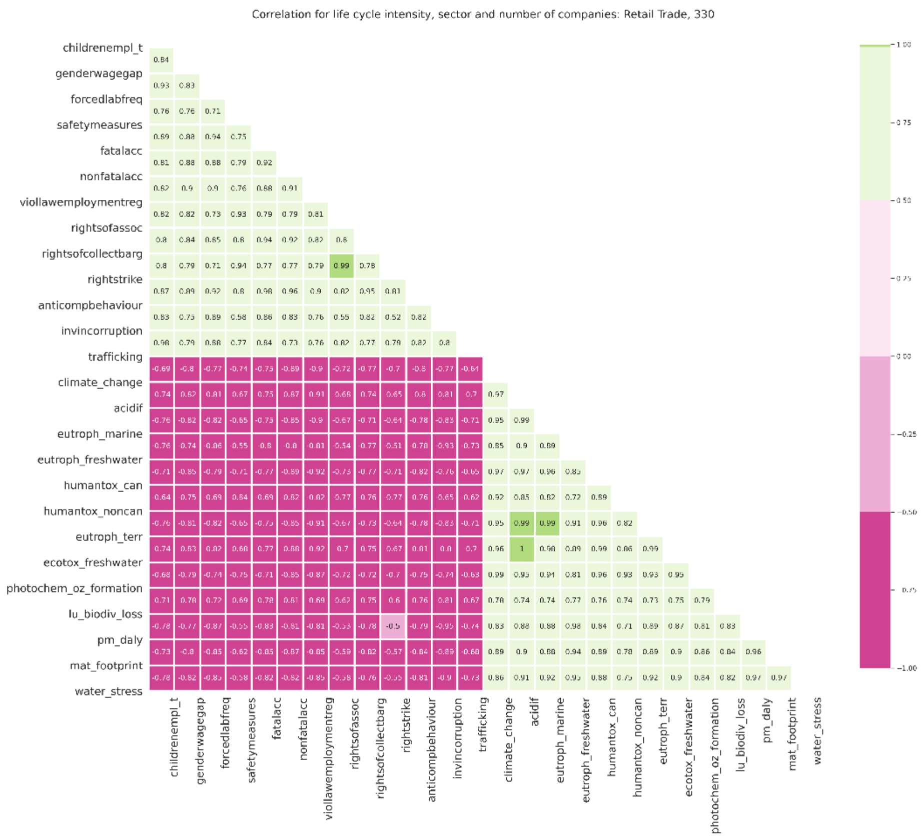
Panel B: Transportation & Public Utilities industry



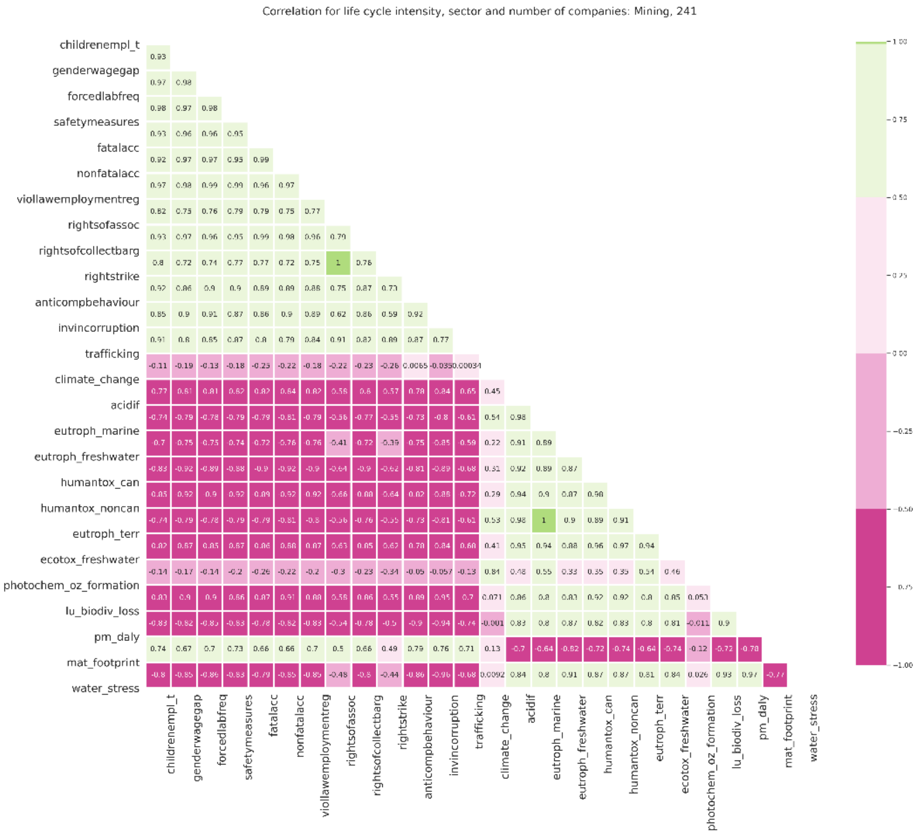
Panel C: Services industry



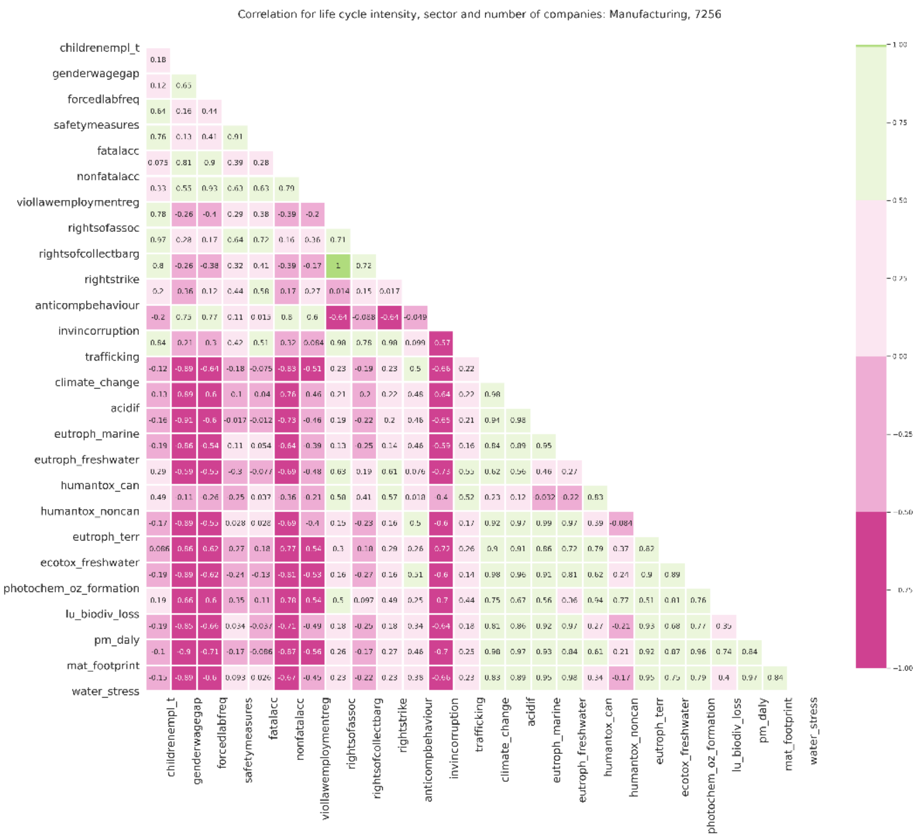
Panel D: Retail Trade industry



Panel E: Mining industry

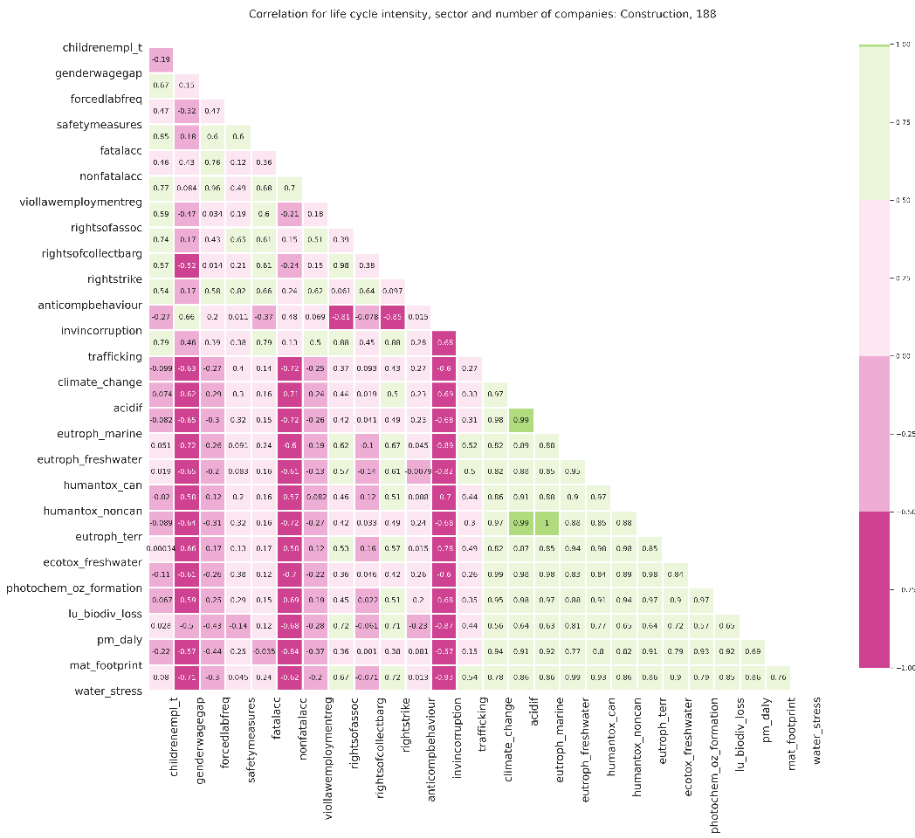


Panel F: Manufacturing industry



Panel G: Finance, Insurance and Real Estate industry

Panel H: Construction industry



Panel I: Agriculture, Forestry & Fishing industry

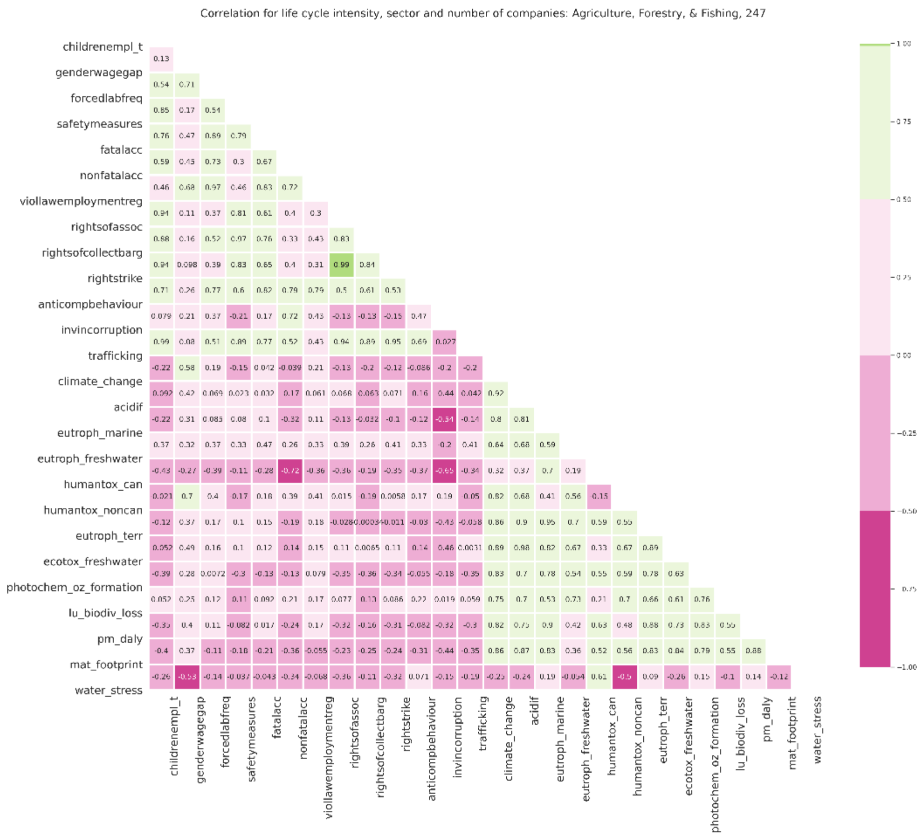
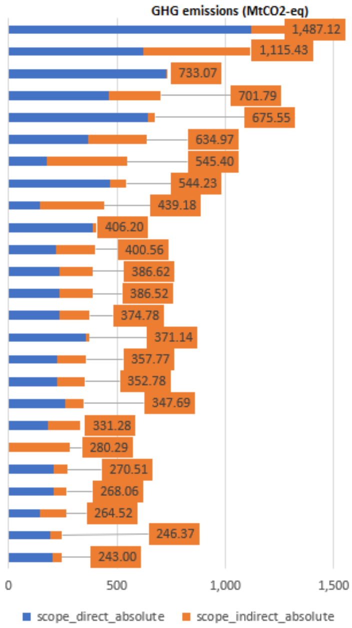


Figure C.3: Classification of environmental and social indicators into "system characteristic", "inventory" and "impact" indicators. The color-filled boxes represent mandatory indicators

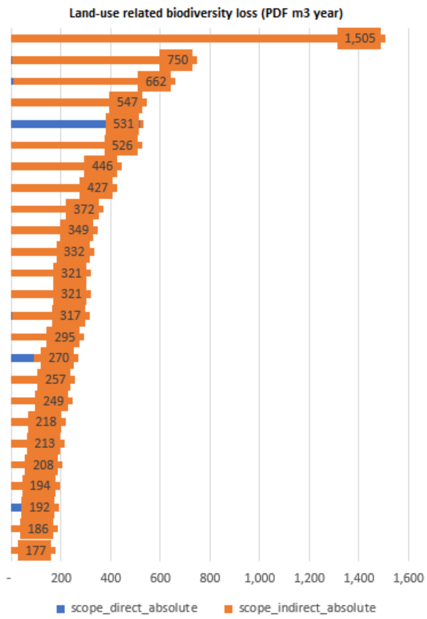
C.7. Listing Top 25 companies by impact

We can use the company-level data estimates to build a ranking of the 25 companies with the highest negative impact by impact category (*Figure C.4*). In this analysis, we do not account for the amount held by investment funds in the companies. For social impacts, for example children employed, companies from retail, hospitality and mining have the highest ranking. For GHG emissions, it is companies from the Utilities and Fossil Fuels sectors. We explored the data in a python script. We show the results for GHG emissions, land-use related biodiversity loss and social indicator of children in employment.

company	country	industry	SIC desc	Sales (MEUR)	GHG emissions (MtCO2-eq)
China Petroleum & Chemical Corp.	CN	Oil & Gas Extr	Crude Petroleum and Natural Gas	352,076	1,487.12
PetroChina Co., Ltd.	CN	Oil & Gas Extr	Crude Petroleum and Natural Gas	304,074	1,115.43
Nippon Yusen KK	JP	Transport & Utilit	Deep Sea Foreign Transportation	14,997	733.07
Saudi Arabian Oil Co.	SA	Oil & Gas Extr	Crude Petroleum and Natural Gas	294,655	701.79
Saudi Basic Industries Corp.	SA	Manufacturing	Chemicals and Chemical Preparations	33,291	675.55
Exxon Mobil Corp.	US	Oil & Gas Extr	Crude Petroleum and Natural Gas	228,710	634.97
Shell Plc	GB	Oil & Gas Extr	Crude Petroleum and Natural Gas	304,503	545.40
Enel SpA	IT	Transport & Utilit	Electric Services	77,366	544.23
BP Plc	GB	Oil & Gas Extr	Oil and Gas Field Exploration Services	249,308	439.18
The Siam Cement Public Co. Ltd.	TH	Manufacturing	Cement, Hydraulic	12,605	406.20
Rosneft Oil Co.	RU	Oil & Gas Extr	Crude Petroleum and Natural Gas	114,799	400.56
Rio Tinto Ltd.	AU	Mining	Lead and Zinc Ores	38,556	386.62
Rio Tinto Plc	GB	Mining	Miscellaneous Metal Ores	38,546	386.52
Vale SA	BR	Mining	Iron Ores	33,669	374.78
Saudi Electricity Co.	SA	Transport & Utilit	Electric Services	15,495	371.14
BHP Group (UK) Ltd.	GB	Mining	Iron Ores	38,984	357.77
BHP Group Ltd.	AU	Mining	Iron Ores	38,441	352.78
China National Building Material Co., Ltd.	CN	Manufacturing	Cement, Hydraulic	32,763	347.69
Glencore Plc	CH	Retail and Trade	Petroleum and Pete. Prods. Whslers.	192,090	331.28
China State Construction Engineering Corp. Ltd.	CN	Construction	Highway and Street Construction	181,310	280.29
Anglo American Plc	GB	Mining	Copper Ores	26,673	270.51
Anhui Conch Cement Co., Ltd.	CN	Manufacturing	Cement, Hydraulic	20,117	268.06
Gazprom PJSC	RU	Oil & Gas Extr	Crude Petroleum and Natural Gas	105,738	264.52
SK Innovation Co., Ltd.	KR	Oil & Gas Extr	Petroleum Refining	38,207	246.37
Iberdrola SA	ES	Transport & Utilit	Electric Services	36,438	243.00



company	country	industry	SIC desc	Sales (MEUR)	Land-use related biodiversity loss (PDF m3 year)
Pepkor Holdings Ltd.	ZA	Retail and Trade	Department Stores	4,342	1,505
Grupo LALA SAB de CV	MX	Manufacturing	Fluid Milk	3,516	750
JBS SA	BR	Manufacturing	Sausages and Other Prepared Meat Products	46,328	662
NestlÃ© SA	CH	Manufacturing	Food Preparations, Not Elsewhere Classified	83,222	547
Japfa Ltd.	SG	Manufacturing	Prepared Feed and Feed	3,475	531
Archer-Daniels-Midland Co.	US	Manufacturing	Vegetable Oil Mills	57,796	526
WH Group Ltd. (HK)	HK	Manufacturing	Sausages and Other Prepared Meat Products	21,533	446
Marfrig Global Foods SA	BR	Manufacturing	Sausages and Other Prepared Meat Products	11,045	427
Danone SA	FR	Manufacturing	Food Preparations, Not Elsewhere Classified	25,244	372
Bunge Ltd.	US	Manufacturing	Vegetable Oil Mills	36,758	349
Unilever Plc	GB	Manufacturing	Perfumes, Cosmetics	51,952	332
Mitsubishi Corp.	JP	Retail and Trade	Durable Goods, Not Elsewhere Classified	132,020	321
China Mengniu Dairy Co., Ltd.	HK	Agriculture	Dairy Farms	10,218	321
Tyson Foods, Inc.	US	Manufacturing	Meat Packing Plants	37,906	317
China Petroleum & Chemical Corp.	CN	Oil & Gas Extr	Crude Petroleum and Natural Gas	352,076	295
Klabin SA	BR	Telecom	Paper Mills	2,327	270
Glencore Plc	CH	Retail and Trade	Petroleum and Pete. Prods. Whslers.	192,090	257
Fonterra Co-operative Group Ltd.	NZ	Agriculture	Dairy Farms	11,831	249
Anheuser-Busch InBev SA/NV	BE	Manufacturing	Malt Beverages	46,754	218
PepsiCo, Inc.	US	Manufacturing	Bottled and Canned Soft Drinks	60,013	213
Wilmar International Ltd.	SG	Agriculture	Crop Planting, Cultivating, and Protecting	38,089	208
Suzano Holding SA	BR	Manufacturing	Cellulosic Manmade Fibers	5,892	194
Stora Enso Oyj	FI	Telecom	Paper Mills	10,055	192
Suzano SA	BR	Telecom	Pulp Mills	5,892	186
Empresas Copec SA	CL	Oil & Gas Extr	Petroleum Refining	21,212	177



company	country	industry	SIC desc	Sales (MEUR)	Children in employment (million worker hours)
ICA Gruppen AB	SE	Retail and Trade	Grocery Stores	11,257	5.95
Axfood AB	SE	Retail and Trade	Grocery Stores	4,791	2.99
OMV AG	AT	Oil & Gas Extraction	Crude Petroleum and Natural Gas	21,815	2.08
McKesson Corp.	US	Retail and Trade	Drugs, Drug Proprietaries, and Druggists' Sundries	191,476	1.43
Gazprom PJSC	RU	Oil & Gas Extraction	Crude Petroleum and Natural Gas	99,294	1.31
JSW SA	PL	Mining	Bituminous Coal Underground Mining	2,017	1.06
NOVATEK JSC	RU	Oil & Gas Extraction	Crude Petroleum and Natural Gas	11,581	0.94
Currys Plc	GB	Retail and Trade	Radio, Television, and Consumer Electronics Stores	11,816	0.84
BP Plc	GB	Oil & Gas Extraction	Oil and Gas Field Exploration Services	228,769	0.82
Ferrexpo Plc	CH	Mining	Iron Ores	1,260	0.80
Vale SA	BR	Mining	Iron Ores	30,303	0.70
Orkla ASA	NO	Other Manufacturing	Food Preparations, Not Elsewhere Classified	4,336	0.69
HKScan Oyj	FI	Other Manufacturing	Sausages and Other Prepared Meat Products	1,720	0.64
Hennes & Mauritz AB	SE	Retail and Trade	Men's and Boys' Clothing and Accessory Stores	20,552	0.54
Tatneft PJSC	RU	Oil & Gas Extraction	Oil and Gas Field Exploration Services	12,430	0.52
Reliance Industries Ltd.	IN	Other Manufacturing	Petroleum Refining	67,020	0.46
Oriola Corp.	FI	Retail and Trade	Medical, Dental, and Hospital Equipment	1,708	0.46
Rio Tinto Ltd.	AU	Mining	Lead and Zinc Ores	35,856	0.42
Rio Tinto Plc	GB	Mining	Miscellaneous Metal Ores	35,847	0.42
Tech Data Corp.	US	Retail and Trade	Computers and Computer Equipment and Software	31,110	0.41
GasLog Ltd.	GR	Transport and Utilities	Deep Sea Foreign Transportation of Freight	597	0.38
PetroChina Co., Ltd.	CN	Oil & Gas Extraction	Crude Petroleum and Natural Gas	281,531	0.36
LG Chem Ltd.	KR	Other Manufacturing	Industrial Organic Chemicals	20,508	0.36
BHP Group (UK) Ltd.	GB	Mining	Iron Ores	35,881	0.35
BHP Group Ltd.	AU	Mining	Iron Ores	35,382	0.35

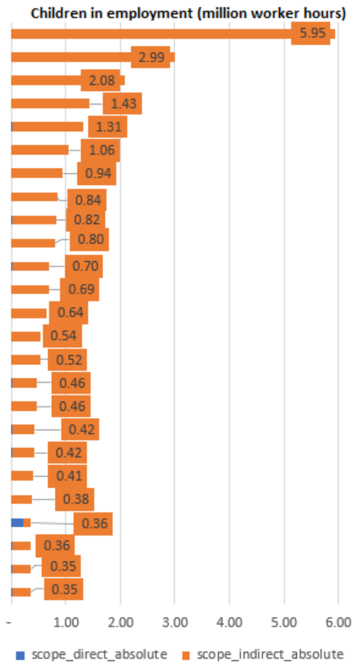


Figure C.4: Top 25 companies by absolute impact, for climate change impacts (A), land-use related biodiversity loss (B) and children in employment (C)

C.8. Impact attributable to final demand in EU27 countries

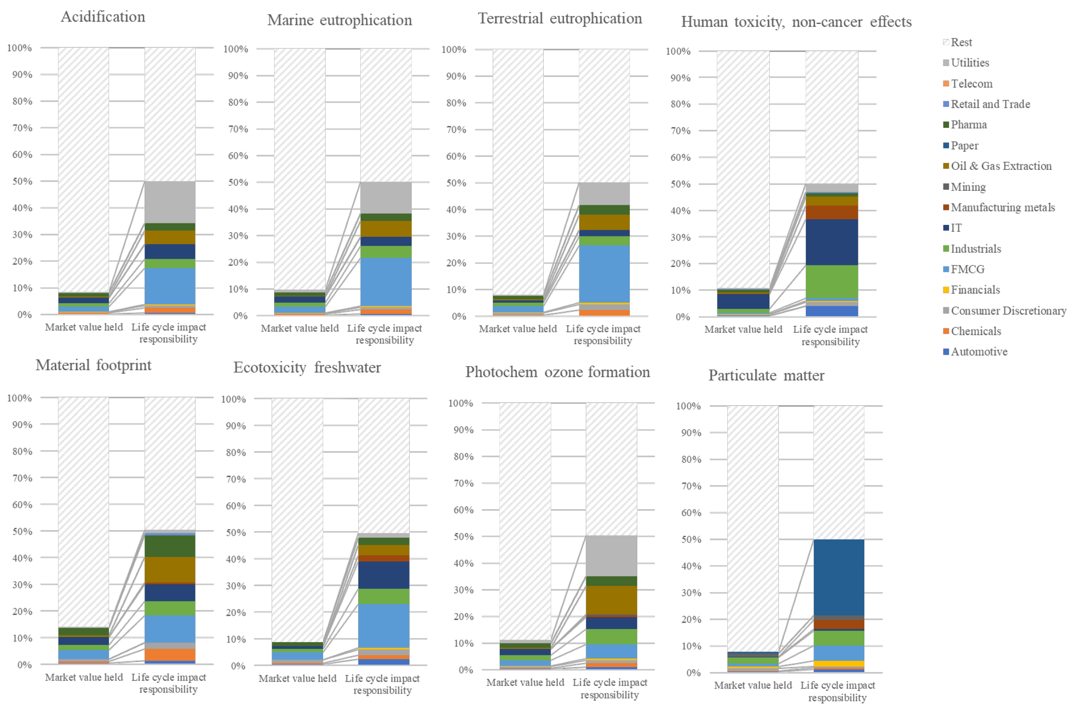
From the need to have a comparable unit on which to display all indicators, we normalize the results by the impact attributable, for the same impact category, to the final demand needed to cover EU citizens, when accounting for their consumption-based footprint. Using EXIOBASE, we compute the final demand of the EU27 countries in year 2019. The final demand categories are: “Final consumption expenditure by households”, “Final consumption expenditure by non-profit organisations serving households”, “Final consumption expenditure by government”, “Gross fixed capital formation”, “Changes in inventories”, “Changes in valuables”, and “Exports: Total (free on board)”. The final demand for year 2019 in the EU was of 13 trillion EUR. The estimated EU population is of 447 million. We compare the values obtained per capita with similar US results, where units are the same. For example, for GHG emissions and Eutrophication we get results for EU that are comparable to the ones in the US, estimated with US EEIO (Ingwersen et al., 2022). This exercise helps us validate the results we produce with EXIOBASE data. In *Table C.3* , we display the values attributable to each impact category, to satisfy the final demand attributable to one million EU27 citizens.

Table C.3: Impacts of the final demand, per one million EU27 citizens.

E/S	impact indicator	unit	Impact	
			direct	indirect
E	Acidification	mol H^+ eq	38,687,205.55	72,359,263.70
E	Climate change, total	kg CO_2 eq	3,024,236,878.86	7,082,115,532.21
E	Ecotoxicity, freshwater	CTUe	1,834,562,341.88	4,130,788,071.13
E	Eutrophication, freshwater	kg P eq	1,866,403.13	2,903,606.43
E	Eutrophication, marine	kg N eq	7,616,004.16	16,289,423.11
E	Eutrophication, terrestrial	mol N eq	145,459,773.33	245,931,141.15
E	Human toxicity, cancer	CTUh * 10^{-3}	8.87	26.89
E	Human toxicity, non-cancer	CTUh	186.68	546.16
E	Land-use related biodiversity loss	global km^2 year PDF	7.77	16.93
E	Material footprint	kt	6,388.77	16,469.93
E	Photochemical ozone formation, human health	kg NMVOC eq	36,829,499.49	171,374,040.40
E	PM health impacts	DALYs	5,420.96	15,153.22
E	Water stress	Mm^3 H_2O-eq	2,285.75	5,588.13
S	Active involvement in corruption and bribery	worker hours	2,527.47	9,053.95
S	Children in employment, total	worker hours	1,464.89	4,366.88
S	Violations of laws and employment regulations	worker hours	717.13	2,236.54
S	Frequency of forced labour	worker hours	91.70	232.71
S	Gender wage gap	worker hours	1,466.87	4,831.04
S	Presence of anti-competitive behaviour	worker hours	596.76	1,278.03
S	Presence of sufficient safety measures	worker hours	2,291.73	14,547.63
S	Rate of fatal accidents at workplace	worker hours	42.41	162.87
S	Rate of non-fatal accidents at workplace	worker hours	1,130.74	6,420.40
S	Right of Association	worker hours	198.73	849.81
S	Right of Collective bargaining	worker hours	55.50	178.70
S	Right to Strike	worker hours	1,944.36	8,308.72
S	Trafficking in persons	worker hours	3,196.94	12,013.60

C.9. Top contributions to impact by companies (grouped by industry)

Environmental



Social

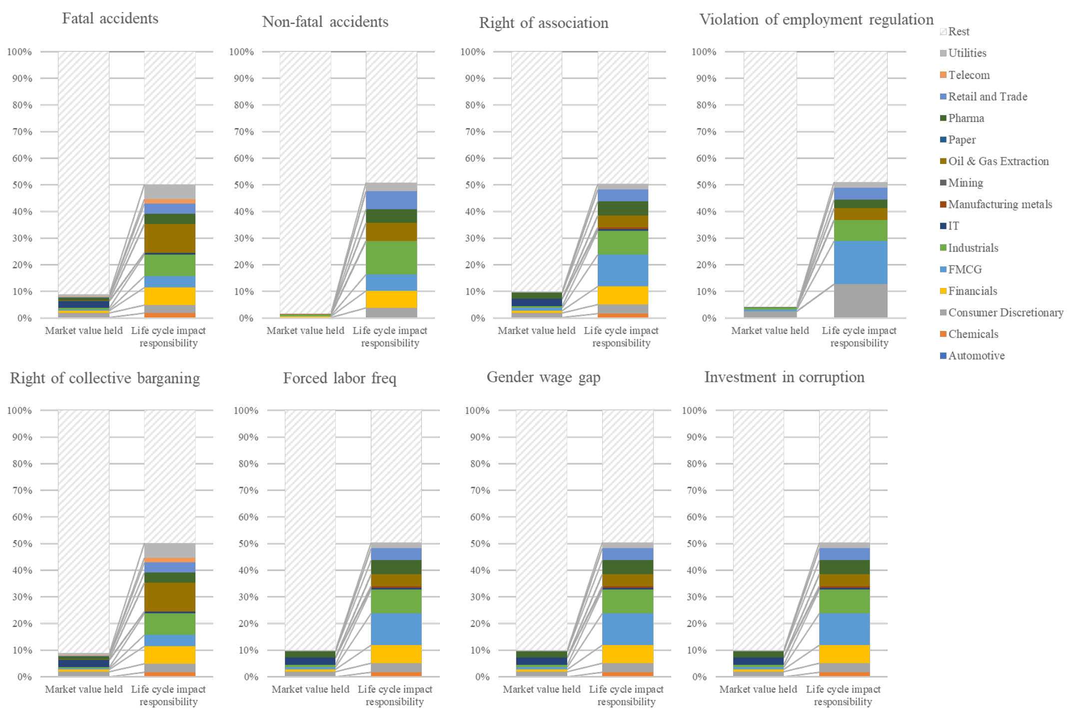


Figure C.5: Companies contributing together to 50% of life-cycle impact, aggregated at industry level, for each environmental (A) and social (B) indicators

D. Appendix to “Life cycle vulnerable employment and carbon emissions of companies – a detailed comparison”

Table D.1: EXIOBASE country and region list and abbreviations

Code	Country / region	Code	Country / region
AT	Austria	SI	Slovenia
BE	Belgium	SK	Slovakia
BG	Bulgaria	GB	United Kingdom
CY	Cyprus	US	United States
CZ	Czech Republic	JP	Japan
DE	Germany	CN	China
DK	Denmark	CA	Canada
EE	Estonia	KR	South Korea
ES	Spain	BR	Brazil
FI	Finland	IN	India
FR	France	MX	Mexico
GR	Greece	RU	Russia
HR	Croatia	AU	Australia
HU	Hungary	CH	Switzerland
IE	Ireland	TR	Turkey
IT	Italy	TW	Taiwan
LT	Lithuania	NO	Norway
LU	Luxembourg	ID	Indonesia
LV	Latvia	ZA	South Africa
MT	Malta	WA	RoW Asia and Pacific
NL	Netherlands	WL	RoW America
PL	Poland	WE	RoW Europe
PT	Portugal	WF	RoW Africa
RO	Romania	WM	RoW Middle East
SE	Sweden		

Table D.2: Social categories and themes in the Social Hotspot Database (SHDB)

Social Category	Social Theme
Labour Rights and Decent Work	Child labor Forced labor Excessive working time Wage assessment Poverty Migrant labor Freedom of association, collective bargaining rights Unemployment Labor laws
Health and Safety	Injuries and fatalities Toxics and hazards
Human Rights	Indigenous rights Gender equity High conflicts Human health issues
Governance	Legal systems Corruption
Community Infrastructure	Hospital beds Drinking water Sanitation Children out of school Smallholder vs. commercial farms

Table D.3: Indicators in the PSILCA Life Cycle Inventory Database

Stakeholder	Subcategory	Indicator	Unit of measurement	Index
WORKERS	Child labor	Children in employment, male	% of male children ages 7-14	W1.1
		Children in employment, female	% of female children ages 7-14	W1.2
		Children in employment, total	% of all children ages 7-14	W1.3
	Forced labour	Goods produced by forced labour	Number of goods in the sector	W2.1
		Frequency of forced labour	Cases per 1000 inhabitants in the country	W2.2
		Tier placement referring to trafficking in persons	Tier placement	W2.3
	Fair salary	Living wage, per month	USD	W3.1
		Minimum wage, per month	USD	W3.2
		Sector average wage, per month	USD	W3.3
	Working time	Hours of work per employee, per day	h	W4.1
		Hours of work per employee, per week	h	W4.2
		Standard weekly hours	h	W4.3
		Standard daily hours	h	W4.4
	Discrimination	Occurrence of discrimination	Text	W5.1
		Women in the labour force	% of economically active female population	W5.2
		Men in the labour force	% of economically active male population	W5.3
		Gender wage gap	%	W5.4
	Health and Safety	Accident rate at workplace	#/yr	W6.1
		Fatal accidents at workplace	#/yr	W6.2
		Occupational risks	Text	W6.3
		DALYs due to indoor and outdoor air and water pollution	DALYs per 1000 inhabitants in the country	W6.4
		Presence of sufficient safety measures	OSHA cases per 10000 employees in the sector	W6.5
		Workers affected by natural disasters	%	W6.6

Stakeholder	Subcategory	Indicator	Unit of measurement	Index
	Social benefits, legal issues	Social security expenditures	Social security expenditures as a % of GDP	W7.1
		Evidence of violations of laws and employment regulations	#	W7.2
	Workers' rights	Freedom of association rights	text	W8.1
		Trade union density as a % of paid employment total	%	W8.1.1
		Right of Association	ordinal 0-3	W8.1.2
		Right of Collective bargaining	ordinal 0-3	W8.1.3
		Right to Strike	ordinal 0-3	W8.1.4
VALUE-CHAIN ACTORS	Fair competition	Presence of anti-competitive behaviour or violation of anti-trust and monopoly legislation	Cases per 10000 employees in the sector	V1.1
		Presence of policies to prevent anti-competitive behaviour	Y/N	V1.2
	Corruption	Corruption index of country	index value	V2.1
		Evidence of an active involvement of the enterprises in corruption and bribery	Text	V2.2
	Promoting social responsibility	Presence of codes of conduct that protect human rights of workers among suppliers	Y/N	V3.1
		Membership in an initiative that promotes social responsibility along the supply chain	%	V3.2
	Supplier relationships	Interaction of the companies with suppliers	Text	V4.1
SOCIETY	Contribution to economic development	Economic situation of the country	Text	S1.1
		Contribution of the sector to economic development	%	S1.2
		Public expenditure on education	USD/yr	S1.3
		Illiteracy rate, male	%	S1.4.1
		Youth illiteracy rate, male	%	S1.4.2
		Illiteracy rate, female	%	S1.5.1
		Youth illiteracy rate, female	%	S1.5.2
		Illiteracy rate, total	%	S1.6.1

Stakeholder	Subcategory	Indicator	Unit of measurement	Index
		Youth illiteracy rate, total	%	S1.6.2
	Health and safety	Health expenditure, Total	%	S2.1.1
		Health expenditure, Public	%	S2.1.2
		Health expenditure, Out of pocket	%	S2.1.3
		Health expenditure, External resources	%	S2.1.4
		Health expenditure out of the total GDP of the country	%	S3.1
		Life expectancy at birth	Years	S3.2
	Prevention and mitigation of conflicts	Risk of conflicts with regard to the sector	Text	S4.1
LOCAL COMMUNITY	Access to material resources	Level of industrial water use	Text	L1.1
		Level of industrial water use, out of total withdrawal	%	L1.1.1
		Level of industrial water use, out of total actual renewable	%	L1.1.2
		Extraction of material resources (other than industrial water)	Text	L1.2
		Extraction (total) of fossil fuels	t/cap	L1.2.1
		Extraction (total) of biomass	t/cap	L1.2.2
		Extraction (total) of ores	t/cap	L1.2.3
		Extraction (total) of biomass	t/km2	L1.2.4
		Extraction (total) of industrial & const. minerals	t/cap	L1.2.5
		Presence of certified environmental management systems	# of CEMS per 100000 employees	L1.3
		Description of (potential) material resource conflicts	Text	L1.4
	Respect of indigenous rights	Presence of indigenous population	Y/N	L2.1
		Human rights issues faced by indigenous people	text	L2.2
		(Company´s) respect of indigenous rights	Text	L2.3
		Pollution level of the country	Text	L3.1
		Contribution of the sector to environmental load	Text	L3.2

Stakeholder	Subcategory	Indicator	Unit of measurement	Index
	Safe and healthy living conditions	Drinking water coverage	%	L3.3
		Sanitation coverage	%	L3.4
		Management effort to improve environmental performance	Text	L3.5
	Local employment	Unemployment rate in the country	%	L4.1
		Work force hired locally	%	L4.2
		Percentage of spending on locally based suppliers	%	L4.3
	Migration	International migrant workers in the sector	%	L5.1
		International Migrant Stock	%	L5.2
		Net migration rate	Net migration per 1000 persons	L5.3
		Emigration rate	%	L5.4
		Immigration rate	%	L5.5
		Human rights issues faced by migrants	Text	L5.6
CONSUMERS	Health and Safety	Violations of mandatory health and safety standards	#	C1.1
		Presence of commissions/institutions to detect violations of standards and protect consumers	Y/N	C1.2
		Presence of management measures to assess consumer health and safety	Y/N	C1.3
	Transparency	Presence of business practices that are deceptive or unfair to consumers	#	C2.1
		Presence of certifications or labels for the product/sites sector	#	C2.2
		Presence of a law or norm regarding transparency (by country and/or sector)	Y/N	C2.3
	End of life responsibility	Strength of national legislation covering product disposal and recycling	Text	C3.1

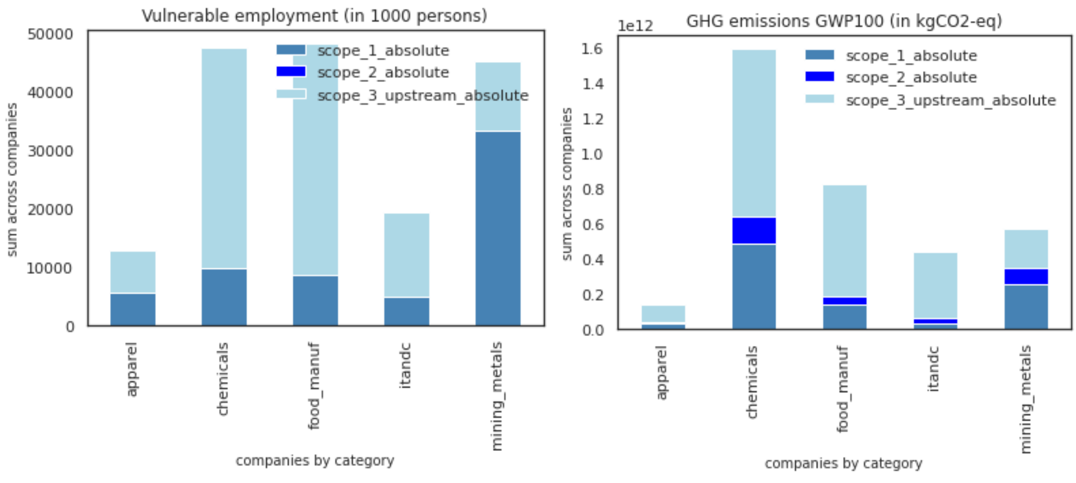


Figure D.1: Total vulnerable employment and GHG emissions, by sector in 2020

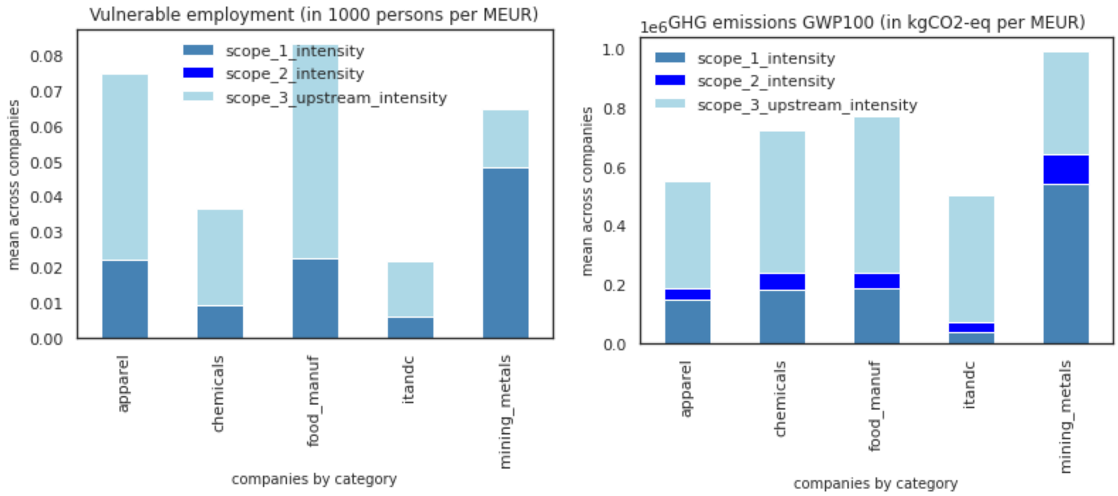


Figure D.2: Mean vulnerable employment and GHG emissions, expressed as intensity (per MEUR of revenue), by sector in 2020

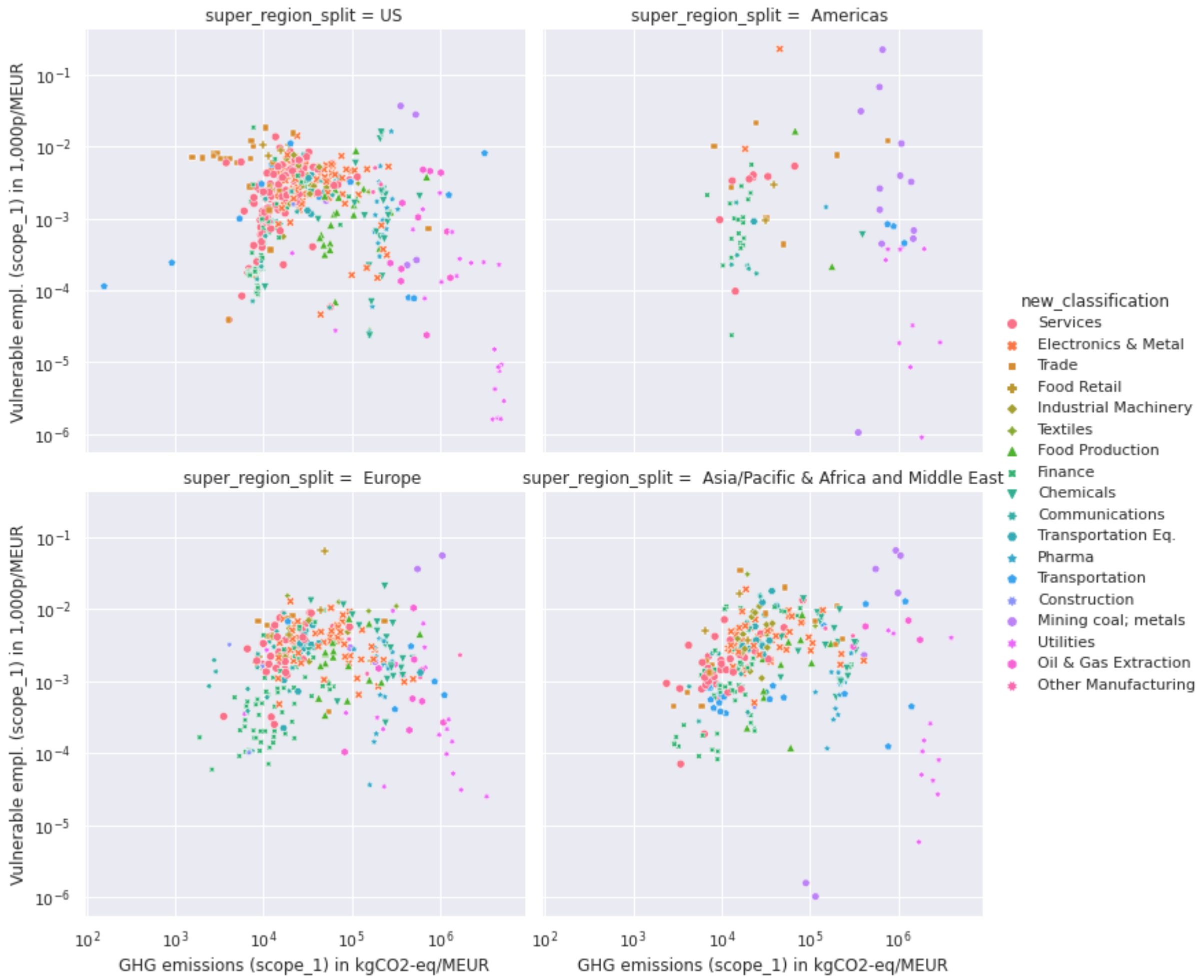


Figure D.3: Companies from the climate transition index, scope 1 intensity

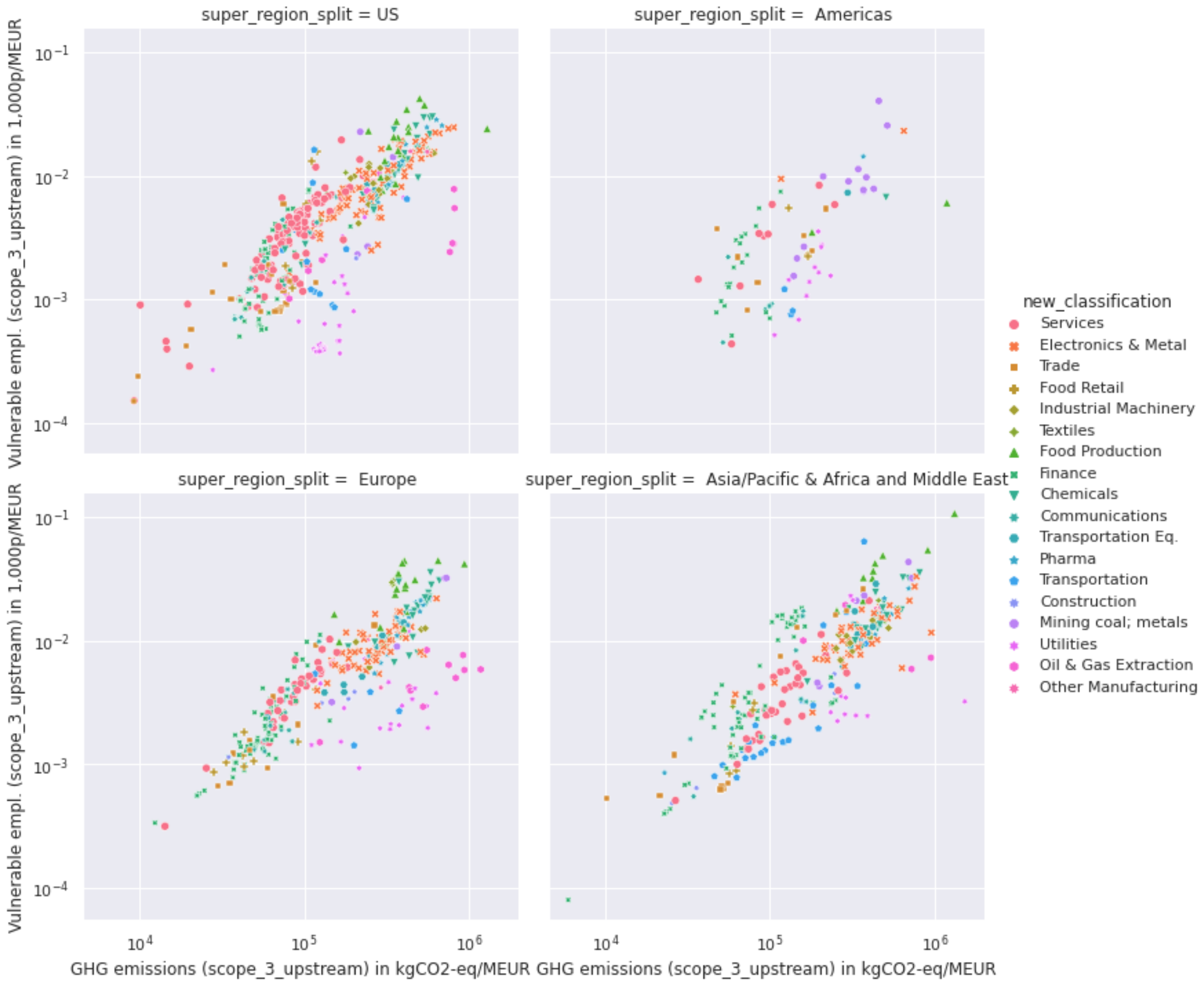


Figure D.4: Companies from the climate transition index, scope 3 upstream intensity

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List of conferences, presentations, and outreach activities

Presentations at academic conferences

- 9th September 2023 | poster preparation for the 11th International Conference on Life Cycle Management held in Lille, France, poster title: *"Streamlined sustainability reporting for corporations and financial institutions using life-cycle-based environmental and social indicators"*
- 14th July 2023 | poster presentation at the 5th Summer School on Sustainable Finance organized by European Commission's Joint Research Centre in Ispra, Italy, poster title *"Stock returns and sustainability beyond carbon: A quantitative approach to environmental and social indicators"*
- 14th December 2022 | presentation at the SESTEF conference, International Conference on Sustainability, Environment, and Social Transition in Economics and Finance held in Paris, presentation title *"Social dimension of green finance: Quantifying vulnerable employment in the value chain of listed companies"*
- 8th September 2022 | presentation at the International Conference on Social Life Cycle Assessment, held at the RWTH Aachen, Germany, presentation title *"Social sustainability of finance – Using input output analysis to shed light on listed companies' vulnerable employment in supply chains"*
- 13th June 2022 | presentation at the 1st Conference on International, Sustainable and Climate Finance and Growth held at the Università degli Studi di Napoli 'Parthenope', Italy, presentation title *"Are SRI funds financing climate change? An input-output life cycle assessment of investment funds"*
- 24th September 2021 | presentation at the CREDIT GRETA 2021 Conference on Compound Risk: Climate, Disaster, Finance, Pandemic, held in Venice and online, presentation title *"The Life Cycle Carbon Footprint of Financed Emissions: An Input-Output Based Model Adapted to Equity Portfolios and their Holdings"*
- 6th September 2021 | presentation at the 10th International Conference on Life Cycle Management held in Stuttgart and online, presentation title *"The reliability of input-output and lifecycle-based data for estimation of corporate carbon emissions: a comparative study of carbon footprints in the automotive sector"*
- 3rd September 2021 | presentation at the PhD seminar of the 4th Annual GRASFI Conference, Beijing, online, presentation title *"The Life Cycle Carbon Footprint of Financed Emissions: An Input-Output Based Model Adapted to Equity Portfolios and their Holdings"*

Presentations at industry conferences and other public outreach activities

- 18th October 2023 | Presentation at the *LuxFlag Sustainable Finance Week*, topic "Estimating environmental and social impacts of investments using life cycle assessment – green bonds and equity funds"
- 17th May 2023 | *Green Finance Konferenz*, workshop to present ongoing PhD research
- 24th November 2022 | panellist in the British Chamber of Commerce discussion on *Science Based Targets – Just another acronym on the race to net zero?*
- March 2022 | participation in the FNR Project *Chercheurs à l'école* (Researchers go back to school) project of the FNR
- February 2022 | *CarbonNerd* presentations to high school students about the carbon footprint of a Luxembourgish citizen (https://carbonnerd.list.lu/)
- 21st June 2021 | participation in workshop on sustainable finance at the Industrial Ecology Day Session on Green Investing.
- 5th June 2021 | Webinar for the public in Luxembourg *"So you think you are green? Focus on Spending"*, organised under the LIST project "Science to be green" (https://youtu.be/Tu3VRYkHRuw?si=_bItkQaQoaNDGkyV)

Memberships in working groups on sustainability and sustainable finance

- March – October 2023 | Member of the Working Group on Climate Measurement and Assessment initiated by the Luxembourg Sustainable Finance Initiative (LSFI). The outcome report summarizes the working group's analysis of the suitability of five key tools to support financial institutions on their journey to Net-zero emissions by 2050 (https://lsfi.lu/lsfi-wg-climate-measurement-reporting-working-group/).
- November 2021 – March 2023 | Member of the Sustainability Coordination and Expertise Group at the University of Luxembourg. Participation in monthly meetings to advise the Chief Sustainability Officer of the University of Luxembourg regarding the strategy on sustainability for the university.

Curriculum Vitae

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Birth date: 11th September 1995
Place of birth: Ploiesti, Romania
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Education

Mar 2020 – Mar 2024	PhD thesis at the Luxembourg Institute of Science and Technology (LIST), Environmental Research and Innovation (ERIN) department and at the University of Luxembourg, Doctoral Programme in Complex Systems Science
Sep 2018 – Jul 2019	Master's Double Degree, Program "Grande Ecole", International and European Management, EM Strasbourg | Final Case Study: "Crisis management and business performance: The Volkswagen emissions scandal"
Sep 2017 – Jul 2019	Master's in Financial Risk Management, Bucharest University of Economic Studies | Master Thesis: "The impact of ESG factors on company value: the case of Glencore"
Sep 2014 – Jul 2017	Bachelor of Economics in English, Bucharest University of Economic Studies, Faculty of Finance, Banking, Insurance and Stock Exchange | Bachelor Thesis: "Investment Decision under uncertainty: the case of a wind farm construction in Romania"

Experience

May 2019 – Oct 2019	Luxembourg Institute of Science and Technology (LIST) – Internship in Green Finance and Life Cycle Assessment, focused on green bonds
Jan 2018 – Aug 2018	Sustainalytics, Bucharest – ESG Analyst on Corporate Governance
Feb 2017 – Dec 2017	McKinsey & Co., Bucharest – Junior Accounting Consultant, part-time
Feb 2016 – Jul 2016	Ernst & Young Romania – Internship in Transaction Advisory Services – Valuation and Business Modeling